Biomimetic tactile sensor and spike train processing for surface roughness discrimination and active exploration

Yi, Zhengkun

2017

Yi, Z. (2017). Biomimetic tactile sensor and spike train processing for surface roughness discrimination and active exploration. Doctoral thesis, Nanyang Technological University, Singapore.

<http://hdl.handle.net/10356/72727>

<https://doi.org/10.32657/10356/72727>

**NANYANG
TECHNOLOGICAL
UNIVERSITY**

SINGAPORE

**Biomimetic Tactile Sensor and Spike Train
Processing for Surface Roughness Discrimination
and Active Exploration**

YI ZHENGKUN

SCHOOL OF MECHANICAL AND AEROSPACE ENGINEERING

2017

Biomimetic Tactile Sensor and Spike Train Processing for Surface Roughness Discrimination and Active Exploration

YI ZHENGKUN

SCHOOL OF MECHANICAL AND AEROSPACE ENGINEERING

A thesis submitted to the Nanyang Technological
University in partial fulfilment of the requirement for the
degree of
Doctor of Philosophy

2017

ACKNOWLEDGEMENT

I would like to thank my supervisors Prof. Yilei Zhang and Prof. Jan Peters for their guidance and support during the four years of my PhD. I have learnt a lot from them including how to do research, manuscript writing, etc.

I am grateful to Fraunhofer Singapore for providing the scholarship, to Prof. Alexei Sourin for coordinating the joint PhD programme and arranging the one-year attachment to Technische Universitaet Darmstadt.

Many thanks go to my group members Qinwei Xu, Cheng Li, Shreyas Kuddannaya, Liew Wen Loogn Andy, and Huynh Phuoc Tho for helping with my project. It was a great experience at Intelligent Autonomous Systems lab during the third year of my PhD. I would like to thank Prof. Tucker Hermans and Dr. Elmar Rueckert for leading the TACMAN project and supervising me. I appreciate the help from Herke van Hoof, Roberto Calandra, Filipe Veiga, Daniel Tanneberg, and Marco Ewerton.

I am grateful to the technical and administrative staff in both Nanyang Technological University and Technische Universitaet Darmstadt for their kindness and support for my project.

Last but certainly not least. I would like to give my thanks to my parents and brothers for their love and always being there when I need support.

.

Table of Contents

ACKNOWLEDGEMENT.....	I
Table of Contents	II
Table of Figures	VII
Publications	XV
Abstract	XVII
Chapter 1. Introduction	- 1 -
1.1 Motivation	- 1 -
1.2 Contributions.....	- 4 -
1.3 Outline.....	- 5 -
Chapter 2. Biomimetic Tactile Sensing and Exploration: A Survey	- 7 -
2.1 Abstract	- 7 -
2.2 Introduction	- 7 -
2.3 The Human Sense of Touch	- 9 -
2.3.1 Human Mechanoreceptors	- 10 -
2.3.2 Fingerprint.....	- 12 -
2.3.3 Human Tactile Sensing in Stimulus Perception	- 13 -
2.4 Robotic Tactile Sensing and Exploration	- 16 -

2.4.1	Working Mechanisms of Tactile Sensors	- 17 -
2.4.2	Artificial Tactile Sensors to Mimic Mechanoreceptors.....	- 22 -
2.4.3	Fingerprint-like Structure.....	- 26 -
2.4.4	Biomimetic Tactile Stimulus Perception with Spikes	- 28 -
Chapter 3.	Bioinspired Tactile FA-I Spiking Generation Under Sinusoidal Stimuli-	34 -
3.1	Abstract	- 34 -
3.2	Introduction.....	- 35 -
3.3	Methods.....	- 37 -
3.3.1	Piezoelectric PVDF Film Sensors.....	- 37 -
3.3.2	Experiment	- 38 -
3.3.3	Spiking Neuron Model.....	- 40 -
3.3.4	Parameter fitting.....	- 41 -
3.4	Results and Discussion.....	- 43 -
3.4.1	Parameter Fitting Results	- 43 -
3.4.2	Model Validation.....	- 45 -
3.4.3	Variability of Spike Trains	- 46 -
3.4.4	Frequency-dependent parameter fitting	- 47 -
3.4.5	Population Activity	- 48 -
3.5	Conclusion	- 52 -

Chapter 4.	Bioinspired Tactile Sensor for Surface Roughness Discrimination	53 -
4.1	Abstract	53 -
4.2	Introduction.....	54 -
4.3	Design and Fabrication of An Artificial Fingertip	58 -
4.3.1	Piezoelectric PVDF film Sensors.....	58 -
4.3.2	Structure of An Artificial Fingertip.....	59 -
4.3.3	Protocol of Fabricating An Artificial Fingertip	60 -
4.4	Tactile Signal Processing of Surface Roughness Discrimination	61 -
4.4.1	Feature Extraction	62 -
4.4.2	Classification Algorithms.....	64 -
4.5	Experimental Setup and Protocol.....	65 -
4.6	Results and Discussion.....	68 -
4.7	Conclusion	73 -
Chapter 5.	Recognizing Tactile Surface Roughness with A Biomimetic Fingertip: A Soft Neuromorphic Approach	75 -
5.1	Abstract	75 -
5.2	Introduction.....	76 -
5.3	Related work	78 -
5.3.1	Neurophysiology of Roughness Perception	78 -

5.3.2	Surface Roughness Classification Using Artificial Tactile Sensor.....	- 79 -
5.4	Contribution	- 80 -
5.5	Materials and Methods	- 81 -
5.5.1	Biomimetic Fingertip	- 81 -
5.5.2	Spiking Neuron Models	- 82 -
5.5.3	Spike Train Decoding Schemes	- 84 -
5.5.4	Experimental Setup and Protocol.....	- 88 -
5.6	Result and Discussion	- 91 -
5.7	Conclusion	- 97 -
Chapter 6.	Active Tactile Object Exploration with Gaussian Processes.....	- 99 -
6.1	Abstract	- 99 -
6.2	Introduction	- 99 -
6.3	Related work	- 101 -
6.4	Active Tactile Object Modeling and Exploration.....	- 103 -
6.4.1	Point Cloud Registration with Tactile Sensing.....	- 104 -
6.4.2	Gaussian Processes as Surface Models	- 105 -
6.4.3	Action Selection	- 106 -
6.5	Experiments and Results	- 107 -
6.5.1	Proof of Concept: A Toy Example	- 108 -

6.5.2	Tactile Object Surface Modeling.....	- 111 -
6.6	Conclusions.....	- 117 -
Chapter 7.	Conclusion and Future Work.....	- 118 -
7.1	Conclusion	- 118 -
7.2	Future Work	- 119 -
References		- 121 -

Table of Figures

Figure 1-1 The framework of tactile sensing and exploration.	4 -
Figure 1-2 The Outline of the thesis. Chapter 2 reviews the domain of biomimetic tactile sensing and exploration. Chapter 3 presents a bioinspired FA-I mechanoreceptor. Chapter 4 and Chapter 5 focus on tactile surface roughness recognition. Chapter 6 describes an active strategy for tactile surface reconstruction. Chapter 7 concludes the thesis and describes the future work.	5 -
Figure 2-1 (a) Mechanosensory information transmitted from the fingertip to the brain [22]. (b) A biomimetic sensing system to mimic the human sense of touch including a biomimetic finger with fingerprint-like structure, analog-to-spike transformation, and processing and interpretation of spike trains.	9 -
Figure 2-2 Human mechanoreceptors. (a) A cross section of the glabrous skin. (b) The receptive field of each type of mechanoreceptors [11]. (c) The Spike trains of each type of mechanoreceptors in response to a specific stimulus [11]. (d) The density of each type of mechanoreceptors [23].	10 -
Figure 2-3 Artificial tactile sensors to mimic the properties of mechanoreceptors. (a) A sensor density of 72 units/cm ² is achieved by aid of MEMS techniques, which mimics the density of SA-I mechanoreceptors [94]. (b) The action potential generation of FA mechanoreceptors is emulated by the single-layer graphene [95]. (3) A 6×4 capacitive sensor array mimics the spatial event plot of tactile SA-I afferent in response to the scanned Braille character J [96].	22 -
Figure 2-4 Human fingerprint and the fingerprint-like structures. (a) Scanning electron	

micrograph of the human fingerprint [11]. (b) A biomimetic tactile sensor (BioTac) with fingerprint-like ridges [109]. (c) The square wave grating on the PDMS cap enhances the perception of fine textured surface [27]. (d). The ridged skin enhances the slip detection capability of the force sensing resistor [110].	- 26 -
Figure 2-5 (a) The structure of neuron and synapse [11]. (b) Classification of two different patterns based on the tempotron [137]. (c) The unsupervised learning STDP observed in hippocampal glutamatergic synapses [139].	- 31 -
Figure 3-1 Experimental setup for acquisition of analog signals from PVDF film embedded in PDMS.	- 39 -
Figure 3-2 Iterative optimization process for average ISI based on response surface methods (the predicted average ISIs are almost the same after 1 & 2 iterations).	- 44 -
Figure 3-3 Observed (red) and predicted (blue) spike trains evoked by six stimuli (black), i.e., three 20 Hz sinusoid stimuli (top) with amplitudes of 34 μm (left), 48 μm (middle), 67 μm (right), and three 30 Hz sinusoid stimuli (bottom) with the same amplitudes for FA-I afferent.	- 44 -
Figure 3-4 Average ISI improvement based on frequency dependent parameter fitting.-	47
-	
Figure 3-5 First spike latency improvement based on frequency dependent parameter fitting.....	- 48 -
Figure 3-6 Tukey simultaneous 95% confidence intervals of the differences of means for the observed average ISI from a pair of mechanoreceptors in response to the stimulus type II: 20 Hz of amplitude 48 μm	- 50 -

Figure 3-7 Number of FA-I mechanoreceptor pairs with significant difference of means for the observed average ISI and FSL in response to the same stimulus type.	51
Figure 3-8 The observed (red) and predicted (blue) spike trains for five FA-I mechanoreceptors in response to a 20 Hz sinusoid stimulus (top) with amplitudes of 34 μm (left), 48 μm (middle), 67 μm (right), and a 30 Hz sinusoid stimulus (bottom) with the same amplitudes. Each alternating shaded and unshaded patch corresponds to the responses of a particular FA-I mechanoreceptor.	51
Figure 4-1 Surface roughness discrimination approach with a bioinspired artificial fingertip. The approach consists of (a) hardware to acquire the tactile data and (b) tactile signal processing for surface roughness discrimination.....	57
Figure 4-2 Structures of (a) the designed artificial fingertip, (b) a developed artificial fingertip, (c) structure of human fingertip, and (d) artificial vs. human fingertip. The structures of both human and artificial fingertips contain two layers with different hardness, and a bone.	59
Figure 4-3 The protocol of fabricating an artificial fingertip. (a) Components for fabricating an artificial fingertip. (b) A soft cured PDMS was bonded to the tip of a PMMA bar. (c) Two PVDF film sensors were arranged perpendicularly on the top of the PDMS cube. (d) The bar was inserted a mold of size resembles human fingertips; then PDMS mixed at a 10:1 mixing ratio was cast into it.	61
Figure 4-4 Standard deviation features extracted from tactile signals of two PVDF films when laterally sliding on eight test surfaces with various roughness values.	63
Figure 4-5 Eight solid nickel test surfaces with roughness values R_a of 50 μm , 25 μm ,	

12.5 μm , 6.3 μm 3.2 μm , 1.6 μm , 0.8 μm , and 0.4 μm were explored. The lateral sliding direction of the artificial fingertip along the test surface during the conducted experiments is indicated by an arrow.	- 67 -
Figure 4-6 Typical tactile signals generated by two PVDF films when laterally sliding on eight test surfaces with various roughness values.	- 68 -
Figure 4-7 Classification accuracy of each feature and classification algorithm with (a) only PVDF film 1, (b) only PVDF film 2, and (c) both PVDF film 1 and PVDF film 2. Error bars represent the standard error.	- 72 -
Figure 4-8 Confusion matrix of the best classification results of classification algorithms (a) the SVM classifier with RBF kernel, SD feature and PVDF film 1, and (b) the kNN classifier with $k = 9$, SD feature and PVDF film 1. The horizontal axis (S1-S8) denotes the ground truth, and the vertical axis represents the classifier output. The far right column presents the classification accuracy for each surface class.	- 73 -
Figure 5-1 Soft neuromorphic method for tactile surface discrimination using a biomimetic fingertip. The analog signals generated by tactile sensors are converted into spikes via spike neuron models. The spike train decoding schemes are based on k-nearest neighbors (kNN) in both spike feature space and spike train space.	- 78 -
Figure 5-2 (a) Biomimetic artificial fingertip, and (b) biomimetic vs. human fingertip. The structures of both human and biomimetic fingertips contain two layers with different hardness, and a bone.	- 81 -
Figure 5-3 Spike train distance based k-nearest neighbors (STD-kNN) algorithm.	- 88 -
Figure 5-4 (a) Eight solid nickel standard surfaces with roughness values R_a of 50 μm , 25	

μm , 12.5 μm , 6.3 μm , 3.2 μm , 1.6 μm , 0.8 μm , and 0.4 μm are explored. The lateral sliding direction of the artificial fingertip along the test surface during the conducted experiments is indicated by an arrow. (b) The locations of PVDF film sensors are indicated.

..... - 90 -

Figure 5-5 Typical tactile signals (top) generated by two PVDF films when laterally sliding on eight test surfaces with various roughness values, and the corresponding spike trains transformed via the Izhikevich model with electrical conductance $G = 0.4 \Omega - 1$ (bottom)..... - 90 -

Figure 5-6 Firing rates of two PVDF film sensors when laterally sliding on eight test surfaces with various roughness values (a) Firing rate, (b) Inverse of average interspike interval. - 92 -

Figure 5-7 Different spike train distances between every spike train pair across eight test surfaces for both PVDF film1 (top) and PVDF film 2 (bottom)..... - 93 -

Figure 5-8 The classification accuracy of each decoding scheme is compared for both PVDF film 1 (top) and PVDF film 2 (bottom). The upper bound (red dash line) is the best classification result based on the analog signal without any analog-to-spike transformation in our previous work [4]..... - 95 -

Figure 5-9 Confusion matrix of the best classification result of the decoding schemes with kNN ($k = 11$) classifier and the Victor-Purpura distance ($q = 0.024 \text{ ms} - 1$). The horizontal axis (S1-S8) denotes the ground truth, and the vertical axis represents the classifier output. The far right column presents the classification accuracy for each surface class..... - 96 -

Figure 5-10 Evaluation of classification accuracy of STD-kNN (the Victor-Purpura distance and $k = 11$) with respect to the spike timing-sensitive parameter q for PVDF film 1 (left). Evaluation of classification accuracy of STD-kNN (the van Rossum distance and $k = 11$) with respect to the time constant τ for PVDF film 1 (right). - 97 -

Figure 5-11 Evaluation of classification accuracy of STD-kNN (the Victor-Purpura distance and the van Rossum distance) with respect to the electrical conductance G . (a) PVDF film 1, (b) PVDF film 2. - 97 -

Figure 6-1 A BioTac finger mounted on a Mitsubishi PA-10 robot arm equipped with a Schunk force torque sensor. The steel container is fixed to a vertical surface in order to ensure the surface data alignment during each touch. Its front surface is to be reconstructed. The red coordinate frame denotes the axis direction of the world reference frame that is located at the base of the robot. - 101 -

Figure 6-2 Example objects (left) and registered tactile point clouds (right) of the front surface of a steel container and the face of a porcelain bird. The rectangular zones are to be reconstructed. The point cloud of the porcelain bird with side view and the point cloud of the front surface of the steel container with top view. Tactile point clouds are obtained with a BioTac tactile sensor. - 105 -

Figure 6-3 A toy example of the active exploration process for reconstructing an unknown 1-D surface (green curve). The 95% confidence of the model prediction is represented by the shaded area. The red (left) and blue area (right) represent optimization based on random touch, and on active touch respectively. The surface model is initialized with 3 random points (blue crosses). The subsequent points to explore are marked with red

crosses. At each iteration, the model is updated using all the obtained points (both blue and red crosses). After a few iterations, the active touch method is able to reconstruct the unknown 1-D curve more accurately. - 110 -

Figure 6-4 The correlation coefficient over 50 evaluations for both the random and active touch. Both methods are initialized with 3 random touches. The shaded areas represent the standard error. The correlation coefficient between the real function and reconstructed function almost reaches 1 after 23 touches with the active touch approach. - 111 -

Figure 6-5 Evolution of the steel container model as function of the number of touches. The optimization is initialized with 5 random touches (blue points). The subsequent points to explore are marked with red points. The top row represents the model build from random samples. The bottom row shows results for the active touch method. The columns from left to right represent the models after (a) 5, (b) 10, and (c) 15 additional touches. (d) The real object for comparison. Each predicted surface is the mean of the GP computer over the test set. The active touch method more accurately reconstructs the object surface for a given number of samples compared to the random touch approach..... - 115 -

Figure 6-6 An example of the active touch method for determining a new touch location. The acquisition function is high where the Gaussian process predicts a high uncertainty (left). The position with the maximum acquisition function value defines the next touch location (right). - 116 -

Figure 6-7 (a) The porcelain bird models for both the random and active touch approaches with 20 randomly selected initial touches (blue points) and 100 additional touches (red points). (b) The real object for comparison. The predicted surfaces are the means of GPs

over the test set. After 100 touches, the active method could model the bird face more accurately, particularly at the edge of the explored zone. - 116 -

Publications

Journal Articles:

- (1) Zhengkun Yi, Yilei Zhang. Bioinspired Tactile FA-I Spiking Generation under Sinusoidal Stimuli. *J. Bionic Eng.*, vol. 13, no. 4, pp. 612–621, Oct. 2016.
- (2) Zhengkun Yi, Yilei Zhang, Jan Peters. Bioinspired Tactile Sensor for Surface Roughness Discrimination. *Sensors Actuators A Phys.*, vol. 255, pp. 46–53, Mar. 2017.
- (3) Zhengkun Yi, Yilei Zhang. Recognizing Tactile Surface Roughness with A Biomimetic Fingertip: A Soft Neuromorphic Approach. *Neurocomputing*, vol. 244, pp. 102-111, Jun. 2017.
- (4) Longhui Qin, Zhengkun Yi, Yilei Zhang, Enhanced Surface Roughness Discrimination with Optimized Features from Bio-inspired Tactile Sensor. *Sensors Actuators A Phys.*, vol 264, pp. 133-140, Sept. 2017.
- (5) Zhengkun Yi, Yilei Zhang, Jan Peters. Biomimetic Tactile Sensors and Signal Processing with Spike Trains: A Review. *Sensors Actuators A Phys.*, (accepted).
- (6) Zhengkun Yi, Yilei Zhang. A Spike Train Distance Based Method to Evaluate the Response of Mechanoreceptive Afferents (submitted).
- (7) Qianzhu Liang, Zhengkun Yi, Qingqing Hu, Yilei Zhang. Sensor Fusion for Surface Roughness Discrimination with Optical and Piezoelectric Sensors (submitted).
- (8) Longhui Qin, Zhengkun Yi, Yilei Zhang, Unsupervised Surface Roughness

Discrimination Based on Bio-inspired Artificial Fingertip (submitted).

Conference Paper:

- (1) Zhengkun Yi, Roberto Calandra, Filipe Veiga, Herke van Hoof, Tucker Hermans, Yilei Zhang, Jan Peters. Active Tactile Object Exploration with Gaussian Processes. IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) 2016; pp 4925-4930.

Abstract

The sense of touch plays a critical role in enabling human beings to interact with the surrounding environments. As robots move from laboratories to domestic environments, they are expected to be endowed with a similar tactile ability to perform complicated tasks such as manipulating objects with arbitrary unknown shapes. This thesis investigates the approaches to improve the tactile capabilities of future robotic systems in two aspects, i.e., biomimetic tactile sensing for surface roughness discrimination and active tactile exploration for object shape reconstruction.

Surface texture discrimination using artificial tactile sensors has attracted increasing attentions in the past decade. However, as a major component of texture, surface roughness has rarely been explored. We present two signal processing methods for tactile surface roughness discrimination based on a biomimetic fingertip. One method focuses on classical machine learning algorithms. Specifically, various extracted features and classification algorithms including support vector machines (SVM) and k -nearest neighbors (k NN) are examined. The other method is based on spike-like signal analysis. The analog tactile signals generated from polyvinylidene difluoride (PVDF) films are fed as input to the Izhikevich neurons in order to obtain spike trains. Two distinct decoding schemes based on k -nearest neighbors (k NN) in both spike feature space and spike train space are used for surface roughness discrimination. We thoroughly examine the different spike train distance based k NN (STD- k NN) algorithms for decoding spike trains. Eight standard rough surfaces with different surface roughness are explored. We find that the highest classification accuracy of $(82.6 \pm 10.8) \%$ can be achieved using solely one PVDF

film sensor with k NN ($k = 9$) classifier and the standard deviation feature. For the soft neuromorphic approach, the highest classification accuracy of $(77.6 \pm 13.7) \%$ can be achieved with k NN ($k = 11$) classifier and the Victor-Purpura distance ($q = 0.024 \text{ ms}^{-1}$)).

In the tactile exploration task, we present an active touch strategy to efficiently reduce the surface geometry uncertainty by leveraging a probabilistic representation of object surface. In particular, we model the object surface using a Gaussian process and use the associated uncertainty information to efficiently determine the next point to explore. We validate the resulting method for tactile object surface modeling using a real robot to reconstruct multiple, complex object surfaces.

Chapter 1. Introduction

Among various human sensations like sight, hearing, taste and smell, touch is also a critical co-existing sensation required to interact with the surrounding environments. The sense of touch plays a significantly important role in our daily activities, and enables us to discriminate between various surface textures, recognize and manipulate objects, etc., all of which have a collection of applications in robotics, minimal invasive surgery, advanced prosthetics and manufacturing industries. The sensory receptors, namely mechanoreceptors, make dexterous manipulation possible by responding to the mechanical stimuli in the form of action potentials.

1.1 Motivation

As robots move from labs to domestic environments, they will be required to work in unstructured environments. For the purpose of operating in such environments, the robots must be able to dexterously manipulate objects. They are expected to perform complex tasks such as distinguishing between different textures, grasping objects of different shapes and sizes and avoiding slip while applying minimal force to the grasped object. Therefore, tactile sensors are urgently introduced in the robot hand in order to achieve the similar functionality as human mechanoreceptors.

Many types of tactile sensors based on various transduction techniques are currently developed. Unfortunately, most of them are not directly applicable to robot hands, due to the limitations like fragility and bulk. Thus, there is a need to develop tactile sensors

specifically tailored for the needs of robot hands. On the other hand, currently, some commercially available robotic hands are equipped with advanced tactile sensors, and their precision such as force and torque sensitivity is much higher than humans. However, robots are still far away from being capable of human-level manipulation skills such as unscrewing bulb and handing over a knife. From the perspective of neuroscience, tactile signals from human mechanoreceptors could be made more substantial use of during tactile exploration, while robots are always clumsy and fail to comprehend signals from artificial tactile sensors. Therefore, there is a need to fill this performance gap. Innovations in machine learning community could help robots be capable of dexterous manipulation. Machine learning algorithms seek to learn a mapping from the tactile sensor measurements to a high-level perception such as slip detection, detection of material properties (shape, stiffness, roughness, etc.), and even grasp stability characterization. Research on statistical machine learning provides a huge number of off-the-shelf algorithms for signal interpretation and data mining. However, many algorithms, especially for high dimensional data, are time-consuming, which are not suitable for real-time robot manipulation. Therefore, there is also a need to adapt existing online statistical machine learning algorithms or developing customized ones for robotic applications.

Another motivation of this project originates from prosthetics, specifically, how tactile signals are processed in human skin. In an able-bodied human, tactile stimuli like force and vibration can be detected by the mechanoreceptors embedded in the skin, and will be conveyed to the afferent targets of these receptors in the brain or spinal cord [1].

The spikes produced in mechanoreceptive afferents are almost discrete. However, the outputs of artificial tactile sensors are quite different in a sensorized neural prosthesis, and the produced signals are usually continuous analog. Unfortunately, most of them are not directly applicable to deliver spike-like signals to tactile afferents. Therefore, there is a need to modify the outputs of artificial tactile sensors by discretizing continuous analog signals.

Figure 1-1 provides the framework of tactile sensing and exploration. The artificial tactile sensor or tactile sensor array is the corner-stone of the tactile sensing system. Analog and continuous tactile signals, which are further processed for high-level recognition like object properties detection, will be generated during the interaction between tactile sensor and the surrounding environment. The amount of tactile data from artificial tactile sensors is always incredibly huge. It is impossible to analyze the data directly using machine learning tools due to the curse of dimensionality. Two general approaches, namely, feature extraction and feature selection are essential pre-processing steps to pattern recognition and machine learning problems for dimensionality reduction. In order to emulate the mechanism of how human brain processes the neural signals or to produce the appropriate signals which are applicable to deliver to tactile afferents, an alternative to the traditional way of direct refining the continuous signals is to transform the analog and continuous signals into spike series using neural spiking models. Machine learning algorithms will provide the capability of high-level recognition by learning from the extracted feature or spike series. Based on the perception step, the action will be performed to better interact with the environments.

Figure 1-1 The framework of tactile sensing and exploration.

1.2 Contributions

This thesis contributes to the domain of biomimetic tactile sensing and exploration.

Specifically, the major contributions are in the following.

- (1) In comparison with previous work on mimicking the spiking activities of slowly adapting type I mechanoreceptors, we provide an approach to mimic the spiking activities of fast adapting type I mechanoreceptors with PVDF film.
- (2) We design and fabricate a biomimetic fingertip that inspired by the human fingertips. This platform might provide new insights into the neurophysiological study.
- (3) Previous works mainly focus on surface texture classification using artificial sensors. As a major component of surface texture, surface roughness has less been explored. In this thesis, we provide two signal processing methods for tactile surface roughness discrimination. One method focuses on various extracted tactile features together with statistical machine learning algorithm including both support vector machines and k -nearest neighbors. The other method is based on

spike-like signal analysis with spiking neuron models and various spike train distances.

- (4) Unlike previous work on object shape reconstruction by touching in a grid manner or touching predefined points, we present an active touch strategy to efficiently reduce the geometry uncertainty by leveraging a probabilistic representation of object surfaces.

1.3 Outline

Figure 1-2 The Outline of the thesis. Chapter 2 reviews the domain of biomimetic tactile sensing and exploration. Chapter 3 presents a bioinspired FA-I mechanoreceptor. Chapter 4 and Chapter 5 focus on tactile surface roughness recognition. Chapter 6 describes an active strategy for tactile surface reconstruction. Chapter 7 concludes the thesis and

describes the future work.

Figure 1-2 illustrates the outline of this thesis. Chapter 2 provides a review of biomimetic tactile sensing and exploration. This chapter begins with the review of human sense of touch, which serves as a reference point in the case of biomimetic tactile sensing and exploration. Then, it focuses on the review of biomimetic technologies to mimic the tactile abilities of human beings. This chapter is based on [2]

Chapter 3 describes an approach to mimic the tactile FA-I spiking generation using a bioinspired tactile sensor under sinusoidal stimuli. This chapter is based on [3].

