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Review

Biomimetic tactile sensors and signal processing with spike trains: A review

Zhengkun Yi[a,b], Yilei Zhang[a,*], Jan Peters[b,c]

[a] School of Mechanical and Aerospace Engineering, Nanyang Technological University, 639798, Singapore
[b] Intelligent Autonomous Systems Lab, Department of Computer Science, Technische Universitaet Darmstadt, 64289, Germany
[c] Max Planck Institute for Intelligent Systems, Tuebingen,72076, Germany

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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. Particularly, biomimetic tactile sensors and signal processing with spike trains have gained a growing interest. In this paper, we firstly review human sense of touch as it serves as a reference point in the case of biomimetic tactile sensing. Then, we focus on biomimetic tactile sensing technologies, which are primarily presented in two aspects: emulating the properties of mechanoreceptors using artificial tactile sensors, and biomimetic tactile signal processing with spike trains. Finally, we discuss the problems in current biomimetic tactile sensing techniques and deduce the future directions.

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* Corresponding author.
E-mail address: ylzhang@ntu.edu.sg (Y. Zhang).

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1. 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 [1]. 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 [2]. The modality of touch can be divided into three categories: cutaneous (tactile), kinesthetic and haptic [3]. 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 [4]. 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 [5]. 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 [6].

The sense of touch also plays a significant role in many applications in robotics [7,8], minimal invasive surgery [1,9–11], advanced prosthetics [12,13] and manufacturing industries [14]. 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 [15], and avoiding slip while applying minimal force to the grasped objects [16]. 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. Fig. 1 shows a growing number of publications on biomimetic touch with spikes.

Previous review articles have mostly concentrated tactile sensing technologies for robot hands [15], for minimal invasive surgery [11], biomedical applications [1], slip detection in hand prostheses [17], dexterous robot hands [