Chapter 4 presents a method to design and fabricate a biomimetic fingertip as well as tactile surface roughness discrimination with statistical machine learning algorithms. This chapter is based on [4].

Chapter 5 presents a soft neuromorphic approach to recognize surface roughness based on spike-like signals. The analog-to-spike conversion is achieved with spiking neuron models. This chapter is based on [5].

Chapter 6 describes an active touch strategy to reconstruct object surfaces. The approach which leverages a probabilistic representation of the object surface is evaluated with a toy example and a real robot. The chapter is based on [6].

Chapter 7 concludes the thesis and has an outlook on future work.

Chapter 2. Biomimetic Tactile Sensing and Exploration: A Survey

2.1 Abstract

The sense of touch plays a critical role in enabling human beings to interact with the surrounding environments. As robots move from laboratories to domestic environments, they are expected to be endowed with a similar tactile ability to perform complicated tasks such as manipulating objects with arbitrary unknown shapes. In the past decade, tremendous effort and progress have been made to mimic the sense of touch in human beings on robotic systems. In this chapter, we firstly review human sense of touch as it serves as a reference point in the case of biomimetic tactile sensing and exploration. Then, we focus on biomimetic tactile sensing and exploration technologies.

2.2 Introduction

Among various human sensations like sight, hearing, taste and smell, touch is a critical co-existing sensation required to interact with the surrounding environments [7]. The exquisite sensitivity provided by the sense of touch enables us to discriminate various surface textures, precisely grasp and manipulate objects, etc. Unlike the other senses based on discrete sensory organs, the sense of touch arises from receptors distributed throughout the entire body [8]. The modality of touch can be divided into three categories: cutaneous (tactile), kinesthetic and haptic [9]. The cutaneous and kinesthetic systems differ in terms of the location of mechanoreceptors in response to the sensory inputs. The former rely on

the receptors embedded in the skin, while the latter functions due to the receptors within joints, muscles, and tendons. The haptic system uses the combined sensory inputs from both the cutaneous and kinesthetic systems [10]. For an able-bodied human, stimuli like force and vibration can be detected by the mechanoreceptors in response to generate spike trains, which will be conveyed to the central nervous system (CNS) for higher level perception [1]. There are two major pathways to enable the sensory information to reach the central nervous system, which encompass the dorsal column-medial lemniscal pathway and the spinothalamic pathway. The dorsal column-medial lemniscal pathway mainly focuses on transmitting the tactile and proprioceptive information, while the spinothalamic pathway is mainly concerned with conveying noxious, visceral, and thermal information [11].

The sense of touch also plays a significant role in many applications in robotics [12], [13], minimal invasive surgery [7], [14]–[16], advanced prosthetics [17], [18] and manufacturing industries [19]. For instance, as robots move from laboratories to domestic environments, they will be required to perform manipulation tasks in unstructured environments. Such robots must be able to achieve sophisticated interactions with the environment and to perform complex tasks such as grasping objects with arbitrary unknown shapes [20], and avoiding slip while applying minimal force to the grasped objects [21]. In these settings, the ability of tactile sensing becomes a particularly valuable and desirable. During the past decade, tremendous efforts and progress have been made by the industry and academia to mimic the sense of touch in humans. Figure 2-1 depicts the organization of the somatic sensory system in human beings and the biomimetic sensing

system to reproduce the human sense of touch.

Figure 2-1 (a) Mechanosensory information transmitted from the fingertip to the brain [22].

(b) A biomimetic sensing system to mimic the human sense of touch including a biomimetic finger with fingerprint-like structure, analog-to-spike transformation, and processing and interpretation of spike trains.

2.3 The Human Sense of Touch

In the section, we review human sense of touch as it serves as a reference point in the case of biomimetic tactile sensing. The section begins with a brief review of the characteristics of human mechanoreceptors, which is followed by a focus on fingerprint structure and its role in enhancing tactile perception. Finally, the neurophysiology of tactile stimulus perception is presented.

2.3.1 Human Mechanoreceptors

Figure 2-2 Human mechanoreceptors. (a) A cross section of the glabrous skin. (b) The receptive field of each type of mechanoreceptors [11]. (c) The Spike trains of each type of mechanoreceptors in response to a specific stimulus [11]. (d) The density of each type of mechanoreceptors [23].

Thanks to the microneurography technology in the late 1960's [24], the tactile afferents have been intensely investigated. There are four main types of mechanoreceptors embedded in the human skin throughout the body [14], and each is responsible for the reception of specific stimuli; these four include Pacinian corpuscles, Meissner's corpuscles, Merkel discs, and Ruffini cylinders, all of which can be divided into two categories, namely, slowly adapting (SA) mechanoreceptors and fast adapting (FA) mechanoreceptors [25]. The slowly adapting mechanoreceptors including Merkel discs (SA-I mechanoreceptors) and Ruffini cylinders (SA-II mechanoreceptors) respond to low frequency stimuli, and they describe the static properties of a stimulus. In contrast, high

frequency stimuli make the fast adapting mechanoreceptors, i.e., Meissner's corpuscles (FA-I mechanoreceptors) and Pacinian corpuscles (FA-II mechanoreceptors) fire in response. The border distinctness and the size of the receptive field differentiate SA-I mechanoreceptors from SA-II mechanoreceptors, and FA-I mechanoreceptors from FA-II mechanoreceptors. In other words, the receptive fields of SA-I mechanoreceptors and FA-I mechanoreceptors have more distinct borders and smaller sizes than those of SA-II mechanoreceptors and FA-II mechanoreceptors. Figure 2-2 illustrates human mechanoreceptors and Table 2-1 summarizes the characteristics of each mechanoreceptor [26].

Pacinian corpuscles: Pacinian corpuscles are nerve endings responsible for sensitivity to deep-pressure touch and high-frequency vibration. They are located beneath the bottom layer of skin, called the dermis which is subcutaneous fat. They are considered fast adaptive receptors. The Pacinian corpuscles are oval shaped and are approximately 1 mm in length and 0.6 mm in diameter.

Meissner's corpuscles: Meissner's corpuscles are responsible for sensitivity to light touch. They are located in the top layer of skin, called the epidermis. Similar to Pacinian corpuscles, they are fast adaptive receptors. Meissner's corpuscles are between 80 and 150 μm in length and between 20 and 40 μm in diameter.

Merkel discs: Merkel discs provide information regarding pressure, vibration, and texture. They are the most sensitive of the four mechanoreceptors to vibrations at low frequencies, at around 15 Hz. They are located in epidermis. In contrast to the two previous receptors, they are slowly adaptive receptors. This means they have sustained response to stimulation

since they are not encapsulated, as are the two previous ones.

Ruffini cylinders: Ruffini cylinders are sensitive to lateral skin stretch and contribute to the kinesthetic sense and control of finger position and movement. They register mechanical deformation within joints, more specifically angle change, with a specificity of up to 2 degrees, as well as continuous pressure states. They are also believed to be useful for monitoring slippage of objects along the surface of the skin, allowing modulation of grip on an object. Ruffini cylinders are located in the dermis layer.

Table 2-1 Characteristics of human mechanoreceptors

Mechanoreceptors	Field diameter (mm)	Frequency range (Hz)	Detected parameters
Merkel disks (SA-I)	3-4	DC-30	Local skin curvature
Ruffini endings (SA-II)	>10	DC-15	Directional skin stretch
Meissner's corpuscles (FA-I)	3-4	10-60	Skin stretch
Pacinian corpuscles (FA-II)	>20	50-1000	Unlocalized vibration

2.3.2 Fingerprint

The fingerprints are unique to each person, which make them suitable for identity authentication. A fingerprint is a regular array of the papillary ridges, which is bordered by the limiting ridges [11]. The study of Scheibert et al.[27], [28] demonstrated that the papillary ridges play a crucial role in enhancing the sense of touch, in particular, the coding of fine textures. This report has led many researchers in other areas such as prosthetics and robotics to develop fingerprint-like structures to improve the tactile sensitivity. Cauna [29] asserted that SA-I adapting mechanoreceptors account for the

encoding of edge discontinuities. However, the belief was strong refuted by Gerling and Thomas [30], where they postulated that the papillary ridges may not directly influence the response of SA-I adapting mechanoreceptors. In addition to the papillary ridges, limiting ridges and intermediate ridges may play a role in stimuli perception as well [30], [31].

2.3.3 Human Tactile Sensing in Stimulus Perception

2.3.3.1 Curvature Perception

Humans can recognize various shapes by touching the objects due to the existence of mechanoreceptors, mainly slowly adapting type I mechanoreceptors and fast adapting type I mechanoreceptors [32]. It has been found that a single mechanoreceptor cannot offer sufficient information to encode object shape, and the shape perception is encoded by a spatial population of both SA-I mechanoreceptors and FA-I mechanoreceptors [33]. SA-I mechanoreceptors offer more information in terms of spatial features of a shape [34]. In comparison, FA-I mechanoreceptors play an important role in the discrimination of fine differences in sharpness [35]. The question of how a stimulus such as object shape is encoded in sensory system is remarkably critical in sensory neuroscience [36]. The recent progress in understanding how the brain perceives the unknown state of the world and forms decisions is reviewed in [37]. An increasing body of evidence shows that human perceptual computation is realized in an optimal Bayesian way [38], wherein the sensory information is represented probabilistically in the brain. The Bayesian sequential analysis is able to strike a balance between speed and accuracy, which is also required in the mechanisms of brain perception [37].

2.3.3.2 Fingertip Force Perception

Goodwin and Wheat [39], found that humans could estimate the magnitude of the contact force regardless of the object shapes, i.e., the shape and contact force information could be independently perceived by humans. Alessandro and Benoni [40], investigated the human ability to discriminate the 3D force stimuli by applying the force stimuli to the volar surface of the index fingertip. The authors showed that the force direction was recognized primarily during the dynamic force stimulation, while the static force stimulation improved the discrimination ability only to a limited extent. A following up work [41] showed that SAII-nail units provides vectorial information about fingertip forces with similar directional properties as for the SA-I, SA-II, and FA-I afferents terminating in volar aspects of the fingertips. Birznieks et al. [42], reported that almost all the tactile afferents including SA-I, SA-II, and FA-I afferents from the whole terminal phalanx responded when forces were applied five distinct directions. The authors concluded the tactile afferents potentially contributed to the encoding of the fingertip forces. Moreover, each type of afferent was tuned to fire in response to the force stimuli from a preferred direction.

2.3.3.3 Slip Detection

Srinivasan et al. [43], investigated the influence of surface microgeometry on tactile slip detection and the underlying peripheral neural codes. Both the psychophysical experiments on human fingerpad and neurophysiological experiments on monkey fingerpad were conducted using three types of plates with distinct stimulus surfaces. For

the blank plate, humans were unable to detect the slip between the plate and the fingerpad. However, the direction of the evoked skin stretch could be perceived by SA-I afferent, which indicated the direction of impending slip. The slip detection during the interaction with both the single dot plate and the textured plate could be achieved due to FA afferents. Specifically, FA-I and FA-II afferent provide a reliable spatiotemporal code when a slip occurred with a single dot plate and a textured plate, respectively.

2.3.3.4 Hardness Perception

Srinivasan and Lamotte [44] investigated the human capability to discriminate hardness of objects. Two set of compliant objects with deformable and rigid surfaces were explored. Tactile information was found to be sufficient to discriminate the rubber specimens regardless of the velocities and forces of specimen application. By contrast, the kinesthetic information was not necessary. For the spring cells, both the tactile and kinesthetic information contributed to the ability of hardness discrimination. A following up work [45] was carried out by performing neurophysiological experiments on monkeys, which showed that the SA-I afferent population might play a vital role in encoding the hardness of the objects. The neurophysiological result was further verified by Condon et al. [46], where they found the mean firing rate of SA-I afferents increased steeply as the hardness of the objects increased. Moreover, the FA-I afferents was reported to encode the hardness of objects as well despite the significantly lower sensitivity compared to SA-I afferents. On the contrary, the SA-II afferent played a relatively minor role by affecting the object hardness solely in certain conditions.

2.3.3.5 Roughness Perception

Human beings possess the capability to sensitively perceive different materials [47], but the question remains as to how human beings encode the surface roughness during the physical finger-surface interactions. Extensive researches have been conducted to investigate the mechanisms underlying the perceived surface roughness [48]–[50]. Connor et al. [49], proposed that the neural coding of tactile texture is closely related to the spatial variations in slowly adapting (SA) mechanoreceptive afferents, which was limited to the coarse surfaces with element spaces of $> 1\text{mm}$. Yoshioka et al. [50] extended Connor et al.'s work by studying the neural coding mechanisms for the roughness perception of the finely textured surface, and found that there is a consistent relationship between human judgements of fine surface roughness and SA-I spatial variations. However, a recent study showed that the tactile roughness discrimination relies mainly on vibration sensitive afferents [48]. The fast adapting type I mechanoreceptors and the fast adapting type II mechanoreceptors are generally regarded to be responsible for modulating the vibratory stimuli occurring at the interface of explored surfaces and the fingers.

2.4 Robotic Tactile Sensing and Exploration

In this section, we present a thorough review of the biomimetic tactile sensing techniques by following a similar line in Section 2. Various tactile transduction techniques are firstly reviewed. Subsequently, we present the methods to mimic the properties of human mechanoreceptors such as the density and spiking activities in response to specific stimuli. We then review the fingerprint-like structure for biomimetic tactile sensing.

Finally, we present the approaches of biomimetic tactile stimulus recognition based on spike-like signals.

2.4.1 Working Mechanisms of Tactile Sensors

Any device with the capability of sensing information such as contact, slip, forces, friction including both the static and dynamic friction, roughness, stiffness, temperature, vibration or curvature, can be considered as a tactile sensor [7]. The past decade has witnessed tremendous efforts and progress made in both academia and the industry for the design and development of artificial tactile sensors. Tactile transduction techniques, with their own strengths and weaknesses, for instance, piezoresistive, piezoelectric, capacitive, optical, and magnetic, are intensively investigated.

2.4.1.1 Piezoresistive Sensors

The resistance of piezoresistive tactile sensors will change when it experiences an applied force. This effect termed as piezoresistive effect is an easy and direct transduction mechanism from pressure to resistance change. The piezoresistive sensors can fall into four categories: strain gauges, piezoresistors, percolative composites, and composites. A detailed review of piezoresistive tactile sensors can be found in the paper [51].

Strain gauges: strain is the amount of deformation of a body due to an applied force. The resistance change of strain gauges is mostly due to geometry change, and electrical resistances vary nonlinearly with the amount of strain [52]. Strain gauges are often mounted onto the test specimen by aid of special glues. The most widely used gauge is the

bonded metallic strain gauge. Strain gauges are available commercially with nominal resistance values from 30 to 3000 Ω , with 120, 350, and 1000 Ω being the most common values. For the purpose of measuring small changes in resistance and compensating for the temperature sensitivity, bridge circuits such as Wheatstone bridge configurations are often employed to measure strain gauges. Strain gauges are commonly used in the applications such as tactile sensing [53], [54]. The mechanical property of strain gauges are considered to be comparable to that of slow-adapting mechanoreceptors [55].

Piezoresistors: the working principle of piezoresistors is based on the band theory of solids. In contrast to strain gauges, the resistance change of piezoresistors is derived from a change in the band structure of a material, which results in a variation in the resistivity. This phenomenon can be observed in silicon and germanium [56].

Percolative composites: percolative composites are formed by dispersed conductive fillers such as carbon black (CB) [57], [58], graphite [59], [60] and carbon nanotubes (CNTs) [61], [62] within an insulating matrix. The conductivity of percolative composites will be altered when a pressure is applied. Specifically, if the density of conductive fillers is high, the conductivity will be greater, while the low density will result in lower conductivity. However, the relationship between the applied force and conductivity is nonlinear. The percolative composites suffer from the limitations such as hysteresis and a response with a long latency. Currently, they are manufactured by some commercial companies like Tekscan.

Quantum tunneling composites (QTCs): quantum tunneling composites [63], [64] are composed of conductive fillers and insulating barriers. The quantum tunneling composites

are perfect insulators in the normal state, while they become more or less perfect conductors when external force is applied. The underlying principle is that fillers can tunnel through the insulating barriers and form a conducting path, which makes it different from percolative composites [65]. Given the unique electrical properties and flexible manufacturing possibilities, QTCs are widely used for a collection of potential applications such as tactile sensors and textile touchpad.

2.4.1.2 Piezoelectric Sensors

Piezoelectric materials will produce electrical charges when they are deformed or subjected to mechanical force [66], [67], and correspondingly a voltage is developed if the surfaces are electroded. A variety of tactile sensors have been developed based on the piezoelectric effect [68]–[73]. In contrast to piezoresistive tactile sensors, the piezoelectric effect makes piezoelectric sensors particularly suitable to measure dynamic stimuli such as vibration. Piezoelectric sensors have some limitations such as high sensitivity to temperature change. Another limitation of piezoelectric sensors is that they are inapplicable for static stimuli measurement, because the generated electric charge is extremely easy to decay when the sensors are connected in any closed circuits. Piezoelectric sensors might measure very low frequency stimuli on the condition that they act as both an actuator and sensor. Polyvinylidene fluoride (PVDF) is a classic example of piezoelectric polymer that is preferred in tactile sensors [74]–[78]. The mechanical property of PVDF films are considered to be comparable to that of fast-adapting mechanoreceptors [55]. In comparison to PVDF sensors, lead zirconate titanate (PZT) offers an advantage of a

relatively high piezoelectricity. However, PZT is not flexible and difficult to be formed on the curved surfaces [79]. Both PVDF and PZT have been incorporated into robotic hand for slip detection [77], [80].

2.4.1.3 Capacitive Sensors

A capacitive sensor is comprised of two conductive plates separated by a dielectric material between them. An applied force can produce change either in the distance between the plates or its area, and hence the capacitance. Capacitive based sensors have been employed by many researchers to develop tactile sensors [81]–[83]. Capacitive tactile sensors exhibit high spatial resolution, good frequency response, and a relatively broader measurement range. However, the capacitive tactile sensors are easy to be affected by noise, and it is especially evident when the sensors are in array configurations. Therefore, particular filter circuits often come with capacitive tactile sensors to eliminate this noise. Microelectromechanical systems (MEMS) technology has also been used to develop capacitive tactile sensors [84]–[86].

2.4.1.4 Optical Sensors

Optical tactile sensors modulate the tactile stimuli in the physical quantities such as light intensity. The optical tactile system is generally comprised of a light source, an optical detector, and an optical waveguide. Optical tactile sensors are immune to electromagnetic interference (EMI) and have a wide sensing range. However, they have some disadvantages such as bulky sizes. The optical sensor called the TacTip [87] is able

to a localization resolution of 0.1 mm, which is much smaller than resolution between sensing elements. Optical tactile sensors are utilized to recognize surface textures [88], identify objects [89], and detect slip [90].

2.4.1.5 Magnetic Sensors

Magnetic tactile sensors modulate the tactile stimuli in the magnetic mode. For example, based on the principle of electromagnetic induction, Takenawa [91], fabricated a tactile magnetic sensor including a permanent magnet and a two-dimensional array of inductors. The displacement of the permanent magnet due to the applied external force generated an induction voltage for each inductor. Magnetic tactile sensors commonly have a high dynamic range, but suffer from the limitations such as bulky size like the optical tactile sensors. Alfadhel and Kosel [92] developed a tactile sensor based on permanent magnetic nanocomposite cilia. The sensor can feel texture and measure fluid flow with a low power consumption. Magnetic tactile sensor are capable of detecting slip as well [91], [93].

2.4.2 Artificial Tactile Sensors to Mimic Mechanoreceptors

Figure 2-3 Artificial tactile sensors to mimic the properties of mechanoreceptors. (a) A sensor density of 72 units/cm² is achieved by aid of MEMS techniques, which mimics the density of SA-I mechanoreceptors [94]. (b) The action potential generation of FA mechanoreceptors is emulated by the single-layer graphene [95]. (3) A 6×4 capacitive sensor array mimics the spatial event plot of tactile SA-I afferent in response to the scanned Braille character J [96].

In order to mimic the tactile capability of the human mechanoreceptors, many types of tactile sensors have been developed based on various transduction techniques together with the utilization of spiking neuron models. Figure 2-3 illustrates how to emulate the properties of mechanoreceptors with artificial tactile sensors.

Spiking neuron models play a vital role of describing neuronal spiking activities and

are used to convert the signals generated by artificial tactile sensors to elicited spikes. The models, expressed in the form of ordinary differential equations (ODE) [97], include the leaky integrate-and-fire model, the quadratic-integrate-and-fire model, the Izhikevich model and The Hodgkin-huxley model. More models can be found in [97], [98]. The leaky integrate-and-fire model is the simplest model, can fire tonic features, and can be considered as an integrator. However, the spikes generated by this model do not have latencies due to the fixed threshold [97]. A simple neural dynamics model was proposed by Izhikevich [99]. The Izhikevich model can exhibit firing all the patterns which exist in kinds of cortical neurons. the quadratic-integrate-and-fire model is a special case of Izhikevich model [100], which is able to describe the dynamics of any Hodgkin-Huxley-type system near the bifurcation, and can regenerate upstroke of the membrane potential. The spikes generated by quadratic integrate and fire model have some biological properties such as spike latencies and activity-dependent threshold in contrast to integrate and fire model. The Hodgkin-huxley model [101], also called as conductance-based model, was proposed by Alan Lloyd Hodgkin and Andrew Huxley in 1952. It explains ionic mechanisms underlying the initiation and propagation of action potential in the squid giant axon. The Hodgkin-huxley model is comprised of a set of four ordinary differential equations. This model is extremely useful as it could be employed to explain a wealth of biological observation.

Piezoresistive (e.g., strain gauges) and piezoelectric (e.g., PVDF) materials are regarded as to be equivalent to SA and FA mechanoreceptors respectively [55]. The capability of a piezoresistive sensor to mimic tactile SA-I afferent has been successfully

demonstrated by employing a spiking-sensor model and the model outputs agree reasonably well with biological measurements under the same external stimulations [102]. With a pulse modulation algorithm [103], the same sensor could generate discrete charge-balanced pulses, which were delivered to a rat's sural nerve and the resulting neural action potentials replicated the natural responses accurately. Moreover, a 2×2 MEMS piezoresistive sensor array was employed to mimic SA-I mechanoreceptors as well [104]–[106], where the density of artificial sensors could resemble that of SA-I mechanoreceptors inside human skin. The analog signals were converted into neural spike trains by an Izhikevich's model and the generated spike trains were able to classify naturalistic textures with a recognition accuracy of 97%. However, the converted spike trains were not compared with the biological recordings under the same stimuli. In addition, capacitive sensors are also candidates to mimic SA-I mechanoreceptors [96], [107], where tactile information was able to discriminate Braille characters based on the multistage processing. However, the capability of sensors to mimic FA-I mechanoreceptors has not been well studied. FA-I mechanoreceptors are exquisitely sensitive to vibratory stimuli between 10 and 50 Hz, which makes them important for the light touch perception. A fabric based binary tactile sensor array was used to replicate the response of FA-I mechanoreceptors with two Izhikevich neurons [108], but no direct comparison with biological recordings are demonstrated. Yi and Zhang [3] mimicked the spiking activities of FA-I mechanoreceptors based on PVDF films. The continuous outputs of PVDF films were converted to spike trains by employing a spiking neuron model, which includes a transduction sub-model and a neural dynamics sub-model. Then the

produced spikes were compared with spikes directly measured from FA-I mechanoreceptors in the glabrous skin of macaque monkeys under the same stimulations. Sul et al. [95], replicated the contact pressure variation sensing in the human somatosensory system using a single-layer graphene. The single-layer graphene mechanoreceptor (SGM) emulated the action potential generation of FA mechanoreceptors. The threshold pressure could be adjusted by changing the gate potential. Table 2-2 compares the related works on mimicking the properties of mechanoreceptors based on artificial tactile sensors.

Table 2-2 Comparison of using artificial tactile sensors to mimic the properties of
mechanoreceptors

Year	Author	Tactile sensor	Mimicked properties of mechanoreceptors	Methodology in mimicking
2006	Hosoda et al. [55]	Strain gauges and PVDF films	Location of SA and FA mechanoreceptors	Strain gauges and PVDF film are distributed in two silicon rubber layers, which mimic the epidermis and dermis of human skins.
2011	Oddo et al. [94]	A 2×2 MEMS piezoresistive sensor array	Density of SA-I mechanoreceptors	A sensor density of 72 units/cm ² is achieved by aid of MEMS techniques
2012	Kim et al. [102]	A single piezoresistive sensor	The spiking activities of tactile SA-I afferent in response to ramp and hold stimuli	The continuous outputs of the piezoresistive sensor were converted to spike trains by employing the integrate and fire model. The model parameters are tuned using response surface method in order to better fit the model to the biological data
2013	Bologna et al. [96]	A 6×4 capacitive sensor array	The spatial event plot (SEP) of tactile SA-I afferent in response to scanned Braille characters	The methodology is similar to that of Kim et al. [102]

2013	Lee et al. [108]	A fabric based binary tactile sensor array	The spiking activities of tactile FA-I mechanoreceptor in response to pressure transition from high to low as well as from low to high	The methodology is similar to that of Kim et al. [102]. The difference is that the spiking neuron are two Izhikevich neurons.
2016	Yi and Zhang [3]	PVDF film	The spiking activities of tactile FA-I afferent in response to sinusoidal stimuli	The methodology is similar to that of Kim et al. [102]
2016	Sul et al. [95]	A Single-layer graphene	The generation of action potentials of FA mechanoreceptors	An action potential is generated when the Fermi level crosses the Dirac point in the graphene energy band. The Fermi level is modulated by the membrane deflection

2.4.3 Fingerprint-like Structure

Figure 2-4 Human fingerprint and the fingerprint-like structures. (a) Scanning electron micrograph of the human fingerprint [11]. (b) A biomimetic tactile sensor (BioTac) with fingerprint-like ridges [109]. (c) The square wave grating on the PDMS cap enhances the perception of fine textured surface [27]. (d). The ridged skin enhances the slip detection capability of the force sensing resistor [110].

Using fingerprint as a source of inspiration, Vászárhelyi et al. [111], introduced a square grating on a strain gauge array to enhance the sensitivity in force detection. Scheibert et al. [27], patterned a square wave grating on a spherical PDMS cap together with a MEMS microforce sensor. The biomimetic parallel ridges played a vital role in fine textural information encoding. Zhang [53] placed an PDMS layer on the micromachined strain gauge array. The epidermal ridges were able to enhance the detection sensitivity of normal force 1.8 times. A similar fingerprint-like structure with 160 μm in height could improve the detection sensitivity of shear force 3 times [112]. Damian et al. [110], presented a triangular ridge to facilitate slippage detection. Ridges with different wavelengths are evaluated to find the suitable inter-ridge distance parameter. Salehi et al. [113], investigated the possibility of enhancing curvature discrimination by adding a fingerprint-like structure to encapsulate the piezoresistive tactile sensors. Three machine learning methods comprised of Naive Bayes (NB), Artificial Neural Networks (ANN), and Support Vector Machines (SVM), were compared in their work. Noda et al. [114] developed a standing piezoresistive cantilever by incorporating the ridged PDMS layer. A tremendous sensitivity enhancement was observed in scanning over patterned silicon target. Figure 2-4 illustrates human fingerprint and examples of the fingerprint-like structures. Table 2-3 shows the comparison of fingerprint-like structure for tactile sensors and applications.

Table 2-3 Comparison of fingerprint-like structure for tactile sensors and applications

Year	Author	Material	Pattern	Incorporated tactile sensor	Application
2006	Vásárhelyi et al. [111]	Silicone layer	Square wave grating with width 250-280 μm and height from 360 to 760 μm .	Strain gauge	Force detection in 3D space
2009	Scheibert et al. [27]	A spherical PDMS cap	Square wave grating with period 220 μm and depth 28 μm .	A MEMS microforce sensor	Fine textural information encoding
2010	Zhang [53]	PDMS layer	Square wave grating with width 400 μm and height 110 μm .	Strain gauge	Normal force detection
2010	Damian et al. [110]	Silicone layer	Triangular wave grating with period from 2.5 to 4 mm	Force sensing resistor	Slip detection
2010	Noda et al. [114]	PDMS layer	Square wave grating with width 300 μm , height 100 μm , and gap 750 μm	A standing piezoresistive cantilever	Texture scanning
2011	Zhang and Miki [112]	PDMS layer	Square wave grating of width 400 μm and height 160 μm .	Strain gauge	Shear force detection
2011	Salehi et al. [113]	Silicone layer	Square wave grating (no detailed dimension)	Piezoresistive tactile sensor array (TactoPad 2×2)	Curvature detection
2014	Harada et al. [115]	PDMS	3D prong with 2 mm diameter and 1 mm height	Strain Sensor	Touch and slip detection

2.4.4 Biomimetic Tactile Stimulus Perception with Spikes

Neurons interact with each other with action potentials or “spikes”. In a biomimetic tactile sensing system, there is a steadily growing interest in processing the tactile signals as spikes, which are generated by aid of spiking neuron models. Spikes carry information for high-level perception, known as neural codes, including rate codes and spike codes

[98], [116], [117]. Multiple neurons, connected through synapses, form a network, which inspires the development of the third generation of neural network called spiking neural networks [118]–[120] .

2.4.4.1 Neural Codes

Neural code is still a topic of debate in the neuroscience community [121]. The neural code generally includes rate code and spike code (or temporal code).

Rate code: Rate code is assumed to be the neuronal representation of stimuli [122]. The definition of rate code is not unique, which is comprised of rate as a spike count, rate as a spike density, and rate as a population activity [98]. Rate codes are commonly served as a benchmark for decoding the tactile stimulus [5], [104].

Spike code: Spike codes are a branch of neural coding methods based on spike timing. As a special case of spike codes, first spike latency (FSL) is the long-lasting period preceding the first spike with respect to the reference signal such as the start of a stimulus. The first spike latency is able to carry information in visual, auditory, and somatosensory system [123]–[126]. The tactile information of surface shape manipulated by the finger is found to be reliably more conveyed by the relative timing of the first spike latencies compared to firing rate [127]. Phase is another special case of spike codes. Unlike first spike latency using a single event as the reference signal, the phase code employs a periodic signal such as oscillations. The phase of a spike relative to the oscillation can encode information, which was observed in the hippocampus of the rat [128].

2.4.4.2 Learning in Spiking Neural Networks

Learning in spiking neuron networks takes the inspiration of synaptic plasticity in the neuroscience. Synaptic plasticity refers to the activity-dependent adjustment of synaptic efficacies [129], [130]. A large body of electrophysiological experiments [131]–[133] shows that the changes of synaptic strength can be induced by following patterned stimuli. Learning in spiking neural network includes supervised learning and unsupervised learning.

Supervised learning: As for supervised learning, the incoming spike patterns are associated with labels. An increasing number of evidence shows that this kind of learning is also exploited by the brain. The most documented evidence for this type of rule comes from studies on the cerebellum and the cerebral cortex. In addition, evidence suggests that the supervisory signals are provided to the learning modules by sensory feedback or other supervisory neural structures in the brain [134]–[136]. One typical example for the supervised learning rule is the tempotron. The tempotron [137] is an integrate-and-fire neuron whose membrane potential is governed by all incoming spikes and is a weighted sum of postsynaptic potentials (PSPs). The tempotron modifies the synaptic efficacies according to the class label in an iterative manner. If a neuron fail to fire when it is stimulated by the desired pattern, the weights will be increased. On the contrary, if the spike is elicited in response to the undesired stimulation pattern, the weights will be decreased.

Unsupervised learning: As opposed to supervised learning rule, the incoming spike patterns come with not any supervisory signals. Spike timing dependent plasticity (STDP)

as a typical instance of unsupervised learning, is a spiking generalization of Hebbian learning [138], [139]. STDP is a learning rule that is dependent on the relative timing of presynaptic and postsynaptic spike. The repeated occurrence of postsynaptic spikes after the coming of presynaptic action potentials leads to a persistent increase of synaptic efficacy, which is known as long-term potentiation (LTP). The opposite is long-term depression (LTD) which refers to a persistent decrease of the synaptic weight in response to the stimulation paradigms. If the effect lasts for a short period such as second or minute scale rather than several hours, they are called short-term potentiation (STP) and short-term depression (STD), respectively. STDP is regarded to be associated with memory formation [140]. Figure 2-5 illustrates the structure of neuron and synapse and examples of learning rules in biomimetic tactile stimulus perception.

Figure 2-5 (a) The structure of neuron and synapse [11]. (b) Classification of two different patterns based on the tempotron [137]. (c) The unsupervised learning STDP observed in

hippocampal glutamatergic synapses [139].

2.4.4.3 Tactile Stimulus Sensing with Spikes

Biomimetic tactile perception with spikes has attracted increasing attention in the past decade. Lee et al. [108], used a fabric based binary tactile sensor array to discriminate local curvature of objects. The tactile signals were converted into spikes using two Izhikevich models. Subsequently, a tempotron classifier [137] was employed to distinguish between the 105 mm indenter and 65 mm indenter based on the relative timings of first spikes. Lee et al. [141], also applied the soft neuromorphic method for gait event detection using a low-cost, foot pressure sensor. The decoding scheme employed in this work is the synaptic kernel inverse method (SKIM) instead of the tempotron classifier. Bologna et al. [96] used a 4×6 capacitive square sensor array to recognize the Braille letters. In contrast to Lee et al.'s work, their work was distinct in both analog-to-spike transformation model and pattern decoding algorithms. Specifically, the transformation was implemented by integrate-and-fire models, and a naïve Bayesian classifier was trained to perform online Braille letter recognition. A more closely related work on naturalistic texture categorization was reported by Rongala et al. [104], where they also performed the analog-to-spike transformation using the Izhikevich models, and implemented two decoding procedures. One was based on spike feature including the average spike rate and the coefficient of variance of the interspike intervals. The other was based on precise spike timing by the aid of the Victor-Purpura distance. One work on surface roughness discrimination in a soft neuromorphic fashion was reported by Spigler et al. [106], where

they presented a grating recognition system by incorporating the Izhikevich model and stimulus decoding scheme via assessing the principal frequency in the spike frequency domain. Table 2-4 summarizes the relevant papers of biomimetic tactile stimulus perception with spikes.

Table 2-4 Comparison of Biomimetic Tactile Perception with Spikes

Year	Author	Tactile Sensor	Analog-to-spike transformation	Spike train decoding	Application
2012	Spigler et al. [106]	A 2×2 piezoresistive tactile sensor array	The Izhikevich model	Spike frequency domain analysis	Grating discrimination
2013	Bologna et al. [96]	A 4×6 capacitive square tactile sensor array	The integrate-and-fire model	Naïve Bayesian classifier	Braille letter recognition
2013	Lee et al. [108]	A fabric based binary tactile sensor array	The Izhikevich model	Tempotron	Curvature discrimination
2014	Lee et al. [141]	A low-cost, foot pressure sensor	The Izhikevich model	The synaptic kernel inverse method (SKIM)	Gait event detection
2015	Rongala et al. [104]	A 2×2 piezoresistive tactile sensor array	The Izhikevich model	Scheme 1: k -nearest neighbors based on spike features Scheme 2: k -nearest neighbors based on Victor-Purpura distance	Texture discrimination

Chapter 3. Bioinspired Tactile FA-I Spiking Generation Under Sinusoidal Stimuli

3.1 Abstract

For the design and development of advanced prosthetic limbs, many attempts have been made to restore the function of mechanoreceptors using artificial tactile sensors. Mechanoreceptors in human skin, which make dexterous manipulation possible, respond to the mechanical stimuli in the form of spike trains. In this chapter, a bio-inspired approach to replicate the fast adapting type I (FA-I) mechanoreceptor is developed, where piezoelectric materials, such as polyvinylidene difluoride (PVDF) films, are used to generate continuous analog electrical signals; then the analog signals are successfully converted into spike trains using the spiking neuron model. By comparing with spike trains measured from the glabrous skin of macaque monkeys, it was found that this approach can mimic FA-I afferent spiking activities in terms of both the average inter-spike interval and the first spike latency. Spike features of the FA-I mechanoreceptors, such as the variability, frequency dependent responses, and population activity, were also explored, which may play a vital role in the understanding of the functionality of FA-I mechanoreceptors and the development of advanced prosthetic limbs.

3.2 Introduction

Among various human sensations like sight, hearing, taste and smell, touch is a critical co-existing sensation required to interact with the surrounding environments [7], which enables us to discriminate various surface textures, recognize and manipulate objects, etc.. The sense of touch also plays a significant role in many applications in robotics, minimal invasive surgery, advanced prosthetics and manufacturing industries. For an able-bodied human, tactile stimuli like force and vibration can be detected by the mechanoreceptors embedded in the skin to generate spike trains, which will be conveyed to the brain for perception [1]. Though the past decade has witnessed tremendous efforts and progress made by the industry and academia for assisting amputees [17], [18], the prosthetic limbs are currently limited by a lack of tactile feedback [142]. Biomimetic mechanoreceptors using artificial sensors are critical to develop advanced prosthetic limbs in the near future.

There are four main types of mechanoreceptors embedded in the human skin throughout the body, i.e., Pacinian corpuscles, Meissner's corpuscles, Merkel's discs, and Ruffini cylinders [14]. Each type of mechanoreceptor is responsible for the reception of a specific stimulus. Those mechanoreceptors can be divided into two categories, i.e., slowly adapting (SA) mechanoreceptors and fast adapting (FA) mechanoreceptors [25]. The slowly adapting mechanoreceptors including Merkel's discs (SA-I) and Ruffini cylinders (SA-II) respond to low frequency stimuli, which describe the static properties of a stimulus. In contrast, high frequency stimuli make the rapidly adapting mechanoreceptors, i.e., Meissner's corpuscles (FA-I) and Pacinian corpuscles (FA-II), to fire in response. The

receptive fields of SA-I and FA-I have more distinct borders and smaller sizes than those of SA-II and FA-II.

In order to mimic the tactile capability of the human finger, many types of tactile sensors have been developed based on various transduction techniques, e.g., capacitive, piezoresistive, piezoelectric, inductive and optical techniques [61], [81], [143], [144] . Piezoresistive (e.g., strain gauges) and piezoelectric (e.g., PVDF) materials are frequently considered to be equivalent to SA and FA mechanoreceptors respectively [55]. The capability of a piezoresistive sensor to mimic tactile SA-I afferent has been successfully demonstrated by employing a spiking-sensor model and the model outputs agree reasonably well with biological measurements under the same external stimulations [102]. With a pulse modulation algorithm [103], the same sensor could generate discrete charge-balanced pulses, which were delivered to a rat's sural nerve and the resulting neural action potentials replicated the natural responses accurately. Moreover, a 2×2 MEMS piezoresistive sensor array was employed to mimic SA-I mechanoreceptors as well [104]–[106], where the density of artificial sensors could resemble that of SA-I mechanoreceptors inside human skin. The analog signals were converted into neural spike trains by an Izhikevich's model and the generated spike trains were able to classify naturalistic textures with a recognition accuracy of 97%. However, the converted spike trains were not compared with the biological recordings under the same stimuli. In addition, capacitive sensors are also candidates to mimic SA-I mechanoreceptors [96], [107], where tactile information was able to discriminate Braille characters based on the multistage processing. However, the capability of sensors to mimic FA-I

mechanoreceptors has not been well studied. FA-I mechanoreceptors are exquisitely sensitive to vibratory stimuli between 10 and 50 Hz, which makes them important for the light touch perception. A fabric based binary tactile sensor array was used to replicate the response of FA-I mechanoreceptors with two Izhikevich neurons [108], but no direct comparison with biological recordings are demonstrated. The objective of this work is to mimic activities of FA-I mechanoreceptors based on PVDF films. The continuous outputs of PVDF films were converted to spike trains by employing a spiking neuron model, which includes a transduction sub-model and a neural dynamics sub-model. Then the produced spikes were compared with spikes directly measured from FA-I mechanoreceptors in the glabrous skin of macaque monkeys under the same stimulations.

3.3 Methods

3.3.1 Piezoelectric PVDF Film Sensors

Piezoelectric materials generate electrical charges when the crystal lattice is deformed under mechanical force and the generated charges are directly proportional to the mechanical stress [67]. However, the generated electric charges decay with a time constant that is determined by the internal impedance and dielectric constant of the piezoelectric material. A collection of tactile sensors have been developed by taking advantage of the piezoelectric effect [69]–[72]. These piezoelectric sensors exhibit a very good high-frequency response, which makes them extremely suitable for measuring vibrations. PVDF film is a classic example of piezoelectric polymer that is widely used as tactile sensors [76]–[78], where the lowest frequency measurable with piezoelectric PVDF film is

in the order of about 0.01 Hz.

3.3.2 Experiment

The experimental setup is illustrated (Figure 3-1). Figure 3-1 Experimental setup for acquisition of analog signals from PVDF film embedded in PDMS.). A commercial 28 μm -thick PVDF film (1-1003703-4, Measurement Specialties, Inc.) was cut into a desired size as small as 4 mm $\times$ 4 mm, and electrodes were bonded using a conductive paste. The PVDF film was embedded in a cross-linked PDMS elastomer, which was prepared by mixing 10 parts of silicone elastomer base to 1 part of curing agent (SYLGARD, Dow Corning, USA). The embedding depth is close to the depth of Meissner's corpuscles in the skin (0.7 mm). The packaged PVDF sensor was bonded using glue to the tip of a shaker (Data Physics) to avoid any pre-indentation [36]. The shaker tip was designed to cover the entire receptive field of the PVDF film [102]. Instead of ramp-and-hold stimuli used for SA-I mechanoreceptors, sinusoidal stimuli were employed for FA-I mechanoreceptors because they are insensitive to static deformation and are more sensitive to vibrations [36]. As a fact, FA-I mechanoreceptors are much more sensitive to dynamic stimuli than SA-I mechanoreceptors [145]. Both frequency and amplitude of the vibratory stimuli used to test the PVDF film sensor are exactly the same as the vibratory stimuli used to test the FA-I mechanoreceptors in the glabrous skin of macaque monkeys [36]. Particularly, sinusoidal stimuli varied in amplitude (34, 48, and 67 μm) and frequency (20 and 30 Hz) were generated using the shaker calibrated by a Calibration Exciter (Type 4294, Brüel & Kjær). The stimulus durations for 20 Hz and 30 Hz were 250 ms and 200 ms respectively.

Therefore, there are six unique coded stimulus types in total (Table 3-1). The experiment for each stimulus type was repeated five times. The PVDF sensor signals were amplified by a custom-built amplifier, and digitalized via an analog-to-digital converter (DAQCard USB-6225, National Instruments). Supporting software was developed to record digital signals (Labview, National Instruments).

Table 3-1 Stimulus type for PVDF film

Stimulus type	Frequency (Hz)	Amplitude (μm)
I	20	34
II	20	48
III	20	67
IV	30	34
V	30	48
VI	30	67

Figure 3-1 Experimental setup for acquisition of analog signals from PVDF film embedded in PDMS.

3.3.3 Spiking Neuron Model

A spiking neuron model is employed to convert PVDF sensor signals to spike trains, which consists of two components: mechanotransduction model and neural dynamics model.

3.3.3.1 Mechanotransduction Model

The mechanotransduction model transforms the external stimuli into the transmembrane current. Unfortunately, the mathematical relation between an external stimuli and the corresponding mechanoreceptor current is still unknown due to the inaccessibility of the whole-cell recording for mechanoreceptors. Inspired by other sensory cells such as hair cells and pain receptors, a sigmoidal function was employed to serve as the transduction model to predict the spike times of SA-I mechanoreceptors [146]. The sigmoidal function is nonlinear and computationally complicated, so linear homogenous second-order differential equations were employed to reduce the model complexity, which has been applied to model SA-I mechanoreceptors [102]. In this work, the simplified mechanotransduction model was used for PVDF film to model FA-I mechanoreceptors.

The transmembrane current $I(t)$ is given by

$$I(t) = \beta + k_s f(t), \quad 3.1$$

where β in mA and k_s in mA/N are intercept constant and gain respectively. $f(t)$ is the sensor-detected force. The values for β and k_s are determined through parameter fitting using response surface methods.

3.3.3.2 Neural dynamics model

Neural dynamics models are employed to transform the membrane current into spikes. The Hodgkin-Huxley-type models are biophysically accurate, but they are computationally prohibitive. On the other hand, the integrate-and-fire model is an idealization of a neuron with Ohmic leakage current [100], which is incapable of generating rich spiking patterns. For instance, it does not have a spike generation mechanism for the regenerative upstroke of the membrane potential. However, it is computationally effective and useful for analytical work or serving as the neural dynamics model [102], [147]. Whenever the membrane potential V is driven to some specific threshold V_T , a spike is produced followed by an absolute refractory period (1 ms) that no spike would be generated [102], [147].

The membrane potential V is given by

$$dV = \left(-\frac{(V-V_r)}{\tau} + \frac{I(t)}{C} \right) dt, \quad 3.2$$

where V_r in mV, τ in ms, C in mF, and $I(t)$ are the resting membrane potential, membrane's time constant, membrane's capacitance and transmembrane current respectively. The values of τ , C , and V_T are also determined through parameter fitting using the response surface method. For simplicity, the resting membrane potential V_r is set to 0 mV.

3.3.4 Parameter fitting

Parameters of the spiking neuron model were fit using the response surface methods (RSM) in an iterative manner, where the initial values of the parameters were obtained by

trial and error. For each step, factorial design is performed to vary the coded parameter set. A first-order response surface model is used to obtain an improved parameter by searching along the path of steepest ascent.

The target function of response surface methods needs to be carefully selected to serve as the metrics for the optimization. How spike trains code information regarding sensory events has been a long debate by neuroscientists. It is generally considered that a majority of sensory neurons convey information by their firing rates, which is closely related to the average inter-spike interval employed in previous work [102], [148]. The tactile information of surface shape manipulated by the finger is found to be more reliably conveyed by the relative timing of the first spike latencies (*FSL*) [127]. In this study, it is proposed to maximize the fractional sum of squares (*FSS*), which is given by

$$FSS = 1 - \frac{\sum_{i=1}^m \sum_{j=1}^n (\overline{obsISI_i} - \overline{preISI_j})^2}{n \sum_{i=1}^m (\overline{obsISI_i})^2}, \quad 3.3$$

where m is the number of stimulus type, and n is the experimental replication number for each stimulus. $\overline{obsISI_i}$ and $\overline{preISI_j}$ are the average time of inter-spike intervals for the observed spikes at the mechanoreceptors in the glabrous skin of macaque monkeys [36] and the predicted average time of the inter-spike intervals using the spiking neuron model respectively. Similar *FSS* could be used for *FSLs*.

Totally thirty experiments (six stimulus types by five replications) were conducted using the PVDF film based sensor to mimic the FA-I mechanoreceptor. All experimental data were randomly split into two sets, namely, a training set with two-thirds (20 traces) of the total data and a test set with the remaining one-third data (10 traces). The purpose of the training set was to fit parameters in the spiking neuron models while the test set was

reserved for model validation. Given each stimulus type, the target value for the optimization is set as the median of five measurements in the glabrous skin of macaque monkeys.

3.4 Results and Discussion

3.4.1 Parameter Fitting Results

Figure 3-2 shows the iterative optimization results of the average ISI using the response surface method (Section 2.4). The starting point is obtained by trial-and-error and no further improvement in *FSS* is obtained after two iterations. Based on parameter values obtained in the third iteration, Figure 3-3 shows the predicted spike trains (blue) evoked by six sinusoidal stimuli on the PVDF film sensor compared to the observed spike trains (red) on FA-I mechanoreceptors measured in the glabrous skin of macaque monkeys. The experimental results indicate that the PVDF film based sensor could mimic the FA-I neural spike features reasonably well. At the same frequencies, the average inter-spike intervals will decrease as the vibratory amplitudes increase (Figure 3-4), and the first spike latencies will decrease as the vibratory amplitudes increase (Figure 3-5). At the same amplitudes, the average inter-spike intervals will also decrease as the vibratory frequencies increase (Figure 3-4), and the first spike latencies will decrease slightly as the vibratory frequencies increase (Figure 3-5). The predicted average inter-spike intervals (ISI) agree reasonably well with the observed average ISIs while the predicted first spike latencies are less than 2 times smaller than the observed *FSLs*. Similar trend had been reported before for SA-I mechanoreceptors, where the predicted average ISIs agree well with the observed

average ISIs while the predicted *FSLs* are one order less than the observed *FSLs* [102].

Figure 3-2 Iterative optimization process for average ISI based on response surface

methods (the predicted average ISIs are almost the same after 1 & 2 iterations).

Figure 3-3 Observed (red) and predicted (blue) spike trains evoked by six stimuli (black), i.e., three 20 Hz sinusoid stimuli (top) with amplitudes of 34 μm (left), 48 μm (middle), 67 μm (right), and three 30 Hz sinusoid stimuli (bottom) with the same amplitudes for FA-I afferent.

3.4.2 Model Validation

FSS (Section 2.4) for both the training and test data are compared to validate the model. *FSS* calculated using the test data is 0.9385, which is very close to the value calculated using the training data, namely, 0.9383. Therefore, the model performance for the test data is similar for the training data, i.e., there is no overfitting.

Next, an analysis of variance (ANOVA) was conducted to investigate effects of the stimulus amplitude and frequency on average ISI and *FSL* were tested on the predicted and observed spiking trains respectively. At a significance level of 0.05, the null hypothesis - stimulus types have no effect on the predicted average ISI and the observed average ISI, is rejected ($F_{\text{NullPredicted}} = 58825 > F_{0.05,5,18} = 2.77$; $F_{\text{NullObserved}} = 23.71 > F_{0.05,5,24} = 2.62$). Therefore, there are differences among the means of the predicted as well as the observed average ISI. The similar result of average ISI for SA-I afferent was also reported [102]. At a significance level of 0.05, the null hypothesis - stimulus types have no effect on predicted *FSL* and observed *FSL*, is also rejected ($F_{\text{NullPredicted}} = 15.72 > F_{0.05,5,18} = 2.77$; $F_{\text{NullObserved}} = 25.25 > F_{0.05,5,24} = 2.62$). Therefore, there are differences among the means of *FSL* in the predicted as well as the observed *FSL*.

The ANOVA *F* test could only tell whether there are significant differences among the means of the whole groups, but it is not able to provide the details of those differences. Therefore, multiple pair-wise comparisons are performed. The multiple pairwise comparison, such as the Tukey method, was conducted to find whether the means of both average ISI and *FSL* for the predicted and observed spike trains are significantly different across the stimulus types. At a significance level of 0.05, means of average ISI for the

predicted and observed spike trains are significantly different except two stimulus pairs: type II vs. III and type V vs. VI. Similarly, means of *FSL* for the observed spike trains are significantly different except the two stimulus pairs: type II vs. III and type V vs. VI at a significance level of 0.05. However, none of the pairs across stimuli at 20 Hz frequency when predicted by the spiking neuron model significantly differ, and all of the pairs across stimuli at 30 Hz frequency when predicted by the spiking neuron model significantly differ.

3.4.3 Variability of Spike Trains

The large error bars of the observed values in Figure 3-2 indicate high variability of spikes measured from FA-I mechanoreceptors, for example, the coefficient of variation of the inter-spike intervals for stimulus type I in Figure 3-2 is 0.18. The origin of the neural signal variability in the sensory or cortical neurons is poorly understood. It might arise from ion channels in a patch of neuronal membrane [149]. Although the complete importance of signal variability in cognitive processing is still unknown, some recent studies demonstrate that it might offer distinct advantages [150]. Spike variability could be beneficial to the sensitivity enhancement of weak signals well known as ‘Stochastic resonance’ [151]. However, the predicted values in Figure 3-2 are very regular, for instance, the coefficient of variation of inter-spike intervals for stimulus type I in Figure 3-2 is only 2.56E-04. Therefore, there is a need to recreate the variability of neural spike activities in biomimetic tactile sensors. For example, a noise term might be added to the neural dynamics model in order to increase variability in the predicted spike trains.

3.4.4 Frequency-dependent parameter fitting

The present spiking neuron model (in Section 2.3) assumes the parameter set, especially the impulse threshold, is constant regardless of stimulus types. However, the dependence of mechanoreceptor sensitivity on stimulus frequency was observed [152]. Particularly, the frequency component of stimuli had an effect on both absolute and entrainment threshold. Therefore, the frequency dependent parameter fitting is proposed to incorporate the influence of stimulus frequency, which is similar to locally weighted regression (LWR) used for real-time control [153]. As one might expect, improvements could be obtained by the frequency dependent parameter fitting in terms of average ISI (Figure 3-4) and *FSL* (Figure 3-5) respectively.

Figure 3-4 Average ISI improvement based on frequency dependent parameter fitting.

Figure 3-5 First spike latency improvement based on frequency dependent parameter fitting.

3.4.5 Population Activity

The question of how a stimulus is encoded in sensory system is remarkably critical in sensory neuroscience [36]. As to the tactile perception of a specific quantity such as stimulus intensity, it has been found that a single mechanoreceptor cannot offer sufficient information to code the stimulus, or discriminate various stimuli^[41]. The tactile perception is based on not only the activity of a single mechanoreceptor, but also on the activity of a single population, such as all FA-I mechanoreceptors, or even on all the mechanoreceptors [36]. Moreover, responses vary substantially across FA-I mechanoreceptors in response to the same stimulus. Thus, the diversity of individual mechanoreceptor activity should be taken into consideration when using artificial tactile sensors and spiking neuron models to mimic population activity.

In this work, ten pairs from five FA-I mechanoreceptors were formed to check

whether each mechanoreceptor in one pair acts differently. Particularly, the Tukey simultaneous 95% confidence intervals were estimated for the difference of means of the two mechanoreceptors in each pair in terms of both average ISI and *FSL*. As an example, Figure 3-6 shows the Tukey simultaneous 95% confidence intervals for the 10 pairs in terms of means for the observed average ISI response to the stimulus type II (20 Hz of amplitude 48 μm). If a confidence interval does not contain zero, the corresponding means are significantly different, i.e., 9 of 10 pairs of mechanoreceptors act differently in response to the stimulus type II. The number of FA-I mechanoreceptor pairs with significant difference of means for the observed average ISI and *FSL* in response to the same stimulus type is shown in Figure 3-7. For average ISI, most of FA-I mechanoreceptors act differently in response to the same stimuli except stimulus type I. For all six types of stimuli, there are 35 of 60 pairs of mechanoreceptors act differently in terms of average ISI. Similarly for *FSL*, most of FA-I mechanoreceptors act differently in response to the same stimuli except stimulus type I and type II. For all six types of stimuli, there are 30 of 60 pairs of mechanoreceptors act differently in terms of *FSL*.

There are two methods to restore the population activity: one is to use an individual set of parameter values for the spiking neuron model to mimic individual mechanoreceptor activity, and the other is to optimize specific quantities of the population activity directly with sparse arrangements of artificial sensors [154]. In this work, an attempt has been made by employing the first method. As an example, Figure 3-8 shows the observed and predicted spike trains for five FA-I mechanoreceptors, where individual parameter set of the spiking neuron model was obtained for each mechanoreceptor. If a fixed parameter set

(for instance, the parameter set for the first mechanoreceptor) is used for all FA-I mechanoreceptors, the other four predicted spike trains will be the same as that for the first one, which obviously does not agree with the observations. The relative good agreement between the predicted and the observed spike trains indicates that the neuron spiking model is capable to model the difference of individual FA-I mechanoreceptors, which is desired for the modeling of population activity.

Figure 3-6 Tukey simultaneous 95% confidence intervals of the differences of means for the observed average ISI from a pair of mechanoreceptors in response to the stimulus type

II: 20 Hz of amplitude 48 μm .

Figure 3-7 Number of FA-I mechanoreceptor pairs with significant difference of means for the observed average ISI and FSL in response to the same stimulus type.

Figure 3-8 The observed (red) and predicted (blue) spike trains for five FA-I mechanoreceptors in response to a 20 Hz sinusoid stimulus (top) with amplitudes of 34 μm (left), 48 μm (middle), 67 μm (right), and a 30 Hz sinusoid stimulus (bottom) with the same amplitudes. Each alternating shaded and unshaded patch corresponds to the responses of a particular FA-I mechanoreceptor.

3.5 Conclusion

This study establishes a bio-inspired approach using the piezoelectric PVDF film to mimic FA-I mechanoreceptors and the spiking neuron model to replicate spiking activities of FA-I mechanoreceptors in response to vibratory stimuli. The predicated and the observed spike trains agree reasonably well in term of both the average inter-spike intervals and the average first spike latency. Spike features of the FA-I mechanoreceptors, such as the variability, frequency dependent responses, and population activity, were also explored, which may play a vital role in the understanding of the functionality of FA-I mechanoreceptors and the development of advanced prosthetic limbs.

Chapter 4. Bioinspired Tactile Sensor for Surface Roughness Discrimination

4.1 Abstract

Surface texture discrimination using artificial tactile sensors has attracted increasing attentions in the past decade as it can endow robot systems with a key missing ability. However, as a major component of texture, roughness has rarely been explored. This chapter presents an approach for tactile surface roughness discrimination, which includes two parts: (1) design and fabrication of a bioinspired artificial fingertip, and (2) tactile signal processing for tactile surface roughness discrimination. The bioinspired fingertip is comprised of two polydimethylsiloxane (PDMS) layers, a polymethyl methacrylate (PMMA) bar, and two perpendicular polyvinylidene difluoride (PVDF) film sensors. This artificial fingertip mimics human fingertips in three aspects: (1) Elastic properties of epidermis and dermis in human skin are replicated by the two PDMS layers with different stiffness, (2) The PMMA bar serves the role analogous to that of a bone, and (3) PVDF film sensors emulate Meissner's corpuscles in terms of both location and response to the vibratory stimuli. Various extracted features and classification algorithms including support vector machines (SVM) and k -nearest neighbors (k NN) are examined for tactile surface roughness discrimination. Eight standard rough surfaces with roughness values (Ra) of 50 μm , 25 μm , 12.5 μm , 6.3 μm , 3.2 μm , 1.6 μm , 0.8 μm , and 0.4 μm are explored. By simply sliding the sensor on the surfaces without any load and speed controller, we found that the highest classification accuracy of $(82.6 \pm 10.8) \%$ can be achieved using

solely one PVDF film sensor with k NN ($k = 9$) classifier and the standard deviation feature, i.e., the developed approach is very affordable, robust and suitable for real time surface roughness evaluation.

4.2 Introduction

Surface texture is an important object property and can significantly affect the friction characteristics, wear resistance, and fatigue life of components [155]. Tremendous efforts have been made to recognize the surface texture using artificial tactile sensors or artificial fingers [156]–[159]. For example, a commercial electret microphone embedded in a silicone rubber was used to classify 18 surface textures [156]. By aid of a supervised learning vector quantization (LVQ) classifier, a classification accuracy of 93% was achieved. Muhammad et al. [157], developed a capacitive tactile sensor array to recognize fabrics including poly cotton and nylon. Oddo et al. [94], fabricated a 2×2 tactile piezoresistive sensor array based on microfabrication technology, which was embedded in a polymeric packaging with fingerprint-like structures. The density of the tactile sensing elements was considered to be comparable to that of human SA-I mechanoreceptors. Three gratings with $400 \mu\text{m}$, $440 \mu\text{m}$, and $480 \mu\text{m}$ spatial periods were explored. The wavelet and cross-wavelet transforms were performed to extract tactile features, and a classification accuracy of 97.6% was achieved by a k -Nearest Neighbors (k NN) classifier. Peiner et al. [160], developed a tactile cantilever sensor intended for high-aspect-ratio micrometrology with a resolution of 10-20 nm when scanning at a velocity of 0.63 mm/s. However, this sensor was prone to wear or damage.

Surface texture is defined by multiple characteristics such as roughness and hardness. Although tactile surface texture has been intensively investigated, surface roughness as a major component of surface texture is rarely explored. Current approaches to measure surface roughness could be divided into two categories [161]: contacting methods and non-contacting methods. The contacting methods are relatively immune to external interference as they depend mainly on the repulsive mechanical contact with the test surfaces. However, the stylus tip is prone to wear, and may cause scratches on the test surface as well. Compared to contacting methods, non-contacting methods measure the surface in a non-destructive way, but suffer from the limitations such as high sensitivity to surface slope and height.

Human beings possess the ability to sensitively perceive different materials [47], but the question remains as to how human beings encode the surface roughness during the physical finger-surface interactions. Extensive researches have been conducted to investigate the mechanisms underlying the perception of surface roughness [23], [48]–[50]. Connor et al. [49], proposed that the neural coding of tactile texture is closely related to the spatial variations in slowly adapting (SA) mechanoreceptive afferents, which was limited to the coarse surfaces with element spaces of $> 1\text{mm}$. Yoshioka et al. [50] extended Connor et al.'s work by studying the neural coding mechanisms for the roughness perception of finely textured surface, and found that there was a consistent relationship between human judgements of fine surface roughness and slowly adapting type I (SA-I) spatial variations. Libouton et al. [48], indicated that the tactile roughness discrimination relies mainly on vibration sensitive afferents. The fast adapting type I

(FA-I) mechanoreceptors (Meissner's corpuscles) and the fast adapting type II (FA-II) mechanoreceptors (Pacinian corpuscles) are generally regarded to be responsible for modulating the vibratory stimuli occurring at the interface of explored surfaces and the fingers [23]. Although many neurophysiological studies of the roles of mechanoreceptors have appeared, it is still an open question as to which mechanoreceptor plays a significant role. In this chapter, we provide an approach to investigate surface roughness recognition with a biomimetic fingertip, which mimics the properties of FA-I mechanoreceptors. We expect this platform could provide new insights into the neurophysiological study.

The main contribution in this chapter is a tactile surface roughness recognition method using a biologically inspired artificial fingertip. The artificial fingertip is designed and fabricated with two distinct polydimethylsiloxane (PDMS) layers. The inner layer is much softer than the outer layer. A polymethyl methacrylate (PMMA) bar is located in the center of this fingertip and plays the role similar to that of the bone in human fingertips. Inspired by Meissner's corpuscles in terms of both the distribution in human fingertip and the response to the vibration, two perpendicular polyvinylidene difluoride (PVDF) film sensors were placed beneath the outer PDMS layer to provide the sensory information. Both the statistical and spectral features are examined with the purpose of figuring out a good feature candidate for surface roughness discrimination. Unlike prior designs such as [94], which mimicked only SA-I mechanoreceptors (Merkel mechanoreceptors), our work reproduces the surface roughness perception ability of Meissner's corpuscles (FA-I mechanoreceptors). Another related approach [157] achieved roughness discrimination by assessing the peak frequency of frequency spectrum generated by capacitive sensors, but

no other features were evaluated. The design of the artificial fingertip for our method differs from the previous work [55], where the receptors are randomly distributed. The regular arrangement of tactile sensing elements in our design is much easier to repeat and more likely to be adopted in commercial production.

The proposed approach is illustrated in Figure 4-1 and the remainder of this chapter is organized as follows. The design and fabrication of a biological inspired fingertip are described in Section II. Subsequently, we give a detailed description of tactile signal processing of surface roughness discrimination in Section III, which is followed by Section IV of experimental setup and protocol. We then present the results and discussion in Section V. Finally, the conclusion is described in Section VI.

Figure 4-1 Surface roughness discrimination approach with a bioinspired artificial fingertip. The approach consists of (a) hardware to acquire the tactile data and (b) tactile signal processing for surface roughness discrimination.

4.3 Design and Fabrication of An Artificial Fingertip

This section describes the approach to develop a bioinspired fingertip. We briefly present the working mechanism of piezoelectric sensors. Subsequently, we give a detailed design of the artificial fingertip to mimic FA-I mechanoreceptors. We then show the protocol of how to fabricate it.

4.3.1 Piezoelectric PVDF film Sensors

Piezoelectric materials generate electrical charges when the crystal lattice is deformed under mechanical force and the generated charges are directly proportional to the mechanical stress [67]. However, the generated electric charges decay with a time constant that is determined by the internal impedance and dielectric constant of the piezoelectric material. A collection of tactile sensors have been developed by taking advantage of the piezoelectric effect [69]–[72]. These piezoelectric sensors exhibit a very good high-frequency response, which makes them extremely suitable for measuring vibrations. PVDF film is a classic example of piezoelectric polymer that is widely used as tactile sensors [76]–[78], where the lowest frequency measurable with piezoelectric PVDF film is in the order of about 0.01 Hz. In our work in Chapter 3, the capability of a PVDF film sensor to mimic tactile FA-I afferent has been successfully demonstrated by employing spiking neuron models and the model outputs agree reasonably well with biological measurements under the vibratory stimuli [3].

4.3.2 Structure of An Artificial Fingertip

Figure 4-2 Structures of (a) the designed artificial fingertip, (b) a developed artificial fingertip, (c) structure of human fingertip, and (d) artificial vs. human fingertip. The structures of both human and artificial fingertips contain two layers with different hardness, and a bone.

Figure 4-2 illustrates the structures of the designed artificial fingertip and human fingertip. The structure of our designed artificial fingertip resembles that of a human fingertip, which is comprised of epidermis, dermis, and a bone. The skin of human beings [14] is inherently elastic and consists of two layers, i.e., the epidermis and dermis. The hardness of the epidermis is higher than that of the dermis. In this chapter, we mimic skin's elastic properties using polydimethylsiloxane (PDMS) elastomer. The hardness difference between epidermis and dermis is emulated by altering the base to curing agent

mixing ratio. A polymethyl methacrylate (PMMA) bar serves the role comparable to that of a bone. In addition, the similar locations of Meissner's corpuscles, which lie just beneath the epidermis [22], are replicated by embedding the PVDF films between the two PDMS layers.

4.3.3 Protocol of Fabricating An Artificial Fingertip

The protocol of fabricating the designed artificial fingertip is shown in Figure 4-3. A commercial 28 μm -thick PVDF film (1-1003703-4, Measurement Specialties, USA) was cut into a desired size as small as 4 mm $\times$ 4 mm, and electrodes are bonded using a conductive paste. The soft PDMS cube is prepared by mixing 20 parts of silicone elastomer base to 1 part of curing agent (SYLGARD, Dow Corning, USA). A cuboid PMMA bar with a size of 4 mm $\times$ 4 mm $\times$ 45 mm is obtained by cutting a PMMA sheet using a laser cutting machine. The soft cured PDMS cube is bonded to either end of the PMMA bar (Figure 4-3 (b)). Two PVDF film sensors are then arranged perpendicularly on the top of the PDMS cube (Figure 4-3 (c)). The PMMA bar incorporated with a soft cured PDMS cube and PVDF films sensor was inserted in to a mold with a size comparable to human fingertips; then PDMS mixed at a 10:1 mixing ratio was cast into the mold (Figure 4-3(d)). Subsequently, the mold was put into a vacuum chamber in order to degas, and baked in an oven to complete the polymerization. The Young's modulus of the outer and inner PDMS with curing time of 1 hour are about 0.435 MPa and 0.147 MPa respectively [162].

Figure 4-3 The protocol of fabricating an artificial fingertip. (a) Components for fabricating an artificial fingertip. (b) A soft cured PDMS was bonded to the tip of a PMMA bar. (c) Two PVDF film sensors were arranged perpendicularly on the top of the PDMS cube. (d) The bar was inserted a mold of size resembles human fingertips; then PDMS mixed at a 10:1 mixing ratio was cast into it.

4.4 Tactile Signal Processing of Surface Roughness

Discrimination

In this section, statistical machine learning approaches are employed to interpret the tactile signals. First, feature extraction from tactile signals is performed. We then apply two distinct classifiers to discriminate surface roughness.

4.4.1 Feature Extraction

Feature extraction is critical for successful pattern recognition. Hand-crafted features such as Mel-frequency cepstral coefficients (MFCCs) [163] in speech recognition and *Scale-invariant feature transform* (SIFT) [164] in image processing are demonstrated to be powerful in practice. In contrast, feature extraction from tactile signals is far from mature due to many reasons such as the diversity of the working principles of tactile sensors. In this chapter, several approaches for tactile feature extraction from PVDF film sensors are compared in order to figure out a good feature candidate for tactile surface roughness discrimination. Table 4-1 describes the distinct features used in this chapter.

Table 4-1 Extracted features from tactile signals

Index	Feature type
1	Standard deviation (SD)
2	Statistical features (SF)
3	Signal roughness parameter Ra (SRa)
4	Power spectral magnitudes (PSM)
5	Combined feature 1 (SD + PSM)
6	Combined feature 2 (SF + PSM)
7	Combined feature 3 (SRa + PSM)

Standard Deviation (SD): The standard deviation is shown to be a promising feature for material texture classification [55]. Given the close relationship between material texture and roughness, the standard deviation is used as a feature for surface roughness recognition. Standard deviation features extracted from tactile signals of two PVDF films

when laterally sliding on eight surfaces (see section IV) with various roughness values are illustrated in Figure 4-4.

Figure 4-4 Standard deviation features extracted from tactile signals of two PVDF films when laterally sliding on eight test surfaces with various roughness values.

Statistical Features (SF): The SD feature can be extended to statistical features by introducing high-order moments. Specifically, the statistical features are defined as statistical moments of the tactile time series signals, which contain standard deviation, skewness, and kurtosis. Some similar features have already been used for vibration sensing [165] and local tactile shape discrimination [113].

Signal roughness parameter Ra (SRa): Inspired by the surface roughness parameters, signal roughness parameters can be defined in a similar way. In this work, we use signal roughness parameter Ra as a feature type, which can be regarded as a type of statistical

features as well.

Power Spectral Magnitudes (PSM): A set of power spectral magnitudes is employed as the tactile features. It is calculated by averaging the power spectral density over the desired sub-band. Spectral power magnitudes are reported to achieve good performance on both electromyography (EMG) [166] and electroencephalogram (EEG) applications [167].

In this chapter, the calculation of PSM is implemented on the whole band.

Combined Features: Single feature may not have the same discriminative power for all classes [168]. Therefore, it could be better to combine a set of diverse features. In this chapter, the feature combination is achieved by concatenating several features, which results in three additional combined features: SF + PSM, SD + PSM, and SRa + PSM. It is worth noting that a better performance could be obtained through nonlinear feature combination [169].

4.4.2 Classification Algorithms

Two classification algorithms are evaluated in this chapter: Support Vector Machines (SVM) and k -Nearest Neighbors (k NN). These two methods have met with significant success in numerous real world classification tasks [170]–[172].

Support Vector Machines (SVM): Support vector machines are developed from statistical learning theory [173], and have been applied in many applications in tactile sensing, such as slip detection [172], object shape recognition [113] and object texture discrimination [170]. Support vector machines are discriminative models which are aimed at finding a hyperplane to maximize the margin among classes. Kernel tricks facilitate the

data processing in high dimensional spaces. Both linear SVM with the kernel function $K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \mathbf{x}_j$ and radial basis function (RBF) SVM with the kernel function $K(\mathbf{x}_i, \mathbf{x}_j) = \exp\left(-\gamma \|\mathbf{x}_i - \mathbf{x}_j\|^2\right)$, where γ is the kernel parameter, are evaluated. The cost parameter C and kernel parameter γ for SVM-RBF are optimized by executing a grid search during the cross-validation procedure. The multi-class SVM classification used in this chapter is based on “one-against-all” scheme [174]. The classifier implemented in this work comes from the LIBSVM library [175].

***k*-Nearest Neighbors (*k*NN):** *k*-Nearest Neighbors is a non-parametric classifier. The class of a test sample is determined by taking majority vote of class labels among the *k* closest training samples. There are a variety of metrics to compute distance between samples such as Euclidean distance (L_2 distance), L_1 distance and cosine distance. In this chapter, the Euclidean distance is employed. The choice of the value of *k* is crucial because a small *k* may lead to a classifier sensitive to noise samples, and a large *k* could result in less distinct boundaries between classes.

4.5 Experimental Setup and Protocol

The PVDF film sensor signals were amplified by a custom-built amplifier, and digitalized at a sampling rate of 1 kHz via an analog-to-digital converter (DAQCard USB-6225, National Instruments, USA). Supporting software was developed to record digital signals (LabVIEW, National Instruments, USA). Eight standard solid nickel test surfaces (Rubert & Co. Ltd., UK) with roughness values (Ra) of 50 μm (Surface 1), 25 μm (Surface 2), 12.5 μm (Surface 3), 6.3 μm (Surface 4), 3.2 μm (Surface 5), 1.6 μm

(Surface 6), $0.8\ \mu\text{m}$ (Surface 7), $0.4\ \mu\text{m}$ (Surface 8) were explored (see Figure 4-5).

The test surface finish was carried out using cylindrical turning.

Experimental neuroscientists have identified lateral sliding movements play a vital role in mediating surface roughness recognition [48]. The cutaneous vibrations generated during the lateral sliding are encoded by the fast adapting mechanoreceptors. In this chapter, we manually performed this simple sliding movement to explore the surface roughness (Figure 4-1). This movement has been used for object identification as well [104], [171]. During the experiments, the sliding direction, speed and contact pressure were roughly controlled by operator. The sliding speed, which is about $0.24\ \text{m/s}$ in our experiments, will affect the surface roughness perception. We believe the classification accuracy could be improved if any speed controller is employed in the future. One PVDF film sensor was purposely put perpendicular to the sliding direction. The lateral sliding direction of the artificial fingertip along the test surface during our experiments is indicated by an arrow in Figure 4-5. The Sample tactile signals generated by two PVDF films when laterally sliding on eight test surfaces with various roughness values are shown in Figure 4-6. The PVDF film sensor parallel to the sliding direction is denoted by PVDF film 2, and the other PVDF film, which is close to the contact surface and perpendicular to PVDF film 2, is denoted by PVDF film 1.

Figure 4-5 Eight solid nickel test surfaces with roughness values Ra of $50\ \mu\text{m}$, $25\ \mu\text{m}$, $12.5\ \mu\text{m}$, $6.3\ \mu\text{m}$, $3.2\ \mu\text{m}$, $1.6\ \mu\text{m}$, $0.8\ \mu\text{m}$, and $0.4\ \mu\text{m}$ were explored. The lateral sliding direction of the artificial fingertip along the test surface during the conducted experiments is indicated by an arrow.

Figure 4-6 Typical tactile signals generated by two PVDF films when laterally sliding on eight test surfaces with various roughness values.

4.6 Results and Discussion

Ten lateral sliding movements were performed on the eight test surfaces, resulting in 80 tactile time series samples. For each test surface, the 10 tactile time series samples were randomly split into 9 samples as the training set and the remaining 1 sample as the test set. This split procedure was repeated 500 times. The feature vectors need to be normalized to

avoid any bias among features and numerical difficulties during the calculation. The effects of extracted features, classification algorithms and sensor number were evaluated.

Table 4-2 The highest classification accuracy based on both individual sensor and sensor combination

Sensor	Feature	Classifier	Accuracy
PVDF film 1	SD	k NN ($k = 9$)	$(82.6 \pm 10.8)\%$
PVDF film 2	SD + PSM	k NN ($k = 7$)	$(57.9 \pm 15.2)\%$
PVDF film1 + PVDF film 2	SRa	SVM (RBF)	$(78.8 \pm 14.2)\%$

Table 4-3 The highest classification accuracy of each classifier

Classifier	Feature	Sensor	Accuracy
SVM (Linear)	SD + PSM	PVDF film 1 + PVDF film 2	$(72.9 \pm 12.4)\%$
SVM (RBF)	SD	PVDF film 1	$(80.3 \pm 11.5)\%$
5NN	SRa	PVDF film 1	$(78.5 \pm 13.8)\%$
7NN	SD	PVDF film 1	$(77.2 \pm 12.3)\%$
9NN	SD	PVDF film 1	$(82.6 \pm 10.8)\%$
11NN	SRa	PVDF film 1	$(75.9 \pm 13.4)\%$

Table 4-4 The highest classification accuracy of each Feature

Feature	Classifier	Sensor	Accuracy
SD	k NN ($k = 9$)	PVDF film 1	$(82.6 \pm 10.8)\%$
SF	SVM (RBF)	PVDF film 1	$(71.2 \pm 14.7)\%$
SRa	SVM (RBF)	PVDF film1 + PVDF film 2	$(78.8 \pm 14.2)\%$
PSM	k NN ($k = 9$)	PVDF film 1	$(82.5 \pm 11.0)\%$
SD + PSM	k NN ($k = 9$)	PVDF film 1	$(82.5 \pm 11.0)\%$
SF + PSM	SVM (RBF)	PVDF film 1	$(72.7 \pm 14.3)\%$
SRa + PSM	k NN ($k = 5$)	PVDF film 1	$(77.8 \pm 13.3)\%$

Figure 4-7 shows the classification accuracy for each feature and algorithm with PVDF film 1 solely (Figure 4-7(a)), PVDF film 2 solely (Figure 4-7(b)), and both PVDF film 1 and PVDF film 2 (Figure 4-7(c)). The highest classification accuracy using solely PVDF film 1 is $(82.6 \pm 10.8) \%$ with k NN ($k = 9$) classifier and SD feature. In contrast, PVDF film 2 possesses a much weak discriminative capability, and the best classification accuracy is $(57.9 \pm 15.2) \%$ with k NN ($k = 7$) classifier and SF+PSM feature. The highest recognition rate using the combination of PVDF film 1 and PVDF film 2 is $(78.8 \pm 14.2) \%$ with SVM (RBF) classifier and SRa feature, i.e., the linear combination of two PVDF sensors on the feature level could not guarantee a performance improvement in terms of classification accuracy, when compared to the individual sensor. However, the approaches of nonlinear feature combination such as multiple kernel learning [176], [177] and boosting [168] may achieve a higher accuracy, which was left to future work. Table 4-2 summaries the highest classification accuracy based on both individual sensor and sensor combination. Table 4-3 and Table 4-4 respectively show the highest classification accuracy

of each classifier and feature.

We take a closer look at the classification accuracy of each surface class in order to investigate the limitation of the developed approach. Figure 4-8 shows the confusion matrix of the best classification results using the SVM classifiers (Figure 4-8(a)) and the k NN classifiers (Figure 4-8(b)). The majority of misclassifications are between surface 7 ($R_a = 0.8 \mu\text{m}$) and surface 8 ($R_a = 0.4 \mu\text{m}$). In other words, our artificial fingertip is highly likely to classify surfaces with roughness above $1 \mu\text{m}$. If these two surfaces are eliminated from the examined set, the best classification accuracy of the remaining six surface classes increases to 88.6% for the SVM (RBF) classifier with the SD feature and PVDF film 1 and 90.3% for the k NN ($k = 9$) classifier with the SD feature and PVDF film 1 respectively.

Figure 4-7 Classification accuracy of each feature and classification algorithm with (a) only PVDF film 1, (b) only PVDF film 2, and (c) both PVDF film 1 and PVDF film 2.

Error bars represent the standard error.

(a) Classifier: SVM (RBF) Feature: SD Sensor: PVDF film 1									
	S1	S2	S3	S4	S5	S6	S7	S8	Accuracy
S1	492	8	0	0	0	0	0	0	98.4%
S2	0	467	33	0	0	0	0	0	93.4%
S3	0	0	452	48	0	0	0	0	90.6%
S4	0	0	41	343	116	0	0	0	68.6%
S5	0	0	0	88	412	0	0	0	82.4%
S6	0	0	0	0	6	494	0	0	98.8%
S7	0	0	0	0	0	0	388	112	77.6%
S8	0	0	0	0	0	11	325	164	32.8%
Overall Accuracy (Mean $\pm$ Standard deviation): (80.3 $\pm$ 11.5)%									

(b) Classifier: kNN ($k = 9$) Feature: SD Sensor: PVDF film 1									
	S1	S2	S3	S4	S5	S6	S7	S8	Accuracy
S1	500	0	0	0	0	0	0	0	100%
S2	0	500	0	0	0	0	0	0	100%
S3	0	81	419	0	0	0	0	0	83.3%
S4	0	0	45	373	82	0	0	0	74.6%
S5	0	0	0	88	412	0	0	0	82.4%
S6	0	0	0	0	0	500	0	0	100%
S7	0	0	0	0	0	0	429	71	85.8%
S8	0	0	0	0	0	0	326	174	34.8%
Overall Accuracy (Mean $\pm$ Standard deviation): (82.6 $\pm$ 10.8)%									

S1 = Surface 1 (Ra = 50 μm)	S2 = Surface 2 (Ra = 25 μm)	S3 = Surface 3 (Ra = 12.5 μm)	S4 = Surface 4 (Ra = 6.3 μm)
S5 = Surface 5 (Ra = 3.2 μm)	S6 = Surface 6 (Ra = 1.6 μm)	S7 = Surface 7 (Ra = 0.8 μm)	S8 = Surface 8 (Ra = 0.4 μm)

Figure 4-8 Confusion matrix of the best classification results of classification algorithms

(a) the SVM classifier with RBF kernel, SD feature and PVDF film 1, and (b) the k NN classifier with $k = 9$, SD feature and PVDF film 1. The horizontal axis (S1-S8) denotes the ground truth, and the vertical axis represents the classifier output. The far right column presents the classification accuracy for each surface class.

4.7 Conclusion

We have presented an approach for performing tactile surface roughness

discrimination with a biologically inspired artificial fingertip. The fabricated bioinspired fingertip has two PDMS layers with different stiffness. It contains a PMMA bar to mimic the bone and two perpendicular PVDF film sensors to be equivalent to fast adapting type I mechanoreceptors. The Ra value range of test surfaces is from 0.4 μm to 50 μm . Five types of features ranging from statistical features to spectral features are extracted from tactile signals, and two classification algorithms (SVM and $k\text{NN}$) are used. The best classification accuracy is $(82.6 \pm 10.8) \%$ which can be obtained using solely PVDF film 1 with $k\text{NN}$ ($k = 9$) classifier and the SD feature. The classification accuracy could be enhanced to 90.3% using the $k\text{NN}$ classifiers for surfaces with roughness larger than 1 μm . All the experimental data were collected by manually sliding the artificial fingertip on the testing surfaces without using any controller for either sliding speed or normal load, i.e., the developed approach is very affordable, robust and suitable for real time surface roughness evaluation, for example, during the polishing process of large propellers, which would not require the tedious work to move the samples to a roughness measurement platform.

Chapter 5. Recognizing Tactile Surface Roughness with A Biomimetic Fingertip: A Soft Neuromorphic Approach

5.1 Abstract

Surface roughness is an important object property and can significantly affect the friction characteristics, wear resistance, and fatigue life of components. Although some work has been done on demonstrating the capability of specific tactile sensors for surface roughness discrimination, the soft neuromorphic approach by taking inspirations from neuroscience for tactile surface roughness discrimination is exceptionally rare. This chapter aims to fill this gap, and presents a soft neuromorphic method for tactile surface roughness discrimination with a biomimetic fingertip. The analog tactile signals generated from polyvinylidene difluoride (PVDF) films are fed as input to the Izhikevich neurons in order to obtain spike trains. Two distinct decoding schemes based on k -nearest neighbors (k NN) in both spike feature space and spike train space are used for surface roughness discrimination. We thoroughly examined the different spike train distance based k NN (STD- k NN) algorithms for decoding spike trains. Eight standard rough surfaces with roughness values (R_a) of 50 μm , 25 μm , 12.5 μm , 6.3 μm , 3.2 μm , 1.6 μm , 0.8 μm , and 0.4 μm are explored. The highest classification accuracy of $(77.6 \pm 13.7) \%$ can be achieved with k NN ($k = 11$) classifier and the Victor-Purpura distance ($q = 0.024 \text{ ms}^{-1}$).

5.2 Introduction

Neuromorphic engineering is an interdisciplinary domain that takes inspirations from neuroscience. It aims to mimic the neuronal architectures and function of nervous systems by the aid of electronic devices [178]. The past decade has witnessed tremendous efforts and progress made by the industry and academia with many neuromorphic designs and hardware developments. For instance, the address event representation (AER) is used as a signal transmission scheme in recent neuromorphic systems, which addresses the connectivity challenge of a large number of neurons on a silicon chip [179]. Neuromorphic scientists have also developed silicon retinas and silicon cochleas to replicate the functionality of retina and cochlea [180]–[185]. These systems have been demonstrated to possess biological properties such as local processing and local gain control. In addition to the surge in hardware development, there is another branch of neuromorphic engineering called soft neuromorphic engineering [106], which focuses on spike-like signal processing, mainly on spiking neural networks. External stimuli in most sensory systems are encoded, processed and transmitted as action potentials namely, spikes [186]. Even though that the transformation from the external information to spikes could impose penalties such as the loss of information and reduction in signal entropy [187], [188], it has many advantages, for instance, spikes are immune to attenuation during propagation over long distances [189], and possess a good anti-noise capability [190].

Recently, soft neuromorphic engineering has been employed in several tactile sensing applications such as gait event detection [141] and Braille letter recognition [96]. However,

a soft neuromorphic approach for tactile surface roughness discrimination is exceptionally rare. As a major component of surface texture apart from other characteristics such as waviness and lay, surface roughness is an important object property and can significantly affect the friction characteristics, wear resistance, and fatigue life of components [155]. Therefore, this chapter aims to fill this gap by investigating a soft neuromorphic method for tactile surface roughness discrimination. Another motivation of this chapter originates from bionic engineering, for example, prosthetic limbs [191]. In an able-bodied human, tactile stimuli like force and vibration can be detected by the mechanoreceptors embedded in the skin, and will be conveyed to the specific target in the brain or spinal cord. However, the outputs of artificial tactile sensors in a sensorized neural prosthesis are usually continuous and need to be processed before delivered to the tactile afferents. Therefore, the study of prosthetics with spike-like signals may provide new insight into the development of advanced neuroprosthesis.

This chapter focuses on two areas: (1) surface roughness encoding with spiking neuron models using a biomimetic fingertip; (2) interpretation of spike trains with distinct decoding schemes based on k -nearest neighbors (k NN) in both spike feature space and spike train space. Figure 5-1 illustrates the soft neuromorphic method for tactile surface roughness discrimination using a biomimetic fingertip in this chapter. The chapter is organized as follows: following the Introduction, the related previous work and contribution are described in Section 5.3 and Section 5.4, respectively. Subsequently, we give a detailed description of the materials and methods for tactile surface roughness discrimination in Section 5.5. We then present the results and discussion in Section 5.6

followed by the conclusion in Section 5.7.

Figure 5-1 Soft neuromorphic method for tactile surface discrimination using a biomimetic fingertip. The analog signals generated by tactile sensors are converted into spikes via spike neuron models. The spike train decoding schemes are based on k -nearest neighbors (k NN) in both spike feature space and spike train space.

5.3 Related work

5.3.1 Neurophysiology of Roughness Perception

Human beings possess the capability to sensitively perceive different materials [47], but the question remains as to how human beings encode the surface roughness during the physical finger-surface interactions. Extensive researches have been conducted to investigate the mechanisms underlying the perceived surface roughness [48]–[50]. Connor et al. [49], proposed that the neural coding of tactile texture is closely related to the spatial

variations in slowly adapting (SA) mechanoreceptive afferents, which was limited to the coarse surfaces with element spaces of $> 1\text{mm}$. Yoshioka et al. [50] extended Connor et al.'s work by studying the neural coding mechanisms for the roughness perception of the finely textured surface, and found that there is a consistent relationship between human judgements of fine surface roughness and slowly adapting type I (SA-I) spatial variations. However, a recent study showed that the tactile roughness discrimination relies mainly on vibration sensitive afferents [48]. The fast adapting type I (FA-I) mechanoreceptors (Meissner's corpuscles) and the fast adapting type II (FA-II) mechanoreceptors (Pacinian corpuscles) are generally regarded to be responsible for modulating the vibratory stimuli occurring at the interface of explored surfaces and the fingers.

5.3.2 Surface Roughness Classification Using Artificial Tactile Sensor

Tremendous efforts have been made to recognize the surface texture using artificial tactile sensors or artificial fingers [156]–[159]. However, relatively few investigations have been conducted to discriminate surface roughness. Oddo et al. [94], fabricated a 2×2 tactile piezoresistive sensor array based on microfabrication technology, which was embedded in a polymeric packaging with fingerprint-like structures. The density of the tactile sensing elements was considered to be equivalent to that of human slow adapting type I (SA-I) mechanoreceptors. Three gratings with $400\text{ }\mu\text{m}$, $440\text{ }\mu\text{m}$ and $480\text{ }\mu\text{m}$ spatial periods were explored. The wavelet and cross-wavelet transforms were performed to extract tactile features, and a classification accuracy of 97.6% was achieved by a

k -Nearest Neighbors (k NN) classifier. Peiner et al. [160], developed a tactile cantilever sensor intended for high-aspect-ratio micrometrology with a resolution of 10-20 nm when scanning at a velocity of 0.63 mm/s. However, this sensor was prone to wear or damage. Muhammad et al. [157], developed a capacitive tactile sensor array to recognize fabrics with groove width varied from 200 μ m to 1000 μ m in increments of 200 μ m. The surface roughness discrimination was performed by assessing the peak frequency of frequency spectrum generated by capacitive sensors.

5.4 Contribution

The main contributions of this chapter include the following: (1) we present a soft neuromorphic method for tactile surface roughness discrimination using a biomimetic fingertip, (2) we set out a straightforward examination of different spike train distance based on k -nearest neighbors (STD- k NN) algorithms in spike train space for tactile surface roughness discrimination.

Comparing with the previous work [94], [104], which mimicked only SA-I mechanoreceptors (Merkel mechanoreceptors), our work is inspired by the surface roughness perception ability of Meissner's corpuscles (FA-I mechanoreceptors). Compared to Rongala et al.'s work [104] that only investigated the Victor-Purpura distance, this paper thoroughly examines various spike train distances including both parameter-dependent and parameter-free distances based on k NN. In addition, any other spike train distance could be easily employed in the unified framework of the STD- k NN. This paper is also different from Rongala et al.'s work [104] by focusing on the

recognition of surface roughness, which is a major component of texture, but has rarely been explored. Compared to the previous work in tactile surface roughness discrimination using a neuromorphic approach [106], our work is different in terms of decoding algorithms and test surfaces to be explored. The problem in this chapter is formulated as a multi-class classification problem instead of binary classification problem, where multiple and complex surface samples are explored.

5.5 Materials and Methods

5.5.1 Biomimetic Fingertip

Figure 5-2 (a) Biomimetic artificial fingertip, and (b) biomimetic vs. human fingertip. The structures of both human and biomimetic fingertips contain two layers with different hardness, and a bone.

The biomimetic fingertip used in the experiment is shown in Figure 5-2. The structure of our designed artificial fingertip resembles that of a human fingertip, which is comprised of epidermis, dermis, and a bone. The skin of human beings [14] is inherently elastic and consists of two layers, i.e., the epidermis and dermis. The hardness of the epidermis is higher than that of the dermis. In this chapter, we mimic skin's elastic properties using polydimethylsiloxane (PDMS) elastomer. The hardness difference between epidermis and

dermis is emulated by altering the base to curing agent mixing ratio. A polymethyl methacrylate (PMMA) bar serves the role comparable to that of a bone. In addition, the similar locations of Meissner's corpuscles, which lie just beneath the epidermis [22], are replicated by embedding the polyvinylidene difluoride (PVDF) films between the two PDMS layers. PVDF film is a classic example of piezoelectric polymers that is widely used as tactile sensors [72], [76]–[78], and exhibit a very good high-frequency response, which makes them extremely suitable for measuring vibrations. In our work in Chapter 3, the capability of a PVDF film sensor to mimic tactile FA-I afferent has been successfully demonstrated by employing spiking neuron models and the model outputs agree reasonably well with biological measurements under the vibratory stimuli [3].

5.5.2 Spiking Neuron Models

Spiking neuron models [98] provide a bridge between analog signals and spike trains, and they are able to convert the analog signals into spike trains. There are many spiking neuron models proposed by neuroscientists, such as the Hodgkin-Huxley model [101] and the integrate-and-fire model [192]. The Hodgkin-Huxley model is rather complicated which is described by four coupled nonlinear differential equations. It is demonstrated to be biophysically accurate. However, the Hodgkin-Huxley model is computationally prohibitive and difficult to analyze mathematically. On the contrary, the integrate-and-fire model which is an idealization of a neuron with Ohmic leakage current [100], is computationally efficient and useful for analytical work. However, it is limited in generating rich spiking patterns. For instance, it does not have a spike generation

mechanism for the regenerative upstroke of the membrane potential. Therefore, the Izhikevich model [99] is proposed to strike a tradeoff between the Hodgkin-Huxley model and the integrated-and-fire model, and inherits the merits of both models, namely biological plausibility and computational efficiency.

The Izhikevich model is given by

$$\frac{dv}{dt} = \alpha v^2 + \beta v + \gamma + I \quad 5.1$$

$$\frac{du}{dt} = a(bv - u), \quad 5.2$$

where v denotes the membrane potential of a neuron, and u is the membrane recovery variable. α , β , γ , a , and b are parameters and I is the input current. Whenever the membrane potential v is driven to some specific threshold $v_T = 30 \text{ mV}$, a spike is produced and the after-spiking resetting is triggered which is given by

$$\text{if } v \geq v_T, \text{ then } \begin{cases} v \leftarrow c \\ u \leftarrow u + d. \end{cases} \quad 5.3$$

The values of α , β , and γ in Equation 5.1 are the same for all Izhikevich neurons. In contrast, the values of a , b in Equation 5.2 and c , d in Equation 5.3 vary according to the type of Izhikevich neurons. In this chapter, we choose the values for the most typical Izhikevich neurons, namely regular spiking neurons [99]. The parameter values for the Izhikevich neuron model used in this chapter are shown in Table 5-1. The input current $I(t) = GV(t)$ is computed based on the tactile voltage signals $V(t)$ from PVDF films. G is the electrical conductance regulating the input current. The classification accuracy with respect to the electrical conductance is evaluated in Section 4.

Table 5-1 Parameter values for the Izhikevich neuron model.

	α	β	γ	a	b	c	d
value	0.04	5	140	0.02	0.2	-65	8
unit	$s^{-1}V^{-1}$	s^{-1}	Vs^{-1}	s^{-1}	N.A.	mV	mV

5.5.3 Spike Train Decoding Schemes

Two spike train decoding schemes are evaluated in this chapter: spike feature based k -nearest neighbors (SF- k NN) and spike train distance based k -nearest neighbors (STD- k NN).

5.5.3.1 Spike Feature:

It is generally considered that a majority of sensory neurons convey information by firing rate (FR), which refers to a temporal average [98]. The inverse of average interspike interval (ISI) is closely related to firing rate. It only considers the period between the first spike time and the last spike time. Another spike feature of equal importance is first spike latency. The tactile information of surface shape manipulated by the finger is found to be more reliably conveyed by the relative timing of the first spike latencies (FSL) [127]. In this work, both the firing rate and the inverse of average ISI are evaluated because the first spike latency is difficult to determine due to the operation of manual sliding.

5.5.3.2 Spike Train Distance

In this section, a wide variety of methods to quantify the similarity for spike trains are

reviewed. Throughout the chapter the following notation is used. The i -th spike train is denoted by $\mathbf{s}^i = \{t_1^i, t_2^i, \dots, t_{N_i}^i\}$ N_i represents the total spike number. $t_j^i (j = 1, \dots, N_i)$ is the j -th spike time of the i -th spike train.

The Victor-Purpura Distance: The Victor-Purpura distance [193] between two spike trains is defined as the minimum cost of carrying out a transformation of one spike train into the other. The distance calculation is performed through three elementary operations, which consists of spike deletion, spike insertion, and spike shift. Each operation is associated with an operation cost. Specifically, the operation of deleting a spike or inserting a spike is assigned a cost of one, while the cost of spike shift is set to $q|\Delta t|$, where $|\Delta t|$ is the temporal distance, and q is a spike timing-sensitive parameter.

The van Rossum Distance: For the van Rossum distance [194], spike train is first converted to continuous function by associating each spike with an exponential function. Given a spike train $\mathbf{s} = \{t_1, t_2, \dots, t_N\}$, the resulting continuous function is defined as

$$f(t; \mathbf{s}) = \sum_{i=1}^N H(t - t_i) e^{-(t-t_i)/\tau}, \quad 5.4$$

where $H(t)$ is the Heaviside step function, and τ is the time constant. It is worth noting that the associated function could be functions other than the exponential. The van Rossum distance between two spike trains m and n is defined as the L_2 distance of the filtered spike trains, which is given by

$$D_R(\mathbf{s}^m, \mathbf{s}^n) = \frac{1}{\tau} \int [f(t; \mathbf{s}^m) - f(t; \mathbf{s}^n)]^2 dt. \quad 5.5$$

The ISI Distance: In a comparison with the previous distances, the ISI distance [195] is parameter free, and is calculated on the basis of the instantaneous interspike interval, which is defined as

$$ISI(t) = t_P(t) - t_F(t), \quad 5.6$$

where $t_P(t) = \min(t_i | t_i > t)$ is the time of the preceding spikes and $t_F(t) = \max(t_i | t_i < t)$ is the time of the following spikes. The resulting ratio function between the spike train m and n is given by

$$I(t) = \begin{cases} \frac{ISI^m(t)}{ISI^n(t)} - 1 & \text{if } ISI^m(t) \leq ISI^n(t) \\ 1 - \frac{ISI^m(t)}{ISI^n(t)} & \text{otherwise.} \end{cases} \quad 5.7$$

The ISI distance is derived by integrating $I(t)$ over time,

$$D_{ISI} = \int |I(t)| dt. \quad 5.8$$

The SPIKE Distance: The SPIKE distance [196] is sensitive to spike coincidences and quantifies the similarity mediated by differences in spike timing. Suppose there are two spike trains m and n , the instantaneous difference of the preceding spikes is defined as

$$\Delta t_P(t) = t_P^m(t) - t_P^n(t). \quad 5.9$$

Similarly, we can obtain the instantaneous difference of the following spike $\Delta t_F(t) = t_F^m(t) - t_F^n(t)$. The weighted average of the instantaneous spike difference is defined as

$$S(t) = \frac{|\Delta t_P(t)| \langle w_F(t) \rangle + |\Delta t_F(t)| \langle w_P(t) \rangle}{\langle ISI(t) \rangle^2}, \quad 5.10$$

where the weights are given by $w_P(t) = t - t_P(t)$ and $w_F(t) = t_F(t) - t$. $\langle \bullet \rangle$ denotes the average over spike trains. The SPIKE distance is then derived by integrating $S(t)$ over time

$$D_{SPIKE} = \int S(t) dt. \quad 5.11$$

The Event-Synchronization Distance: The Event-Synchronization distance [197] is based on the relative timings of events. In this chapter, the event is defined as spikes in the

spike trains. The spikes t_i and t_j in the distinct spike trains, are assumed to be synchronous if the time difference is smaller than a time lag τ_{ij} , which is given by

$$\tau_{ij} = \min\{t_{i+1} - t_i, t_i - t_{i-1}, t_{j+1} - t_j, t_j - t_{j-1}\}/2 \quad 5.12$$

The number of times a spike appears in the spike train m shortly after a spike appears in spike train n is denoted by

$$c(m|n) = \sum_{i=1}^{N_m} \sum_{j=1}^{N_n} J_{ij}, \quad 5.13$$

where J_{ij} is given by $J_{ij} = \begin{cases} 1 & \text{if } 0 < t_i^m - t_j^n \leq \tau_{ij} \\ 1/2 & \text{if } t_i^m = t_j^n \\ 0 & \text{otherwise.} \end{cases}$

Similarly, we can define $c(n|m)$. The Event-Synchronization distance is computed as

$$D_{\text{Event-Syn}} = 1 - \frac{c(m|n) + c(n|m)}{\sqrt{N_m N_n}} \quad 5.14$$

5.5.3.3 k -Nearest Neighbors (k NN)

k -nearest neighbors is a non-parametric classifier. The class of a test sample is determined by taking a majority vote of class labels among the k closest training samples. There are a variety of metrics to compute the distance between samples such as Euclidean distance (L_2 distance), L_1 distance and cosine distance. In this chapter, the Euclidean distance is employed together with spike feature for SF- k NN, while the spike train distance is used for STD- k NN in spike train space. The choice of the value of k is crucial because a small k may lead to a classifier sensitive to noise samples, and a large k could result in less distinct boundaries between classes. The spike train distance based k -nearest neighbors algorithm is outlined in Figure 5-3.

Algorithm 1. Spike Train Distance based k NN (STD- k NN)

```
1: Input:
    • Training set  $\mathbf{S} = \{(\mathbf{s}^1, y^1), (\mathbf{s}^2, y^2), \dots, (\mathbf{s}^N, y^N)\}$ , where
       $\mathbf{s}^i (i = 1, \dots, N)$  is the spike train and  $y^i \in (1, \dots, C)$  is the
      associated class label
    • Test sample  $\mathbf{t}$ 
2: for  $i = 1, \dots, N$  do
3:   Compute the spike train distance  $D(\mathbf{s}^i, \mathbf{t})$ 
4: end for
5: Obtain the set  $\mathbf{S}'$  of  $k$  closest training samples to  $\mathbf{t}$ 
6: Output:
     $y^* = \arg \max_{y'} \sum_{(\mathbf{s}^i, y^i) \in \mathbf{S}'} I(y^i = y')$ , where  $I(\cdot)$  is the indicator
    function
```

Figure 5-3 Spike train distance based k -nearest neighbors (STD- k NN) algorithm.

5.5.4 Experimental Setup and Protocol

The PVDF film sensor signals were amplified by a custom-built amplifier, and digitalized at a sampling rate of 1 kHz via an analog-to-digital converter (DAQCard USB-6225, National Instruments, USA). Supporting software was developed to record digital signals (LabVIEW, National Instruments, USA). Eight solid nickel test surfaces (Rubert & Co. Ltd., UK) with roughness values Ra of 50 μm (S1: Surface 1), 25 μm (S2: Surface 2), 12.5 μm (S3: Surface 3), 6.3 μm (S4: Surface 4), 3.2 μm (S5: Surface 5), 1.6 μm (S6: Surface 6), 0.8 μm (S7: Surface 7), 0.4 μm (S8: Surface 8) were explored (Figure 5-4). The test surface finish was carried out using cylindrical turning.

Experimental neuroscientists have identified lateral sliding movements play a vital role in mediating surface roughness recognition [48]. The cutaneous vibrations generated

during the lateral sliding are encoded by the fast adapting mechanoreceptors. In this chapter, we manually performed this simple sliding movement to explore the surface roughness (Figure 5-4(b)). This movement has been used for object identification as well with precise motion control [104], [171]. During the experiments, the sliding direction, speed and contact pressure were roughly controlled by the operator without relying on any motorized system. One PVDF film sensor was purposely put perpendicular to the sliding direction and denoted by PVDF film 1 while the other PVDF film sensor parallel to the sliding direction was denoted by PVDF film 2 (Figure 5-4(b)). The lateral sliding direction of the artificial fingertip along the test surface during our experiments is indicated by an arrow in Figure 5-4. Ten lateral sliding movements were performed on the eight test surfaces, resulting in 80 tactile time series samples. The sliding speed in our experiments was around 0.24 m/s. We also observed that the magnitude of the signals will be smaller if the sliding speed is lower because the frequency of vibration is smaller when the sliding speed is lower. The sliding speed consistency and surface classification accuracy could be easily improved at the cost of including a speed controller.

The sensor outputs $V(t)$ were tuned with the electrical conductance G prior to analog-to-spike conversion. Specifically, the input current of the Izhikevich neuron model was obtained through the equation $I(t) = GV(t)$. The sample tactile signals generated by PVDF films and the corresponding spike trains transformed by spiking neuron models (i.e., the Izhikevich model) with the electrical conductance $G = 0.4 \Omega^{-1}$ are shown in Figure 5-5. The effect of how to regulate the input current $I(t)$ by change the value of the electrical conductance is discussed in Section 5.6.

Figure 5-4 (a) Eight solid nickel standard surfaces with roughness values R_a of 50 μm , 25 μm , 12.5 μm , 6.3 μm , 3.2 μm , 1.6 μm , 0.8 μm , and 0.4 μm are explored. The lateral sliding direction of the artificial fingertip along the test surface during the conducted experiments is indicated by an arrow. (b) The locations of PVDF film sensors are indicated.

Figure 5-5 Typical tactile signals (top) generated by two PVDF films when laterally sliding on eight test surfaces with various roughness values, and the corresponding spike trains transformed via the Izhikevich model with electrical conductance $G = 0.4 \Omega^{-1}$ (bottom).

5.6 Result and Discussion

For each test surface, ten tactile time series samples were randomly split into the training set and the test set. This split procedure was repeated 500 times with ratios of 5:5, 7:3 and 9:1 between the training set and the test set. Table 5-2 shows that the highest classification accuracy based on different distributions between the training set and the test set. The highest classification accuracy is achieved with the ratio of 9:1, i.e., overfitting is not a problem with ratio of 9:1. In addition, the same split procedure was used in tactile object recognition [171]. The ratio between the training set and the test set is fixed to 9:1 in the following discussion.

Table 5-2 The highest classification accuracy based on various distributions between the training set and the test set.

Ratio Between the Training Set and the Test Set	<i>k</i> Value	Decoding Scheme	Best Classification Accuracy
5 : 5	7	<i>k</i> NN based on the Victor-Purpura distance	(72.3 ± 5.3)%
7 : 3	11	<i>k</i> NN based on the Victor-Purpura distance	(75.1 ± 6.5)%
9 : 1	11	<i>k</i> NN based on the Victor-Purpura distance	(77.6 ± 13.7)%

Figure 5-6 Firing rates of two PVDF film sensors when laterally sliding on eight test surfaces with various roughness values (a) Firing rate, (b) Inverse of average interspike interval.

Figure 5-6 shows the spike features of two PVDF film sensors when laterally sliding on eight test surfaces. Each point represents the result of one trial. It is shown that Surface 8 is distinguishable from other test surfaces for both firing rate and the inverse of average ISI. Surface 7 is more distinguishable for firing rate compared to average ISI. Firing rates of PVDF films, in particular for PVDF film 2 are completely overlapped for some trials, because the first spike time and the last spike time were not taken into account. Figure 5-7 depicts different spike train distances between every spike train pair across eight test surfaces for both PVDF films. It can be observed that the spike train distances between the pairs associated with the same test surface are much closer for both PVDF films. Ranges of all spike distances are much larger for PVDF film 1 compared to PVDF film 2.

Figure 5-7 Different spike train distances between every spike train pair across eight test surfaces for both PVDF film1 (top) and PVDF film 2 (bottom).

The performances of spike train decoding schemes including SF- k NN and STD- k NN are evaluated. Classification accuracy of each decoding scheme for both PVDF film 1 (top) and PVDF film 2 (bottom) is compared (Figure 5-8). The highest classification accuracy using PVDF film 1 is $(77.6 \pm 13.7) \%$ with k NN ($k = 11$) classifier and the Victor-Purpura

distance ($q = 0.024 \text{ ms}^{-1}$). In contrast, PVDF film 2 possesses a much weak discriminative capability, and the best classification accuracy is $(36.8 \pm 13.0) \%$ with k NN ($k = 9$) classifier and the van Rossum distance ($\tau = 96.81 \text{ ms}$). As expected, the decoding schemes based on parameter-dependent spike train distances outperform the spike feature based decoding schemes, because parameter-dependent spike train distances take spike times into account and the parameters could be optimized for performance improvement. It is worth mentioning that a classification accuracy of $(72.2 \pm 10.9) \%$ can be achieved by decoding scheme based on firing rate with k NN ($k = 7$) classifier, which means that the rate code might be accurate enough for roughness discrimination without taking the spike timing into further consideration.

The upper bound (red dash line in Figure 5-8) is the best classification result based on the analog signal without any analog-to-spike transformation, which can be found in our work in Chapter 4 [4]. The analog-to-spike conversion could be formulated as reduction of dimensionality [198]. Spike train has only one dimensional property, i.e., the spike time. The information loss arising from the transformation can be quantified by many measures such as information capacity and entropy [199]. For instance, Juusola and French [200] reported that the information capacity dropped from around 1400 bits/s to around 200 bits/s. In the context of the representation of surface roughness, it is shown (Figure 5-8) that the tactile information is mostly preserved, i.e., the transformation results in a decrease of the best classification accuracy by 5%.

Figure 5-9 shows the confusion matrix of the best classification results. The majority of misclassifications are between surface 7 ($R_a = 0.8 \text{ } \mu\text{m}$) and surface 8 ($R_a = 0.4 \text{ } \mu\text{m}$). In

other words, the artificial fingertip is much more accurate to classify surfaces with roughness above 1 μm . If these two surfaces are eliminated from the examined set, the best classification accuracy of the remaining six surface classes increases to 83.4%. Furthermore, all the results in this paper have the same trend as those in our previous work based on analog signal processing [4].

Figure 5-8 The classification accuracy of each decoding scheme is compared for both PVDF film 1 (top) and PVDF film 2 (bottom). The upper bound (red dash line) is the best classification result based on the analog signal without any analog-to-spike transformation in our previous work [4].

Classifier: $k\text{NN}$ ($k = 11$) The Victor-Purpura Distance $q = 0.024$									
	S1	S2	S3	S4	S5	S6	S7	S8	Accuracy
S1	500	0	0	0	0	0	0	0	100%
S2	0	494	6	0	0	0	0	0	98.8%
S3	0	0	338	114	48	0	0	0	84.5%
S4	0	0	50	317	133	0	0	0	63.4%
S5	0	0	0	92	387	21	0	0	77.4%
S6	0	0	0	0	34	466	0	0	93.2%
S7	0	0	0	0	0	0	258	242	51.6%
S8	0	0	0	0	0	0	154	346	69.2%
Overall Accuracy (Mean $\pm$ Standard deviation): (77.6 $\pm$ 13.7)%									

Figure 5-9 Confusion matrix of the best classification result of the decoding schemes with k NN ($k = 11$) classifier and the Victor-Purpura distance ($q = 0.024 \text{ ms}^{-1}$). The horizontal axis (S1-S8) denotes the ground truth, and the vertical axis represents the classifier output.

The far right column presents the classification accuracy for each surface class.

Both the Victor-Purpura distance and the van Rossum distance are parameter-dependent. We investigate the classification accuracy using both spike train distances with respect to the associated parameters. Figure 5-10 depicts the evaluation of classification accuracy for PVDF film 1 with both parameter-dependent spike train distances (the value of $k = 11$). For the value of $k = 5, 7, 9$, the recognition performance as a function of the associated parameters have the similar trend.

The electrical conductance can regulate the input current of the Izhikevich model and eventually influence the classification accuracy. We tune the electrical conductance and evaluate the performance of classifiers based on the Victor-Purpura distance and the van Rossum distance. It is shown (Figure 5-11) that the highest classification accuracy is $(77.6 \pm 13.7) \%$ with the Victor-Purpura distance ($G = 0.4 \text{ } \Omega^{-1}$) for PVDF film 1 and $(47.5 \pm 16.2) \%$ with the Victor-Purpura distance ($G = 1.4 \text{ } \Omega^{-1}$) for PVDF film 2.

Figure 5-10 Evaluation of classification accuracy of STD- k NN (the Victor-Purpura distance and $k = 11$) with respect to the spike timing-sensitive parameter q for PVDF film 1 (left). Evaluation of classification accuracy of STD- k NN (the van Rossum distance and $k = 11$) with respect to the time constant τ for PVDF film 1 (right).

Figure 5-11 Evaluation of classification accuracy of STD- k NN (the Victor-Purpura distance and the van Rossum distance) with respect to the electrical conductance G . (a) PVDF film 1, (b) PVDF film 2.

5.7 Conclusion

We have presented a soft neuromorphic approach for performing tactile surface roughness discrimination with a biologically inspired artificial fingertip. The Ra value

range of test surfaces is from 0.4 μm to 50 μm . Five spike train distance and spike features together with the $k\text{NN}$ classifiers were used and the best classification accuracy is $(77.6 \pm 13.7) \%$ obtained using $k\text{NN}$ ($k = 11$) classifier and the Victor-Purpura distance ($q = 0.024 \text{ ms}^{-1}$). The best classification accuracy decreases by only 5% compared to the analog tactile signal interpretation in our previous work, which indicated that the tactile information is mostly preserved in the context of surface roughness representation during the analog-to-spike transformation. All the experimental data were collected by manually sliding the artificial fingertip on the testing surfaces without using any controller for either sliding speed or normal load, i.e., the developed approach is very robust and suitable for real time surface roughness evaluation. The study of a soft neuromorphic approach for tactile surface roughness discrimination may provide new insight into the development of advanced neuroprosthesis and neurorobots.

Chapter 6. Active Tactile Object Exploration with Gaussian Processes

6.1 Abstract

Accurate object shape knowledge provides important information for performing stable grasping and dexterous manipulation. When modeling an object using tactile sensors, touching the object surface at a fixed grid of points can be sample inefficient. In this chapter, we present an active touch strategy to efficiently reduce the surface geometry uncertainty by leveraging a probabilistic representation of object surface. In particular, we model the object surface using a Gaussian process and use the associated uncertainty information to efficiently determine the next point to explore. We validate the resulting method for tactile object surface modeling using a real robot to reconstruct multiple, complex object surfaces.

6.2 Introduction

As robots move from laboratories to domestic environments, they will be required to perform manipulation tasks in unstructured environments. Such robots must be able to achieve sophisticated interactions with the environment and to perform complex tasks such as grasping objects with arbitrary unknown shapes [20], and avoiding slip while applying minimal force to the grasped objects [21]. Object surface property reconstruction plays a vital role in allowing robots to implement these tasks. For instance, shape information is often important for stable grasping as robots can adjust the grasping pose

accordingly if shape of the object is known [20]. Surface roughness is closely related to the minimal force applied on the object to counteract slip events [21].

Surface property reconstruction from photos, especially shape reconstruction, has extensively been investigated by the computer vision community [201]–[203]. However, vision based methods suffer from limitations such as the available illumination and are not applicable when the object is not visible or occluded. In this case, the sense of touch becomes a particularly valuable and complementary sensation to surface property modelling. Compared to vision-based methods, tactile-based approaches are always local [204], i.e., during each touch, only a small part of the object surface can be touched. Thus a robot must touch a given object at several locations along its surface to recover the shape.

State-of-the-art tactile sensors show similar sensing capabilities such as dynamic tactile sensing [76] when compared to humans. In particular, for detecting vibrations, these sensors are more sensitive and accurate than humans [205]. A number of approaches have explored these enhanced capabilities to perform tactile-based object shape reconstruction [204], [206]–[209]. These methods commonly begin with touching the object at a grid of points, which can be sample inefficient for real robot systems. For example, a grid of 50 hand poses is necessary to cover the entire surface of an object when using the Schunk hand in [204]. However, grid search might not be the best solution for object surface reconstruction as adjacent points on the object surface tend to be highly correlated in terms of local geometrical features. In this article, we represent the tactile-based object surface models using Gaussian processes. Based on these models, an active touch strategy is used

to reduce the number of sampling iterations necessary for reconstructing the object surface. We demonstrate this approach is capable of achieving faster reconstruction rates when compared to random sampling.

Figure 6-1 A BioTac finger mounted on a Mitsubishi PA-10 robot arm equipped with a Schunk force torque sensor. The steel container is fixed to a vertical surface in order to ensure the surface data alignment during each touch. Its front surface is to be reconstructed. The red coordinate frame denotes the axis direction of the world reference frame that is located at the base of the robot.

6.3 Related work

Shape is one of the most important surface properties of an object. It can be decomposed into global and local shape [113]. The global shape emphasizes the form of an object, while the local shape is linked to local features such as curvatures and edges.

Montana [206], used the kinematics of contact to estimate the local curvature of an unknown object. The kinematics of contact could be employed in contour following as well under the assumption that the end-effector velocity relative to the immobilized object

was measurable by proprioceptive sensors. Jia and Tian [209], presented a method for surface patch reconstruction using “one-dimensional” tactile data. The tactile data was obtained by a two-axis joystick sensor. By simply sliding the fingers over the object surface and using contour tracking techniques, the problem of probing the surface at a grid of points is alleviated. Moll and Erdmann [210], used two tactile sensors to reconstruct an unknown smooth convex planar shape without requiring object immobilization. A closed-form solution regarding the relationship between curvature at the contact points and the rotational speed of the object was provided. Reznik and Lumelsky [211], assumed that every point of the robot hand surface was endowed with the capability of tactile sensing. Based on this assumption, the robot hand was expected to be able to manipulate objects with arbitrary unknown shapes. However, this assumption is quite unrealistic and unfeasible with current technology. Allen and Michelman [208], made an attempt to represent the object surface geometry as a superquadric surface. Dragiev et al. [212], presented a tactile exploration strategy based on Gaussian process implicit shape potential (GPISP) for grasping. The uncertainty aware grasping method improved the performance of tactile exploration. However, this strategy was not implemented on a real robot. Inspired by the method used in mobile robot navigation, Bierbaum et al. [213], presented a tactile exploration strategy with an anthropomorphic five-finger hand. This approach was able to guide the robotic hand along the surface of previously unknown objects.

Traditionally, visual information is preferred for object reconstruction. Li et al. [214], developed a novel tactile sensor known as Gelsight. With this sensor, they were able to reconstruct the 3-D surface geometry of several objects with the aid of photometric stereo

algorithms. This new tactile sensing technique was shown to be highly accurate during small parts manipulation and insertion of a USB connector into its socket. Another vision-based tactile sensor was developed to estimate the irregularity of object surfaces [215]. The intensity of the traveling light produced by a LED carries the geometrical information of the touchpad surface. Bjoerkman et al. [207] proposed a probabilistic approach based on Gaussian process regression to enhance visual perception of shape. Tactile measurements iteratively improved the object surface model that was initialized with visual features. Ilonen et al. [216], proposed a method for optimally fusing visual and tactile measurements for symmetrical objects. The visual information was captured by an RGB-D sensor, and tactile information from grasping the unknown object in varying angles was employed to refine the object model.

In this chapter, we solely focus on object surface modelling with tactile information. The main contribution is an active touch strategy to reduce the surface geometry uncertainty using a probabilistic representation of the object surface. In particular, we use a Gaussian process in conjunction with the acquisition function to efficiently find the next points to explore.

6.4 Active Tactile Object Modeling and Exploration

We now focus our attention on our approach for efficiently reconstructing an object surface model. We first describe how to convert our raw tactile measurements into a consistent reference frame. Subsequently, we give a detailed description of estimating an object surface model using a Gaussian process. We then show how we use uncertainty

estimates to drive our active tactile data exploration strategy.

6.4.1 Point Cloud Registration with Tactile Sensing

In our experiments to explore the object surface geometry, the BioTac sensor is used for acquiring the necessary tactile data. The BioTac tactile sensor is a multimodal tactile sensor that pressure, vibration, and temperature [217]. It contains $N_e = 19$ impedance sensing electrodes, which measure the local deformation on the finger surface. We combine these readings into an estimate of a single point of contact (PoC). This estimate is calculated by a weighted average of the Cartesian coordinates of all electrodes. The weights are the impedance values from each of the electrodes. The point of contact (x_c, y_c, z_c) is given by

$$(x_c, y_c, z_c) = \frac{\sum_{i=1}^{N_e} |e_i^*|^2 (x_i, y_i, z_i)}{\sum_{i=1}^{N_e} |e_i^*|^2} \quad 6.1$$

where e_i^* is the normalized value of the electrodes, and (x_i, y_i, z_i) is the Cartesian coordinate of each electrode on the finger surface. The obtained PoC is in a coordinate frame attached locally to the BioTac. In order to use these PoC estimates for surface reconstruction, we must transform the position $\mathbf{m}_n = (x_c, y_c, z_c)$ into the world coordinate frame using the robot's forward kinematics. We denote the transformed point $\mathbf{x}_n$. Figure 6-2 depicts the two objects we used in experiments along with registered point clouds built from tactile data samples.

Figure 6-2 Example objects (left) and registered tactile point clouds (right) of the front surface of a steel container and the face of a porcelain bird. The rectangular zones are to be reconstructed. The point cloud of the porcelain bird with side view and the point cloud of the front surface of the steel container with top view. Tactile point clouds are obtained with a BioTac tactile sensor.

6.4.2 Gaussian Processes as Surface Models

Gaussian processes (GPs) [218] are a powerful tool for regression problems. In this chapter, we use Gaussian processes to model object surfaces. These models are a probabilistic representation of the surface geometry. While implicit surface models have been proposed using GPs [207], [219], we elect to use an explicit representation in order to avoid the need of creating artificial interior and exterior boundary points to stabilize the surface model. However, the active touch approach we present is still valid for the implicit

GP model, as long as some care is taken to account for these artificial points. Our explicit model of the surface takes the form $y_n = f(x_n, z_n)$, with (x_n, y_n, z_n) defined as the contact coordinate, x_n , in the world reference frame (refer to Figure 6-1).

A GP is fully specified by mean function $\mu(\tilde{\mathbf{x}})$ and covariance function $k(\tilde{\mathbf{x}}_i, \tilde{\mathbf{x}}_j)$, where $\tilde{\mathbf{x}}_i = (x_i, z_i)$. We choose as covariance function the squared exponential

$$k(\tilde{\mathbf{x}}_i, \tilde{\mathbf{x}}_j) = \sigma_f^2 \exp \left\{ -\frac{1}{2} (\tilde{\mathbf{x}}_i - \tilde{\mathbf{x}}_j)^T \mathbf{\Lambda}^{-1} (\tilde{\mathbf{x}}_i - \tilde{\mathbf{x}}_j) \right\} + \sigma_\omega^2 \delta_{ij} \quad 6.2$$

where $\mathbf{\Lambda}$ is a diagonal matrix and δ_{ij} is the Kronecker delta. The prior mean function $\mu(\tilde{\mathbf{x}})$ is specified by $\mu(\tilde{\mathbf{x}}) = \mathbf{0}$. We define the training data set as $\mathbf{T} = [(\tilde{\mathbf{x}}_1, y_1), \dots, (\tilde{\mathbf{x}}_N, y_N)]$. For a new observation $\tilde{\mathbf{x}}_*$, the predictive distribution of a GP is Gaussian with the mean $\mu(\tilde{\mathbf{x}}_*)$ and the variance $\sigma^2(\tilde{\mathbf{x}}_*)$

$$\mu(\tilde{\mathbf{x}}_*) = \mathbf{k}_*^T \mathbf{K}^{-1} \mathbf{y} \quad \sigma^2(\tilde{\mathbf{x}}_*) = k_{**} - \mathbf{k}_*^T \mathbf{K}^{-1} \mathbf{k}_* \quad 6.3$$

where $\mathbf{k}_*$ is a vector with N entries $k(\tilde{\mathbf{x}}_i, \tilde{\mathbf{x}}_*)$, $\mathbf{K}$ is the matrix with $\mathbf{K}_{ij} = k(\tilde{\mathbf{x}}_i, \tilde{\mathbf{x}}_j)$ and $k_{**} = k(\tilde{\mathbf{x}}_*, \tilde{\mathbf{x}}_*)$. The posterior mean defines an estimate of the object's shape and the posterior variance defines the uncertainty regarding the unexplored area.

6.4.3 Action Selection

Due to the inherent locality of tactile sensing, a robot must touch an object at multiple locations in order to cover the entire surface of the object. Performing many touch actions can be sample inefficient. We devise an efficient strategy for deciding the next touch action in order to reduce the total number of object probes. By updating the probabilistic representation given in Equation 6.3 after each touch, we can employ a straightforward strategy for exploring the object.

We draw our inspiration from Bayesian optimization (BO), which uses different “acquisition functions” to address the choice of which point to sample from a target object function when performing black-box optimization in an iterative manner [220]. BO has been used in various robotic applications such as gait optimization [221], grasp optimization [222], and policy search [223]. In the literature, a number of acquisition functions $\alpha(\tilde{\mathbf{x}})$ have been proposed, such as upper confidence bound (UCB) [224], probability of improvement (PI) [225] and expected improvement (EI) [226]. All of these proposed acquisition functions implicitly handle the exploration versus exploitation trade-off. Our active touch approach focuses on exploration of uncertain surface regions and thus does not need to account for exploitation of well-known surface areas. We base our acquisition function on the predicted standard deviation $\sigma(\tilde{\mathbf{x}})$, as it can be seen as a measure of surface uncertainty at a given location. The surface point with highest uncertainty serves as a good candidate for the next touch location, as it is either far from any recorded measurements or near areas of large surface variation. We thus define our acquisition function as $\alpha(\tilde{\mathbf{x}}) = \sigma(\tilde{\mathbf{x}})$. Our active tactile exploration approach is outlined in Algorithm 1, and it will be subsequently referred to as the “active touch method”. To find the global optima of the acquisition function, we use DIRECT [227] to find the approximately optimal solution, which is subsequently refined by LBFGS [228].

6.5 Experiments and Results

We evaluate our active touch method on a benchmark task and realistic experiments. First, we validate the proposed method on a 1-D toy example. Second, we apply the active

tactile exploration approach to the task of object surface reconstruction using a real robot.

As a baseline, we compare to a method which chooses touch locations uniformly randomly.

6.5.1 Proof of Concept: A Toy Example

The toy example is a 1-D function which consists of a curved part and a flat part. It is defined as

$$f(x) = \begin{cases} \sin(\omega x) + 1 & \text{if } -1 \leq x \leq 1 \\ 1 & \text{if } -2 \leq x < -1 \text{ or } 1 < x \leq 2, \end{cases} \quad 6.4$$

where $\omega = 4\pi$.

The active exploration process for an unknown 1-D function is illustrated in Figure 6-3. The left and right columns represent the optimization process with the random and active touch approaches respectively. The green curve shows the true function. The shaded area (red and blue) represents the 95% confidence bound of the GP model. The exploration process is initialized with five random points (shown as blue crosses). These points are also used to initialize the GP models. The maximum of the acquisition function determines the next points (i.e. the red crosses) to be explored by the active exploration method. The GP models are updated after each sampling iteration. After a few iterations, the GPs could accurately model the true function. We conclude that the active touch method is more accurate at reconstructing the unknown 1-D curve while using fewer points than the random touch method. In this experiment, we quantify the similarity between the true function and the reconstructed function by measuring the correlation coefficient between the two, defined by:

$$R = \frac{\int f(x)\hat{f}(x)dx}{\sqrt{\int f(x)^2\hat{f}(x)^2dx}} \quad 6.5$$

where $f(x)$ and $\hat{f}(x)$ are the true function and reconstructed function respectively. The integrals in Equation 6.5 are approximated as sums over the test set. Figure 6-4 shows the average correlation coefficient between the real and predicted function over ten trials for both the active and the random touch method. As expected, the correlation coefficient almost converges to 1 much faster when using the active touch approach. The random approach obtains a higher correlation coefficient initially up until about 15 samples. We attribute this to the hyperparameter estimation being overly-confident, causing the system to select a larger characteristic length-scale than the true function. We could potentially fix this by bounding the length scale to some maximum value, proportional to the desired resolution of our result. We leave this to future work.

Figure 6-3 A toy example of the active exploration process for reconstructing an unknown 1-D surface (green curve). The 95% confidence of the model prediction is represented by the shaded area. The red (left) and blue area (right) represent optimization based on random touch, and on active touch respectively. The surface model is initialized with 3 random points (blue crosses). The subsequent points to explore are marked with red crosses. At each iteration, the model is updated using all the obtained points (both blue and red crosses). After a few iterations, the active touch method is able to reconstruct the unknown 1-D curve more accurately.

Figure 6-4 The correlation coefficient over 50 evaluations for both the random and active touch. Both methods are initialized with 3 random touches. The shaded areas represent the standard error. The correlation coefficient between the real function and reconstructed function almost reaches 1 after 23 touches with the active touch approach.

6.5.2 Tactile Object Surface Modeling

We explain how we perform tactile object surface modeling using a real robot. Starting with a description of the experimental robot platform, we follow with a detailed explanation of the tactile data collection procedure. Finally, we present the results of the tactile object surface reconstruction.

6.5.2.1 Experimental Setup

The experiments were conducted on a Mitsubishi PA-10, a robot arm with seven degrees of freedom. A BioTac tactile sensor, used to touch the object, is rigidly attached to

a force-torque sensor. The force-torque sensor is mounted to the end effector of the robot arm. It allows the robot to perceive the force exerted on the object, and is used in order to avoid any unexpected collisions. An inverse Jacobian controller is implemented to drive the robot end effector to the desired task space locations. The objects used include the steel container and porcelain bird shown in Figure 6-2. We affix the objects to a vertical surface in order to ensure that the surface data remains aligned during the entire data collection procedure. The complete setup can be seen in Figure 6-1. In addition to the signals from 19 electrical impedance electrodes, the BioTac sensor produces another four types of tactile signals: absolute fluid pressure (PDC) signal, dynamic fluid vibration (PAC) signal, temperature (TDC) and heat flow (TAC). In our experiments, a contact between the BioTac finger and touched objects is considered to occur if a change in the absolute fluid pressure passes a small threshold.

6.5.2.2 Data Collection:

The area to be reconstructed for both the steel container and the porcelain bird is constrained to a predefined rectangular zone (refer to Figure 6-2). For both the random and active touch approaches, the first several touches are randomly performed. Specifically, a random value of (x, z) in the world reference frame is uniformly sampled from the predefined zone, and then the end effector moves in the negative y-axis direction until it detects contact and stops. The actual contact position between the BioTac finger and the object surface is computed using the 19 electrodes and is registered after the homogeneous transformation described in Section III-A. After obtaining these random

tactile surface samples, the end effector will move back concluding the random sampling phase. It is worth mentioning that the contact position computed from the BioTac may not have the same (x, z) components as the point chosen by the acquisition functions. This can easily occur since the BioTac will likely make contact with the object at some location other than the commanded position for the finger center. These initial samples are used to initialize the Gaussian process surface model. Subsequent touch locations (x, z) are calculated differently for the active touch and random touch approaches. The active touch approach is based on Algorithm 1, while the random touch approach continues to randomly sample from the predefined zone. The GP model is updated after each sampling iteration. This iterative sampling procedure is repeated by both approaches until a reasonable tactile data set is collected.

6.5.2.3 Surface Estimation Results

The active exploration process for the steel container is illustrated in Figure 6-5. The top and bottom row represent the optimization process of random touch and active touch respectively. The exploration process is initialized with five random touch points (i.e. the blue points). The GP models are initially trained on those random touches and iteratively determine subsequent touch points (i.e. the red points) to explore. The predicted surfaces are the means of GPs computed over the test set. It is shown that the GP models based on active touch accurately model the surface using only ten additional touches. Figure 6-6 illustrates an example of using the active touch method to determine the next touch location. We see that the GP models a larger characteristic length-scale of the covariance

function in the Z-dimension compared to the X-dimension. This characteristic was automatically learned by the GP and is consistent with the real object.

Figure 6-7 depicts the active exploration process for the porcelain bird. The top and bottom rows represent the exploration strategies of random touch and active touch respectively. Each exploration process is initialized with 20 random touch points (i.e. the blue points). The figure represents the models after 100 additional touches. The active touch method better reconstructs the face of the porcelain bird. In particular, it more accurately models the boundaries of the reconstruction zone. However, both methods fail to model the nose of the porcelain bird. Several factors lead to this issue. First it may be caused either by the smoothness limitations imposed by the covariance function or samples being averaged out in computing the maximum a posteriori (MAP) estimate. This problem arises from data being difficult to collect near the edge of the nose, because of the relatively large size of the BioTac sensor compared to the nose.

Figure 6-5 Evolution of the steel container model as function of the number of touches.

The optimization is initialized with 5 random touches (blue points). The subsequent points to explore are marked with red points. The top row represents the model build from random samples. The bottom row shows results for the active touch method. The columns from left to right represent the models after (a) 5, (b) 10, and (c) 15 additional touches. (d)

The real object for comparison. Each predicted surface is the mean of the GP computer over the test set. The active touch method more accurately reconstructs the object surface

for a given number of samples compared to the random touch approach.

Figure 6-6 An example of the active touch method for determining a new touch location.

The acquisition function is high where the Gaussian process predicts a high uncertainty (left). The position with the maximum acquisition function value defines the next touch

location (right).

Figure 6-7 (a) The porcelain bird models for both the random and active touch approaches

with 20 randomly selected initial touches (blue points) and 100 additional touches (red

points). (b) The real object for comparison. The predicted surfaces are the means of GPs

over the test set. After 100 touches, the active method could model the bird face more

accurately, particularly at the edge of the explored zone.

6.6 Conclusions

Tactile object surface reconstruction is a complex task. In this chapter, we circumvent exhaustively touching the object in a grid by presenting an active exploration approach. We validate our method on a toy example and on tactile object surface modeling using a real robot. The toy example successfully shows that our active touch approach can reconstruct an unknown 1-D surface more accurately while using fewer points compared to the random touch method. For the tactile object modeling task, our robot strategically chooses the point to be touched. This approach makes a reasonable estimate of an object's shape, while dramatically reducing the exploration time. The reconstructed object features have great promise for a number of applications, such as object recognition and stable grasping. A limiting assumption of our method is that the object has to be rigid and must be immobilized during the entire data collection procedure.

Chapter 7. Conclusion and Future Work

7.1 Conclusion

In this thesis, we have addressed the problems in biomimetic tactile sensing and exploration. This thesis establishes a bio-inspired approach using the piezoelectric PVDF film to mimic FA-I mechanoreceptors and the spiking neuron model to replicate spiking activities of FA-I mechanoreceptors in response to vibratory stimuli. The predicated and the observed spike trains agree reasonably well in term of both the average inter-spike intervals and the average first spike latency. Spike features of the FA-I mechanoreceptors, such as the variability, frequency dependent responses, and population activity, were also explored.

We have designed and fabricated a biomimetic fingertip, which has two PDMS layers with different stiffness. It contains a PMMA bar to mimic the bone and two perpendicular PVDF film sensors to emulate fast adapting type I mechanoreceptors. Based on the developed artificial fingertip, we demonstrated the recognition ability of the fingertip in terms of discriminating surface roughness. We explored eight test surfaces with Ra value range from $0.4\text{ }\mu\text{m}$ to $50\text{ }\mu\text{m}$ with two distinct signal processing approaches. One is based on analog signals, where five types of features ranging from statistical features to spectral features are extracted from tactile signals, and two classification algorithms (SVM and k NN) are used. The best classification accuracy is $(82.6 \pm 10.8)\%$ which can be obtained using solely PVDF film 1 with k NN ($k = 9$) classifier and the SD feature. Another method is within the scope of soft neuromorphic techniques. Specifically, five spike train

distance and spike features including the firing rate and the inverse of interspike interval, together with the k NN classifiers were used and the best classification accuracy is $(77.6 \pm 13.7) \%$ obtained using k NN ($k = 11$) classifier and the Victor-Purpura distance ($q = 0.024 \text{ ms}^{-1}$). The study of a soft neuromorphic approach for tactile surface roughness discrimination may provide new insight into the development of advanced neuroprostheses.

For the tactile object surface reconstruction task, we circumvent exhaustively touching the object in a grid by presenting an active exploration approach. We validate our method on a toy example and on tactile object surface modeling using a real robot. The toy example successfully shows that our active touch approach can reconstruct an unknown 1-D surface more accurately while using fewer points compared to the random touch method. For the tactile object modeling task, our robot strategically chooses the point to be touched. This approach makes a reasonable estimate of an object's shape, while dramatically reducing the exploration time. The reconstructed object features have great promise for a number of applications, such as object recognition and stable grasping. A limiting assumption of our method is that the object has to be rigid and must be immobilized during the entire data collection procedure.

7.2 Future Work

The work of tactile surface roughness recognition can be extended in several directions that might improve the classification accuracy. One direction is to improve the hardware. For instance, more PVDF films could be integrated in the biomimetic fingertip

in order to obtain more information. The investigation of how the positions of sensing elements affect the performance would be interesting as well. Another direction focuses on the signal processing level. The spike trains from multiple sensors form a spike network. Therefore, supervised learning algorithms such as Tempotron [137] could be employed to fuse the spike trains.

The tactile exploration work can be extended in several directions as well. We will further incorporate visual perception to facilitate the surface reconstruction. Another interesting direction involves incorporating active contour following, a natural form of exploration used by human beings. Finally, we would like to combine the shape information provided by reconstruction with our previous work [171] on tactile object recognition.

References

- [1] S. S. Kim, A. P. Sripati, R. J. Vogelstein, R. S. Armiger, A. F. Russell, and S. J. Bensmaia, “Conveying tactile feedback in sensorized hand neuroprostheses using a biofidelic model of mechanotransduction,” *IEEE Trans. Biomed. Circuits Syst.*, vol. 3, no. 6, pp. 398–404, 2009.
- [2] Z. Yi, Y. Zhang, and J. Peters, “Biomimetic tactile sensors and signal processing with spike trains: a review (accepted),” *Sensors Actuators A Phys.*
- [3] Z. Yi and Y. Zhang, “Bio-inspired Tactile FA-I Spiking Generation under Sinusoidal Stimuli,” *J. Bionic Eng.*, vol. 13, no. 4, pp. 612–621, Oct. 2016.
- [4] Z. Yi, Y. Zhang, and J. Peters, “Bioinspired tactile sensor for surface roughness discrimination,” *Sensors Actuators A Phys.*, vol. 255, pp. 46–53, Mar. 2017.
- [5] Z. Yi and Y. Zhang, “Recognizing tactile surface roughness with a biomimetic fingertip: A soft neuromorphic approach,” *Neurocomputing*, vol. 244, pp. 102–111, Jun. 2017.
- [6] Z. Yi, R. Calandra, F. Veiga, H. van Hoof, T. Hermans, Y. Zhang, and J. Peters, “Active tactile object exploration with Gaussian processes,” in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2016, pp. 4925–4930.
- [7] M. I. Tiwana, S. J. Redmond, and N. H. Lovell, “A review of tactile sensing technologies with applications in biomedical engineering,” *Sensors Actuators, A Phys.*, vol. 179, pp. 17–31, 2012.
- [8] A. Chaudhuri, *Fundamentals of sensory perception*. Oxford University Press, 2011.
- [9] J. N. Loomis and S. J. Lederman, *Handbook of perception and human performance: Cognitive processes and performance*, vol. 2, no. August. New York: Wiley, 1986.
- [10] A. F. Healy and R. W. Proctor, *Handbook of psychology: Experimental psychology*, vol. 2, no. 4. New York: Wiley, 2003.
- [11] E. R. Kandel, J. H. Schwartz, and T. M. Jessell, *Principles of neural science*, 4th ed. New York: McGraw-Hill Medical, 2000.
- [12] R. S. Dahiya, G. Metta, M. Valle, and G. Sandini, “Tactile Sensing - From Humans to Humanoids,” *IEEE Trans. Robot.*, vol. 26, no. 1, pp. 1–20, Feb. 2010.
- [13] Z. Kappassov, J.-A. Corrales, and V. Perdereau, “Tactile sensing in dexterous robot hands — Review,” *Rob. Auton. Syst.*, vol. 74, pp. 195–220, Dec. 2015.
- [14] S. Najarian, J. Dargahi, and A. A. Mehrizi, *Artificial tactile sensing in biomedical engineering*, 1st ed. New York: McGraw-Hill Education, 2009.
- [15] P. Saccomandi, E. Schena, C. Oddo, L. Zollo, S. Silvestri, and E. Guglielmelli, “Microfabricated Tactile Sensors for Biomedical Applications: A Review,” *Biosensors*, vol. 4, no. 4, pp. 422–448, Nov. 2014.
- [16] A. A. A. Hamed, S. C. Tang, H. Ren, C. Payne, K. Masamune, G. Tang, A. Squires, J. Mohammadpour, and Z. T. H. Tse, “Advances in Haptics, Tactile Sensing, and Manipulation for Robot-Assisted Minimally Invasive Surgery, Noninvasive Surgery, and Diagnosis,” *J. Robot.*, vol. 2012, pp. 1–14, 2012.
- [17] B. A. Kent, J. Lavery, and E. D. Engeberg, “Anthropomorphic control of a dexterous artificial hand via task dependent temporally synchronized synergies,” *J.*

- Bionic Eng.*, vol. 11, no. 2, pp. 236–248, 2014.
- [18] H. Zheng and X. Shen, “Design and Control of a Pneumatically Actuated Transtibial Prosthesis,” *J. Bionic Eng.*, vol. 12, no. 2, pp. 217–226, 2015.
 - [19] J. Dargahi and S. Najarian, “Advances in tactile sensors design/manufacturing and its impact on robotics applications – a review,” *Ind. Robot An Int. J.*, vol. 32, no. 3, pp. 268–281, Jun. 2005.
 - [20] H. Yousef, M. Boukallel, and K. Althoefer, “Tactile sensing for dexterous in-hand manipulation in robotics - A review,” *Sensors Actuators, A Phys.*, vol. 167, no. 2, pp. 171–187, 2011.
 - [21] C. Melchiorri, “Slip detection and control using tactile and force sensors,” *IEEE/ASME Trans. Mechatronics*, vol. 5, no. 3, pp. 235–243, 2000.
 - [22] G. J. Augustine, D. M. Chikaraishi, M. D. Ehlers, G. Einstein, D. Fitzpatrick, W. C. Hall, E. Jarvis, L. C. Katz, J. Kauer, A.-S. LaMantia, J. O. McNamara, R. D. Mooney, M. A. L. Nicolelis, D. Purves, P. H. Reinhart, S. A. Simon, J. H. P. Skene, J. Voyvodic, L. E. White, and S. M. Williams, *Neuroscience*, 3rd ed. Massachusetts: Sinauer Associates, Inc., 2004.
 - [23] Å. B. Vallbo and R. S. Johansson, “Properties of cutaneous mechanoreceptors in the human hand related to touch sensation,” *Hum Neurobiol*, vol. 3, no. 1, pp. 3–14, 1984.
 - [24] Å. B. Vallbo and K.-E. Hagbarth, “Activity from skin mechanoreceptors recorded percutaneously in awake human subjects,” *Exp. Neurol.*, vol. 21, no. 3, pp. 270–289, Jul. 1968.
 - [25] N. Jamali and C. Sammut, “Material classification by tactile sensing using surface textures,” *IEEE International Conference on Robotics and Automation*. IEEE, Anchorage, United States, pp. 2336–2341, 2010.
 - [26] J. Dargahi, S. Sokhanvar, S. Najarian, and S. Arbatani, *Tactile Sensing and Display: Haptic Feedback For Minimally Invasive Surgery And Robotics*. John Wiley & Sons, 2012.
 - [27] J. Scheibert, S. Leurent, A. Prevost, and G. Debregeas, “The Role of Fingerprints in the Coding of Tactile Information Probed with a Biomimetic Sensor,” *Science (80-.)*, vol. 323, no. 5920, pp. 1503–1506, Mar. 2009.
 - [28] J. Scheibert, G. Debregeas, and A. Prevost, “A MEMS-based tactile sensor to study human digital touch: mechanical transduction of the tactile information and role of fingerprints,” *EPJ Web Conf.*, vol. 6, p. 21006, Jun. 2010.
 - [29] N. Cauna, “Nature and functions of the papillary ridges of the digital skin,” *Anat. Rec.*, vol. 119, no. 4, pp. 449–468, Aug. 1954.
 - [30] G. J. Gerling and G. W. Thomas, “Fingerprint lines may not directly affect SA-I mechanoreceptor response,” *Somatosens. Mot. Res.*, vol. 25, no. 1, pp. 61–76, 2008.
 - [31] R. S. Dahiya and M. Gori, “Probing with and into fingerprints,” *J. Neurophysiol.*, vol. 104, no. 1, pp. 1–3, 2010.
 - [32] R. S. Johansson and J. R. Flanagan, “Coding and use of tactile signals from the fingertips in object manipulation tasks,” *Nat. Rev. Neurosci.*, vol. 10, no. 5, pp. 345–59, 2009.

- [33] P. S. Khalsa, R. M. Friedman, M. A. Srinivasan, and R. H. Lamotte, "Encoding of shape and orientation of objects indented into the monkey fingerpad by populations of slowly and rapidly adapting mechanoreceptors," *J. Neurophysiol.*, vol. 79, no. 6, pp. 3238–3251, 1998.
- [34] R. H. LaMotte and M. A. Srinivasan, "Tactile discrimination of shape: responses of slowly adapting mechanoreceptor afferents to a step stroked across the monkey fingerpad," *J. Neurosci.*, vol. 7, no. 6, pp. 1655–1671, 1987.
- [35] R. H. LaMotte and M. A. Srinivasan, "Tactile discrimination of shape: responses of rapidly adapting mechanoreceptive afferents to a step stroked across the monkey fingerpad," *J. Neurosci.*, vol. 7, no. 6, pp. 1672–1681, 1987.
- [36] M. A. Muniak, S. Ray, S. S. Hsiao, J. F. Dammann, and S. J. Bensmaia, "The neural coding of stimulus intensity: linking the population response of mechanoreceptive afferents with psychophysical behavior," *J. Neurosci.*, vol. 27, no. 43, pp. 11687–11699, 2007.
- [37] J. I. Gold and M. N. Shadlen, "The neural basis of decision making," *Annu. Rev. Neurosci.*, vol. 30, pp. 535–574, 2007.
- [38] D. C. Knill and A. Pouget, "The Bayesian brain: the role of uncertainty in neural coding and computation," *Trends Neurosci.*, vol. 27, no. 12, pp. 712–719, Dec. 2004.
- [39] A. W. Goodwin and H. E. Wheat, "Magnitude estimation of contact force when objects with different shapes are applied passively to the fingerpad," *Somatosens. Mot. Res.*, vol. 9, no. 4, pp. 339–344, Jan. 1992.
- [40] A. Panarese and B. B. Edin, "Human ability to discriminate direction of three-dimensional force stimuli applied to the finger pad," *J. Neurophysiol.*, vol. 105, no. 2, pp. 541–547, Feb. 2011.
- [41] I. Birznieks, V. G. Macefield, G. Westling, and R. S. Johansson, "Slowly adapting mechanoreceptors in the borders of the human fingernail encode fingertip forces," *J. Neurosci.*, vol. 29, no. 29, pp. 9370–9379, Jul. 2009.
- [42] I. Birznieks, P. Jenmalm, a W. Goodwin, and R. S. Johansson, "Encoding of direction of fingertip forces by human tactile afferents," *J. Neurosci.*, vol. 21, no. 20, pp. 8222–8237, 2001.
- [43] M. a Srinivasan, J. M. Whitehouse, and R. H. LaMotte, "Tactile detection of slip: surface microgeometry and peripheral neural codes.," *Journal of neurophysiology*, vol. 63, pp. 1323–1332, 1990.
- [44] M. A. Srinivasan and R. H. LaMotte, "Tactual discrimination of softness," *J. Neurophysiol.*, pp. 88–101, 1995.
- [45] M. A. Srinivasan and R. H. LaMotte, "Tactual discrimination of softness: abilities and mechanisms," in *Somesthesia and the Neurobiology of the Somatosensory Cortex*, Basel: Birkhäuser Basel, 1996, pp. 123–135.
- [46] M. Condon, I. Birznieks, K. Hudson, D. K. Chelvanayagam, D. Mahns, H. Olausson, and V. G. Macefield, "Differential sensitivity to surface compliance by tactile afferents in the human finger pad," *J. Neurophysiol.*, vol. 111, no. 6, pp. 1308–1317, Mar. 2014.
- [47] L. Skedung, M. Arvidsson, J. Y. Chung, C. M. Stafford, B. Berglund, and M. W.

- Rutland, "Feeling small: exploring the tactile perception limits," *Sci. Rep.*, vol. 3, 2013.
- [48] X. Libouton, O. Barbier, Y. Berger, L. Plaghki, and J.-L. Thonnard, "Tactile roughness discrimination of the finger pad relies primarily on vibration sensitive afferents not necessarily located in the hand," *Behav. Brain Res.*, vol. 229, no. 1, pp. 273–279, 2012.
 - [49] C. E. Connor and K. O. Johnson, "Neural coding of tactile texture: comparison of spatial and temporal mechanisms for roughness perception," *J. Neurosci.*, vol. 12, no. 9, pp. 3414–3426, 1992.
 - [50] T. Yoshioka, B. Gibb, A. K. Dorsch, S. S. Hsiao, and K. O. Johnson, "Neural coding mechanisms underlying perceived roughness of finely textured surfaces," *J. Neurosci.*, vol. 21, no. 17, pp. 6905–6916, 2001.
 - [51] C. F. abrizio Pirri, "Flexible tactile sensing based on piezoresistive composites: a review," *Sensors (Basel)*, vol. 14, no. 3, pp. 5296–5332, 2014.
 - [52] A. L. Window and G. S. Holister, *Strain gauge technology*. Applied science publishers, 1982.
 - [53] Y. Zhang, "Sensitivity enhancement of a micro-scale biomimetic tactile sensor with epidermal ridges," *J. Micromechanics Microengineering*, vol. 20, no. 8, p. 85012, Aug. 2010.
 - [54] Y. Hu, R. Katragadda, H. Tu, Q. Zheng, Y. Li, and Y. Xu, "Bioinspired 3-D tactile sensor for minimally invasive surgery," *Microelectromechanical Syst. J.*, vol. 19, no. 6, pp. 1400–1408, 2010.
 - [55] K. Hosoda, Y. Tada, and M. Asada, "Anthropomorphic robotic soft fingertip with randomly distributed receptors," *Rob. Auton. Syst.*, vol. 54, no. 2, pp. 104–109, 2006.
 - [56] C. S. Smith, "Piezoresistance effect in germanium and silicon," *Phys. Rev.*, vol. 94, no. 1, pp. 42–49, 1954.
 - [57] M. W. Strohmayer, H. P. Saal, A. H. Potdar, and P. van der Smagt, "The DLR touch sensor I: a flexible tactile sensor for robotic hands based on a crossed-wire approach," in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2010, pp. 897–903.
 - [58] M. Knite, V. Teteris, A. Kiploka, and J. Kaupuzs, "Polyisoprene-carbon black nanocomposites as tensile strain and pressure sensor materials," *Sensors Actuators, A Phys.*, vol. 110, no. 1–3, pp. 142–149, 2004.
 - [59] O. Kerpa, K. Weiss, and H. Worn, "Development of a flexible tactile sensor system for a humanoid robot," in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2003, vol. 1, pp. 1–6.
 - [60] L. Chen, G. Chen, and L. Lu, "Piezoresistive behavior study on finger-sensing silicone rubber/graphite nanosheet nanocomposites," *Adv. Funct. Mater.*, vol. 17, no. 6, pp. 898–904, 2007.
 - [61] W.-S. Su, C.-F. Hu, C.-M. Lin, and W. Fang, "Development of a 3D distributed carbon nanotubes on flexible polymer for normal and shear forces measurement," *IEEE 23rd International Conference on Micro Electro Mechanical Systems*. Hong Kong, China, pp. 615–618, 2010.

- [62] T. Tombler, C. Zhou, L. Alexseyev, J. Kong, H. Dai, L. Liu, C. Jayanthi, M. Tang, and S. Wu, "Reversible electromechanical characteristics of carbon nanotubes under local-probe manipulation," *Nature*, vol. 405, no. 6788, pp. 769–72, 2000.
- [63] M. Park, H. Kim, and J. P. Youngblood, "Strain-dependent electrical resistance of multi-walled carbon nanotube/polymer composite films," *Nanotechnology*, vol. 19, no. 5, p. 55705, 2008.
- [64] S. Stassi, V. Cauda, G. Canavese, D. Manfredi, and C. F. Pirri, "Synthesis and characterization of gold nanostars as filler of tunneling conductive polymer composites," *Eur. J. Inorg. Chem.*, no. 16, pp. 2669–2673, 2012.
- [65] D. Bloor, A. Graham, E. J. Williams, P. J. Laughlin, and D. Lussey, "Metal–polymer composite with nanostructured filler particles and amplified physical properties," *Appl. Phys. Lett.*, vol. 88, no. 10, p. 102103, 2006.
- [66] D. A. Skoog, F. J. Holler, and T. A. Nieman, "Principles of instrumental analysis," 1998.
- [67] B. Jaffe, *Piezoelectric ceramics*, 1st ed., vol. 3. New York: Academic press, 1971.
- [68] X. XI and Z. LUO, "A Tele-manipulator with Tactile Tele-presence and Myoelectric Bionic Control [J]," *Robot*, vol. 3, p. 15, 2009.
- [69] A. Bonakdar and N. Narayanan, "Determination of tissue properties using microfabricated piezoelectric tactile sensor during minimally invasive surgery," *Sens. Rev.*, vol. 30, no. 3, pp. 233–241, 2010.
- [70] C. Li, P.-M. Wu, S. Lee, A. Gorton, M. J. Schulz, and C. H. Ahn, "Flexible dome and bump shape piezoelectric tactile sensors using PVDF-TrFE copolymer," *J. Microelectromechanical Syst.*, vol. 17, no. 2, pp. 334–341, 2008.
- [71] K. Takashima, S. Horie, T. Mukai, K. Ishida, and K. Matsushige, "Piezoelectric properties of vinylidene fluoride oligomer for use in medical tactile sensor applications," *Sensors Actuators A Phys.*, vol. 144, no. 1, pp. 90–96, 2008.
- [72] S. Sokhanvar, M. Packirisamy, and J. Dargahi, "A multifunctional PVDF-based tactile sensor for minimally invasive surgery," *Smart Mater. Struct.*, vol. 16, no. 4, p. 989, 2007.
- [73] Y. Tanaka, M. Tanaka, and S. Chonan, "Measurement of tactile sensation using sensor system for collecting tactile information," *Nippon Kikai Gakkai Ronbunshu C Hen(Transactions Japan Soc. Mech. Eng. Part C)(Japan)*, vol. 19, no. 3, pp. 817–824, 2007.
- [74] R. D. Howe and M. R. Cutkosky, "Sensing skin acceleration for slip and texture perception," in *IEEE International Conference on Robotics and Automation*, 1989, pp. 145–150.
- [75] P. Dario, A. Sabatini, B. Allotta, M. Bergamasco, and G. Buttazzo, "A fingertip sensor with proximity, tactile and force sensing capabilities," in *Intelligent Robots and Systems '90. 'Towards a New Frontier of Applications', Proceedings. IROS'90. IEEE International Workshop on*, 1990, pp. 883–889.
- [76] R. D. Howe and M. R. Cutkosky, "Dynamic tactile sensing: Perception of fine surface features with stress rate sensing," *IEEE Trans. Robot. Autom.*, vol. 9, no. 2, pp. 140–151, 1993.
- [77] Byungjune Choi, Hyouk Ryeol Choi, and Sungchul Kang, "Development of tactile

- sensor for detecting contact force and slip,” in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2005, pp. 2638–2643.
- [78] A. Kimoto, N. Sugitani, and S. Fujisaki, “A multifunctional tactile sensor based on PVDF films for identification of materials,” *IEEE Sens. J.*, vol. 10, no. 9, pp. 1508–1513, 2010.
 - [79] A. Jain, P. K. J., A. K. Sharma, A. Jain, and R. P.N, “Dielectric and piezoelectric properties of PVDF/PZT composites: A review,” *Polym. Eng. Sci.*, vol. 55, no. 7, pp. 1589–1616, Jul. 2015.
 - [80] D. P. J. Cotton, P. H. Chappell, A. Cranny, N. M. White, and S. P. Beeby, “A novel thick-film piezoelectric slip sensor for a prosthetic hand,” *Sensors Journal, IEEE*, vol. 7, no. 5, pp. 752–761, 2007.
 - [81] M. I. Tiwana, A. Shashank, S. J. Redmond, and N. H. Lovell, “Characterization of a capacitive tactile shear sensor for application in robotic and upper limb prostheses,” *Sensors Actuators A Phys.*, vol. 165, no. 2, pp. 164–172, 2011.
 - [82] B. L. Gray and R. S. Fearing, “A surface micromachined microtactile sensor array,” in *IEEE International Conference on Robotics and Automation*, 1996, vol. 1, pp. 1–6.
 - [83] A. Schmitz, M. Maggiali, L. Natale, B. Bonino, and G. Metta, “A tactile sensor for the fingertips of the humanoid robot iCub,” in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2010, pp. 2212–2217.
 - [84] Z. Chu, P. M. Sarro, and S. Middelhoek, “Silicon three-axial tactile sensor,” *Sensors Actuators A Phys.*, vol. 54, no. 1, pp. 505–510, 1996.
 - [85] H.-K. Lee, S.-I. Chang, and E. Yoon, “A flexible polymer tactile sensor: fabrication and modular expandability for large area deployment,” *Microelectromechanical Syst. J.*, vol. 15, no. 6, pp. 1681–1686, 2006.
 - [86] H. B. Muhammad, C. M. Oddo, L. Beccai, C. Recchiuto, C. J. Anthony, M. J. Adams, M. C. Carrozza, D. W. L. Hukins, and M. C. L. Ward, “Development of a bioinspired MEMS based capacitive tactile sensor for a robotic finger,” *Sensors Actuators A Phys.*, vol. 165, no. 2, pp. 221–229, 2011.
 - [87] N. F. Lepora and B. Ward-Cherrier, “Superresolution with an optical tactile sensor,” in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2015, pp. 2686–2691.
 - [88] R. Li and E. H. Adelson, “Sensing and Recognizing Surface Textures Using a GelSight Sensor,” in *IEEE Conference on Computer Vision and Pattern Recognition*, 2013, pp. 1241–1247.
 - [89] H. Yamazaki, M. Nishiyama, K. Watanabe, and M. Sokolov, “Tactile sensing for object identification based on hetero-core fiber optics,” *Sensors Actuators A Phys.*, vol. 247, pp. 98–104, Aug. 2016.
 - [90] W. Yuan, R. Li, M. A. Srinivasan, and E. H. Adelson, “Measurement of shear and slip with a GelSight tactile sensor,” in *IEEE International Conference on Robotics and Automation (ICRA)*, 2015, pp. 304–311.
 - [91] S. Takenawa, “A magnetic type tactile sensor using a two-dimensional array of inductors,” *IEEE Int. Conf. Robot. Autom.*, no. 1, pp. 3295–3300, 2009.
 - [92] A. Alfadhel and J. Kosel, “Magnetic Nanocomposite Cilia Tactile Sensor,” *Adv.*

- Mater.*, vol. 27, no. 47, pp. 7888–7892, Dec. 2015.
- [93] M. Goka, H. Nakamoto, and S. Takenawa, “A magnetic type tactile sensor by GMR elements and inductors,” in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2010, pp. 885–890.
 - [94] C. M. Oddo, M. Controzzi, L. Beccai, C. Cipriani, and M. C. Carrozza, “Roughness encoding for discrimination of surfaces in artificial active-touch,” *IEEE Trans. Robot.*, vol. 27, no. 3, pp. 522–533, 2011.
 - [95] O. Sul, H. Chun, E. Choi, J. Choi, K. Cho, D. Jang, S. Chun, W. Park, and S.-B. Lee, “Touch stimulated pulse generation in biomimetic single-layer graphene,” *Nanoscale*, vol. 8, no. 6, pp. 3425–3431, 2016.
 - [96] L. L. Bologna, J. Pinoteau, J.-B. Passot, J. A. Garrido, J. Vogel, E. R. Vidal, and A. Arleo, “A closed-loop neurobotic system for fine touch sensing,” *J. Neural Eng.*, vol. 10, no. 4, p. 46019, Aug. 2013.
 - [97] E. M. Izhikevich, “Which model to use for cortical spiking neurons?,” *IEEE Trans. neural networks*, vol. 15, no. 5, pp. 1063–1070, 2004.
 - [98] W. Gerstner and W. M. Kistler, *Spiking neuron models: Single neurons, populations, plasticity*. Cambridge university press, 2002.
 - [99] E. M. Izhikevich, “Simple model of spiking neurons,” *IEEE Trans. Neural Networks*, vol. 14, no. 6, pp. 1569–1572, 2003.
 - [100] E. M. Izhikevich, *Dynamical systems in neuroscience*, 1st ed. London: The MIT press, 2007.
 - [101] A. L. Hodgkin and A. F. Huxley, “A quantitative description of membrane current and its application to conduction and excitation in nerve,” *J. Physiol.*, vol. 117, no. 4, p. 500, 1952.
 - [102] E. K. Kim, S. A. Wellnitz, S. M. Bourdon, E. A. Lumpkin, and G. J. Gerling, “Force sensor in simulated skin and neural model mimic tactile SAI afferent spiking response to ramp and hold stimuli,” *J Neuroeng Rehabil*, vol. 9, p. 45, 2012.
 - [103] E. K. Kim, K. B. Sugg, N. B. Langhals, S. M. Lightbody, M. E. Baltrusaitis, M. G. Urbanek, P. S. Cedema, and G. J. Gerling, “An engineered tactile afferent modulation platform to elicit compound sensory nerve action potentials in response to force magnitude,” *World Haptics Conference. IEEE*, Daejeon, Korea, pp. 241–246, 2013.
 - [104] U. B. Rongala, A. Mazzoni, and C. M. Oddo, “Neuromorphic Artificial Touch for Categorization of Naturalistic Textures,” *IEEE Trans. Neural Networks Learn. Syst.*, 2015.
 - [105] C. M. Oddo, S. Raspopovic, F. Artoni, A. Mazzoni, G. Spigler, F. Petrini, F. Giambattistelli, F. Vecchio, F. Miraglia, and L. Zollo, “Intraneural stimulation elicits discrimination of textural features by artificial fingertip in intact and amputee humans,” *Elife*, vol. 5, p. e09148, 2016.
 - [106] G. Spigler, C. M. Oddo, and M. C. Carrozza, “Soft-neuromorphic artificial touch for applications in neuro-robotics,” *4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics*. Rome, Italy, pp. 1913–1918, 2012.

- [107] L. L. Bologna, J. Pinoteau, R. Brasselet, M. Maggiali, and A. Arleo, "Encoding/decoding of first and second order tactile afferents in a neurobotic application," *J. Physiol. Paris*, vol. 105, no. 1–3, pp. 25–35, 2011.
- [108] W. W. Lee, J.-J. Cabibihan, and N. V Thakor, "Bio-mimetic strategies for tactile sensing," *IEEE SENSORS*. IEEE, Baltimore, United States, pp. 1–4, 2013.
- [109] J. A. Fishel and G. E. Loeb, "Bayesian Exploration for Intelligent Identification of Textures," *Front. Neurobot.*, vol. 6, 2012.
- [110] D. D. Damian, H. Martinez, K. Dermitzakis, A. Hernandez-Arieta, and R. Pfeifer, "Artificial ridged skin for slippage speed detection in prosthetic hand applications," in *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2010, pp. 904–909.
- [111] G. Vásárhelyi, M. Ádám, É. Vázsonyi, I. Bársony, and C. Dücső, "Effects of the elastic cover on tactile sensor arrays," *Sensors Actuators A Phys.*, vol. 132, no. 1, pp. 245–251, Nov. 2006.
- [112] Y. Zhang and N. Miki, "An Optimal Design of Epidermal Ridges to the Tactile Sensor for Sensitivity Enhancement during Shear Force Detection," *IEEE Trans. Sensors Micromachines*, vol. 131, no. 4, pp. 141–147, 2011.
- [113] S. Salehi, J.-J. Cabibihan, and S. S. Ge, "Artificial skin ridges enhance local tactile shape discrimination," *Sensors (Basel)*, vol. 11, no. 9, pp. 8626–8642, 2011.
- [114] K. Noda, K. Matsumoto, and I. Shimoyama, "Skin-type tactile sensor using standing piezoresistive cantilever for micro structure detection," in *IEEE Sensors*, 2010, pp. 2089–2092.
- [115] S. Harada, K. Kanao, Y. Yamamoto, T. Arie, S. Akita, and K. Takei, "Fully Printed Flexible Fingerprint-like Three-Axis Tactile and Slip Force and Temperature Sensors for Artificial Skin," *ACS Nano*, vol. 8, no. 12, pp. 12851–12857, Dec. 2014.
- [116] W. Gerstner, A. K. Kreiter, H. Markram, and A. V. M. Herz, "Neural codes: Firing rates and beyond," *Proc. Natl. Acad. Sci.*, vol. 94, no. 24, pp. 12740–12741, Nov. 1997.
- [117] R. Brette, "Philosophy of the Spike: Rate-Based vs. Spike-Based Theories of the Brain," *Front. Syst. Neurosci.*, vol. 9, Nov. 2015.
- [118] S. Ghosh-dastidar and H. Adeli, "Spiking neural network," *Int. J. Neural Syst.*, vol. 19, no. 4, pp. 295–308, 2009.
- [119] A. Grüning and S. M. Bohte, "Spiking Neural Networks: Principles and Challenges," in *European Symposium on Artificial Neural Networks*, 2014, no. April, pp. 23–25.
- [120] H. Paugam-Moisy and B. Sander, *Handbook of natural computing: Computing with Spiking Neuron Networks*. Springer Berlin Heidelberg, 2012.
- [121] P. Dayan and L. F. Abbott, *Theoretical Neuroscience: Computational and Mathematical Modeling of Neural Systems*. The MIT press, 2001.
- [122] E. D. Adrian and Y. Zotterman, "The impulses produced by sensory nerve-endings," *J. Physiol.*, vol. 61, no. 2, pp. 151–171, Apr. 1926.
- [123] D. S. Reich, F. Mechler, and J. D. Victor, "Temporal coding of contrast in primary visual cortex: when, what, and why.," *J. Neurophysiol.*, vol. 85, no. 3, pp. 1039–50,

Mar. 2001.

- [124] I. Nelken and G. A. L. Chechik, “Encoding Stimulus Information by Spike Numbers and Mean Response Time in Primary Auditory Cortex,” pp. 199–221, 2005.
- [125] S. Panzeri, R. S. Petersen, S. R. Schultz, M. Lebedev, and M. E. Diamond, “The Role of Spike Timing in the Coding of Stimulus Location in Rat Somatosensory Cortex,” *Neuron*, vol. 29, no. 3, pp. 769–777, Mar. 2001.
- [126] S. M. Chase and E. D. Young, “First-spike latency information in single neurons increases when referenced to population onset,” *Proc. Natl. Acad. Sci.*, vol. 104, no. 12, pp. 5175–5180, Mar. 2007.
- [127] R. S. Johansson and I. Birznieks, “First spikes in ensembles of human tactile afferents code complex spatial fingertip events,” *Nat. Neurosci.*, vol. 7, no. 2, pp. 170–177, 2004.
- [128] J. O’Keefe, “Hippocampus, theta, and spatial memory,” *Curr. Opin. Neurobiol.*, vol. 3, no. 6, pp. 917–924, Dec. 1993.
- [129] L. F. Abbott and S. B. Nelson, “Synaptic plasticity: taming the beast,” *Nat. Neurosci.*, vol. 3, no. Supp, pp. 1178–1183, Nov. 2000.
- [130] A. Citri and R. C. Malenka, “Synaptic Plasticity: Multiple Forms, Functions, and Mechanisms,” *Neuropsychopharmacology*, vol. 33, no. 1, pp. 18–41, Jan. 2008.
- [131] R. C. Froemke, I. Carcea, A. J. Barker, K. Yuan, B. A. Seybold, A. R. O. Martins, N. Zaika, H. Bernstein, M. Wachs, P. A. Levis, D. B. Polley, M. M. Merzenich, and C. E. Schreiner, “Long-term modification of cortical synapses improves sensory perception,” *Nat. Neurosci.*, vol. 16, no. 1, pp. 79–88, Nov. 2012.
- [132] G. Q. Bi and M. M. Poo, “Synaptic modifications in cultured hippocampal neurons: dependence on spike timing, synaptic strength, and postsynaptic cell type,” *J. Neurosci.*, vol. 18, no. 24, pp. 10464–10472, 1998.
- [133] G. Bi and M. Poo, “Synaptic modification by correlated activity: Hebb’s postulate revisited,” *Annu. Rev. Neurosci.*, vol. 24, no. 1, pp. 139–166, Mar. 2001.
- [134] M. Kawato, S. Kuroda, and N. Schweighofer, “Cerebellar supervised learning revisited: biophysical modeling and degrees-of-freedom control,” *Curr. Opin. Neurobiol.*, vol. 21, no. 5, pp. 791–800, Oct. 2011.
- [135] M. Ito, “Mechanisms of motor learning in the cerebellum,” *Brain Res.*, vol. 886, no. 1–2, pp. 237–245, Dec. 2000.
- [136] E. I. Knudsen, “Supervised learning in the brain,” *J. Neurosci.*, vol. 14, no. 7, pp. 3985–3997, 1994.
- [137] R. Gütig and H. Sompolinsky, “The tempotron: a neuron that learns spike timing–based decisions,” *Nat. Neurosci.*, vol. 9, no. 3, pp. 420–428, Mar. 2006.
- [138] N. Caporale and Y. Dan, “Spike Timing–Dependent Plasticity: A Hebbian Learning Rule,” *Annu. Rev. Neurosci.*, vol. 31, no. 1, pp. 25–46, Jul. 2008.
- [139] H. Shouval, “Spike timing dependent plasticity: a consequence of more fundamental learning rules,” *Front. Comput. Neurosci.*, 2010.
- [140] S. J. Martin, P. D. Grimwood, and R. G. M. Morris, “Synaptic Plasticity and Memory: An Evaluation of the Hypothesis,” *Annu. Rev. Neurosci.*, vol. 23, no. 1, pp. 649–711, Mar. 2000.

- [141] W. W. Lee, H. Yu, and N. V. Thakor, "Gait event detection through neuromorphic spike sequence learning," in *5th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics*, 2014, pp. 899–904.
- [142] D. M. Rager, D. Alvares, I. Birznies, S. J. Redmond, J. W. Morley, N. H. Lovell, and R. M. Vickery, "Generating tactile afferent stimulation patterns for slip and touch feedback in neural prosthetics," *35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Osaka, Japan, pp. 5922–5925, 2013.
- [143] M. Ohka, N. Morisawa, H. Suzuki, J. Takata, H. Koboyashi, and H. B. Yussuf, "A robotic finger equipped with an optical three-axis tactile sensor," *IEEE International Conference on Robotics and Automation (ICRA)*. Pasadena, United States, pp. 3425–3430, 2008.
- [144] C. M. Oddo, L. Beccai, G. G. Muscolo, and M. C. Carrozza, "A biomimetic MEMS-based tactile sensor array with fingerprints integrated in a robotic fingertip for artificial roughness encoding," *IEEE International Conference on Robotics and Biomimetics*. Hong Kong, China, pp. 894–900, 2009.
- [145] K. O. Johnson, "The roles and functions of cutaneous mechanoreceptors," *Curr. Opin. Neurobiol.*, vol. 11, no. 4, pp. 455–461, 2001.
- [146] D. R. Lesniak and G. J. Gerling, "Predicting SA-I mechanoreceptor spike times with a skin-neuron model," *Math. Biosci.*, vol. 220, no. 1, pp. 15–23, 2009.
- [147] D. R. Lesniak, S. A. Wellnitz, G. J. Gerling, and E. A. Lumpkin, "Statistical analysis and modeling of variance in the SA-I mechanoreceptor response to sustained indentation," *31st Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Minneapolis, United States, pp. 6814–6817, 2009.
- [148] J. R. Phillips and K. O. Johnson, "Tactile spatial resolution. III. A continuum mechanics model of skin predicting mechanoreceptor responses to bars, edges, and gratings," *J. Neurophysiol.*, vol. 46, no. 6, pp. 1204–1225, 1981.
- [149] J. A. White, J. T. Rubinstein, and A. R. Kay, "Channel noise in neurons," *Trends Neurosci.*, vol. 23, no. 3, pp. 131–137, 2000.
- [150] R. B. Stein, E. R. Gossen, and K. E. Jones, "Neuronal variability: noise or part of the signal?," *Nat. Rev. Neurosci.*, vol. 6, no. 5, pp. 389–397, 2005.
- [151] P. Cordo, J. T. Inglis, S. Verschueren, J. J. Collins, D. M. Merfeld, S. Rosenblum, S. Buckley, and F. Moss, "Noise in human muscle spindles," *Nature*, vol. 383, no. 6603, pp. 769–770, 1996.
- [152] A. W. Freeman and K. O. Johnson, "A model accounting for effects of vibratory amplitude on responses of cutaneous mechanoreceptors in macaque monkey," *J. Physiol.*, vol. 323, no. 1, pp. 43–64, 1982.
- [153] W. S. Cleveland and S. J. Devlin, "Locally weighted regression: an approach to regression analysis by local fitting," *J. Am. Stat. Assoc.*, vol. 83, no. 403, pp. 596–610, 1988.
- [154] I. I. Rivest and G. J. Gerling, "Optimizing populations of sai tactile mechanoreceptors to enable activities of daily living," *World Haptics Conference*. IEEE, Istanbul, Turkey, pp. 53–58, 2011.

- [155] W. Tang, Y. Zhou, H. Zhu, and H. Yang, "The effect of surface texturing on reducing the friction and wear of steel under lubricated sliding contact," *Appl. Surf. Sci.*, vol. 273, pp. 199–204, 2013.
- [156] W. W. Mayol-Cuevas, J. Juarez-Guerero, and S. Munoz-Gutierrez, "A first approach to tactile texture recognition," *IEEE International Conference on Systems, Man, and Cybernetics*, vol. 5. San Diego, United States, pp. 4246–4250, 1998.
- [157] H. B. Muhammad, C. Recchiuto, C. M. Oddo, L. Beccai, C. J. Anthony, M. J. Adams, M. C. Carrozza, and M. C. L. Ward, "A capacitive tactile sensor array for surface texture discrimination," *Microelectron. Eng.*, vol. 88, no. 8, pp. 1811–1813, 2011.
- [158] F. De Boissieu, C. Godin, B. Guilhamat, D. David, C. Serviere, and D. Baudois, "Tactile texture recognition with a 3-axial force MEMS integrated artificial finger," in *Robotics: Science and Systems*, 2009.
- [159] O. Kroemer, C. H. Lampert, and J. Peters, "Learning dynamic tactile sensing with robust vision-based training," *IEEE Trans. Robot.*, vol. 27, no. 3, pp. 545–557, 2011.
- [160] E. Peiner, M. Balke, and L. Doering, "Slender tactile sensor for contour and roughness measurements within deep and narrow holes," *IEEE Sens. J.*, vol. 8, no. 12, pp. 1960–1967, 2008.
- [161] T. V. Vorburger, H.-G. Rhee, T. B. Renegar, J.-F. Song, and A. Zheng, "Comparison of optical and stylus methods for measurement of surface texture," *Int. J. Adv. Manuf. Technol.*, vol. 33, no. 1–2, pp. 110–118, 2007.
- [162] Q. Xu, C. Li, Y. Kang, and Y. Zhang, "Long term effects of substrate stiffness on the development of hMSC mechanical properties," *RSC Adv.*, vol. 5, no. 128, pp. 105651–105660, 2015.
- [163] S. B. Davis and P. Mermelstein, "Comparison of parametric representations for monosyllabic word recognition in continuously spoken sentences," *IEEE Trans. Acoust. Speech Signal Process.*, vol. 28, no. 4, pp. 357–366, 1980.
- [164] D. G. Lowe, "Distinctive image features from scale-invariant keypoints," *Int. J. Comput. Vis.*, vol. 60, no. 2, pp. 91–110, 2004.
- [165] P. Dallaire, P. Giguère, D. Émond, and B. Chaib-Draa, "Autonomous tactile perception: A combined improved sensing and Bayesian nonparametric approach," *Rob. Auton. Syst.*, vol. 62, no. 4, pp. 422–435, 2014.
- [166] K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," *Med. Eng. Phys.*, vol. 21, no. 6, pp. 431–438, 1999.
- [167] K. Schaaff and T. Schultz, "Towards an EEG-based emotion recognizer for humanoid robots," in *The 18th IEEE International Symposium on Robot and Human Interactive Communication*, 2009, pp. 792–796.
- [168] P. Gehler and S. Nowozin, "On feature combination for multiclass object classification," in *IEEE 12th International Conference on Computer Vision*, 2009, pp. 221–228.
- [169] J. Ngiam, A. Khosla, M. Kim, J. Nam, H. Lee, and A. Y. Ng, "Multimodal deep learning," in *Proceedings of the 28th International Conference on Machine*

- Learning (ICML-11)*, 2011, pp. 689–696.
- [170] A. Drimus, M. B. Petersen, and A. Bilberg, “Object texture recognition by dynamic tactile sensing using active exploration,” in *The 21st IEEE International Symposium on Robot and Human Interactive Communication*, 2012, pp. 277–283.
 - [171] J. Hoelscher, J. Peters, and T. Hermans, “Evaluation of tactile feature extraction for interactive object recognition,” in *IEEE-RAS 15th International Conference on Humanoid Robots*, 2015, pp. 310–317.
 - [172] F. Veiga, H. van Hoof, J. Peters, and T. Hermans, “Stabilizing novel objects by learning to predict tactile slip,” in *IEEE/RSJ International Conference on Intelligent Robots and Systems*, 2015, pp. 5065–5072.
 - [173] C. Cortes and V. Vapnik, “Support vector machine,” *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, 1995.
 - [174] C.-W. Hsu and C.-J. Lin, “A comparison of methods for multiclass support vector machines,” *Neural Networks, IEEE Trans.*, vol. 13, no. 2, pp. 415–425, 2002.
 - [175] C.-C. Chang and C.-J. Lin, “LIBSVM: a library for support vector machines,” *ACM Trans. Intell. Syst. Technol.*, vol. 2, no. 3, p. 27, 2011.
 - [176] A. Rakotomamonjy, F. Bach, S. Canu, and Y. Grandvalet, “SimpleMKL,” *J. Mach. Learn. Res.*, vol. 9, pp. 2491–2521, 2008.
 - [177] M. Gönen and E. Alpaydın, “Localized algorithms for multiple kernel learning,” *Pattern Recognit.*, vol. 46, no. 3, pp. 795–807, 2013.
 - [178] S. C. Liu and T. Delbruck, “Neuromorphic sensory systems,” *Curr. Opin. Neurobiol.*, vol. 20, no. 3, pp. 288–295, 2010.
 - [179] K. A. Boahen, “Point-to-point connectivity between neuromorphic chips using address events,” *IEEE Trans. Circuits Syst. II Analog Digit. Signal Process.*, vol. 47, no. 5, pp. 416–434, 2000.
 - [180] C. Sciences, “The Artificial Silicon Retina Microchip for the Treatment of Vision Loss From Retinitis Pigmentosa,” vol. 122, 2016.
 - [181] K. A. Zaghloul and K. Boahen, “A silicon retina that reproduces signals in the optic nerve,” *J. Neural Eng.*, vol. 3, no. 4, pp. 257–67, Dec. 2006.
 - [182] M. Mahowald, *An Analog VLSI System for Stereoscopic Vision*. Boston, MA: Springer US, 1994.
 - [183] R. F. Lyon and C. Mead, “An Analog Electronic Cochlea,” *IEEE Trans. Acoust.*, vol. 36, no. 7, pp. 1119–1134, 1988.
 - [184] T. J. Hamilton, C. Jin, A. van Schaik, and J. Tapson, “An active 2-D silicon cochlea,” *IEEE Trans. Biomed. Circuits Syst.*, vol. 2, no. 1, pp. 30–43, 2008.
 - [185] S. Mandal, S. M. Zhak, and R. Sarpeshkar, “A bio-inspired active radio-frequency silicon cochlea,” *IEEE J. Solid-State Circuits*, vol. 44, no. 6, pp. 1814–1828, 2009.
 - [186] A. Roberts and B. M. H. Bush, *Neurons without impulses: their significance for vertebrate and invertebrate nervous systems*. Cambridge University Press, 1981.
 - [187] R. A. DiCaprio, C. P. Billimoria, and B. C. Ludwar, “Information rate and spike-timing precision of proprioceptive afferents,” *J. Neurophysiol.*, vol. 98, no. July 2007, pp. 1706–1717, 2007.
 - [188] B. Sengupta, S. B. Laughlin, and J. E. Niven, “Consequences of Converting Graded to Action Potentials upon Neural Information Coding and Energy

- Efficiency,” *PLoS Comput. Biol.*, vol. 10, no. 1, 2014.
- [189] T. R. Jack JJB, Noble D, “Electric Current Flow in Excitable Cells,” *Clarendon Press. Oxford*, no. January, 1975.
 - [190] S. B. Laughlin, R. R. D. R. Van Steveninck, and J. C. Anderson, “The metabolic cost of neural information,” vol. 1, no. 1, 1998.
 - [191] M. A. L. Nicolelis and M. A. Lebedev, “Principles of neural ensemble physiology underlying the operation of brain-machine interfaces,” *Nat. Rev. Neurosci.*, vol. 10, no. 7, pp. 530–40, 2009.
 - [192] R. B. Stein, “Some Models of Neuronal Variability,” *Biophys. J.*, vol. 7, no. 1, pp. 37–68, Jan. 1967.
 - [193] J. D. Victor and K. P. Purpura, “Nature and precision of temporal coding in visual cortex: a metric-space analysis,” *J. Neurophysiol.*, vol. 76, no. 2, pp. 1310–1326, 1996.
 - [194] M. C. W. van Rossum, “A novel spike distance,” *Neural Comput.*, vol. 13, no. 4, pp. 751–763, 2001.
 - [195] T. Kreuz, J. S. Haas, A. Morelli, H. D. I. Abarbanel, and A. Politi, “Measuring spike train synchrony,” *J. Neurosci. Methods*, vol. 165, no. 1, pp. 151–161, 2007.
 - [196] T. Kreuz, D. Chicharro, M. Greschner, and R. G. Andrzejak, “Time-resolved and time-scale adaptive measures of spike train synchrony,” *J. Neurosci. Methods*, vol. 195, no. 1, pp. 92–106, 2011.
 - [197] R. Quiñero, T. Kreuz, and P. Grassberger, “Event synchronization: A simple and fast method to measure synchronicity and time delay patterns,” *Phys. Rev. E*, vol. 66, no. 4, p. 41904, Oct. 2002.
 - [198] B. A. y Arcas, A. L. Fairhall, and W. Bialek, “Computation in a Single Neuron: Hodgkin and Huxley Revisited,” *Neural Comput.*, vol. 15, no. 8, pp. 1715–1749, Aug. 2003.
 - [199] A. S. French and K. Pfeiffer, “Measuring entropy in continuous and digitally filtered neural signals,” *J. Neurosci. Methods*, vol. 196, no. 1, pp. 81–87, Mar. 2011.
 - [200] M. Juusola and A. S. French, “The efficiency of sensory information coding by mechanoreceptor neurons,” *Neuron*, vol. 18, no. 6, pp. 959–968, 1997.
 - [201] S. M. Seitz, B. Curless, J. Diebel, D. Scharstein, and R. Szeliski, “A Comparison and Evaluation of Multi-View Stereo Reconstruction Algorithms,” in *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR’06)*, 2006, vol. 1, pp. 519–528.
 - [202] R. Bolle and B. Vemuri, “On three-dimensional surface reconstruction methods,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 13, no. 1, pp. 1–13, 1991.
 - [203] V. Lippiello, F. Ruggiero, B. Siciliano, and L. Villani, “Visual Grasp Planning for Unknown Objects Using a Multifingered Robotic Hand,” *IEEE/ASME Trans. Mechatronics*, vol. 18, no. 3, pp. 1050–1059, Jun. 2013.
 - [204] M. Meier, M. Schopfer, R. Haschke, and H. Ritter, “A Probabilistic Approach to Tactile Shape Reconstruction,” *IEEE Trans. Robot.*, vol. 27, no. 3, pp. 630–635, Jun. 2011.
 - [205] J. A. Fishel and G. E. Loeb, “Sensing tactile microvibrations with the BioTac —

- Comparison with human sensitivity,” in *2012 4th IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob)*, pp. 1122–1127.
- [206] D. J. Montana, “The Kinematics of Contact and Grasp,” *Int. J. Rob. Res.*, vol. 7, no. 3, pp. 17–32, Jun. 1988.
 - [207] M. Bjoerkman, Y. Bekiroglu, V. Hoegman, and D. Kragic, “Enhancing visual perception of shape through tactile glances,” in *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 3180–3186.
 - [208] P. Allen and P. Michelman, “Acquisition and interpretation of 3-D sensor data from touch,” *IEEE Trans. Robot. Autom.*, vol. 6, no. 4, pp. 397–404, 1990.
 - [209] Y. Bin Jia and J. Tian, “Surface patch reconstruction from one-dimensional tactile data,” *IEEE Trans. Autom. Sci. Eng.*, vol. 7, no. 2, pp. 400–407, 2010.
 - [210] M. Moll and M. A. Erdmann, “Reconstructing shape from motion using tactile sensors,” *Robot. Inst.*, p. 239, 2001.
 - [211] D. Reznik and V. Lumelsky, “Multi-finger ‘hugging’: a robust approach to sensor-based grasp planning,” in *IEEE International Conference on Robotics and Automation*, 1994, pp. 754–759.
 - [212] S. Dragiev, “Uncertainty Aware Grasping And Tactile Exploration.pdf,” 2013.
 - [213] A. Bierbaum, M. Rambow, T. Asfour, and R. Dillmann, “A potential field approach to dexterous tactile exploration,” *IEEE/RAS Int. Conf. Humanoid Robot.*, pp. 360–366, 2008.
 - [214] R. Li, R. Platt, W. Yuan, A. Ten Pas, N. Roscup, M. A. Srinivasan, and E. Adelson, “Localization and manipulation of small parts using GelSight tactile sensing,” *IEEE Int. Conf. Intell. Robot. Syst.*, vol. 1, pp. 3988–3993, 2014.
 - [215] Y. Ito, Y. Kim, C. Nagai, and G. Obinata, “Vision-based tactile sensing and shape estimation using a fluid-type touchpad,” *IEEE Trans. Autom. Sci. Eng.*, vol. 9, no. 4, pp. 734–744, Oct. 2012.
 - [216] J. Ilonen, J. Bohg, and V. Kyrki, “Fusing visual and tactile sensing for 3-D object reconstruction while grasping,” in *2013 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 3547–3554.
 - [217] N. Wettels, V. J. Santos, R. S. Johansson, and G. E. Loeb, “Biomimetic Tactile Sensor Array,” *Adv. Robot.*, vol. 22, no. 8, pp. 829–849, 2008.
 - [218] C. E. Rasmussen, *Gaussian Processes for Machine Learning*. The MIT press, 2006.
 - [219] S. Dragiev, M. Toussaint, and M. Gienger, “Gaussian process implicit surfaces for shape estimation and grasping,” in *2011 IEEE International Conference on Robotics and Automation (ICRA)*, pp. 2845–2850.
 - [220] J. Snoek, H. Larochelle, and R. Adams, “Practical Bayesian Optimization of Machine Learning Algorithms,” in *Advances in Neural Information Processing Systems (NIPS)*, 2012, pp. 2951–2959.
 - [221] R. Calandra, A. Seyfarth, J. Peters, and M. P. Deisenroth, “Bayesian optimization for learning gaits under uncertainty,” *Ann. Math. Artif. Intell.*, vol. 76, no. 1–2, pp. 5–23, Feb. 2016.
 - [222] A. Boularias, J. A. Bagnell, and A. Stentz, “Efficient Optimization for Autonomous

- Robotic Manipulation of Natural Objects,” in *the Twenty-Eighth AAAI Conference on Artificial Intelligence*, 2014, pp. 2520–2526.
- [223] R. Martinez-Cantin, N. de Freitas, A. Doucet, and J. Castellanos, “Active Policy Learning for Robot Planning and Exploration under Uncertainty,” in *Robotics: Science and Systems*, 2007, pp. 321–328.
 - [224] D. D. Cox and S. John, “SDO : A Statistical Method for Global Optimization,” *Multidiscip. Des. Optim.*, vol. 2, no. October, pp. 315–329, 1997.
 - [225] H. J. Kushner, “A New Method of Locating the Maximum Point of an Arbitrary Multipeak Curve in the Presence of Noise,” *J. Basic Eng.*, vol. 86, no. 1, p. 97, 1964.
 - [226] J. Moćkus, “On Bayesian Methods for Seeking the Extremum,” in *Optimization Techniques IFIP Technical Conference*, Berlin, Heidelberg: Springer Berlin Heidelberg, 1975, pp. 400–404.
 - [227] D. R. Jones, C. D. Perttunen, and B. E. Stuckman, “Lipschitzian optimization without the Lipschitz constant,” *J. Optim. Theory Appl.*, vol. 79, no. 1, pp. 157–181, Oct. 1993.
 - [228] R. H. Byrd, P. Lu, J. Nocedal, and C. Zhu, “A Limited Memory Algorithm for Bound Constrained Optimization,” *SIAM J. Sci. Comput.*, vol. 16, no. 5, pp. 1190–1208, Sep. 1995.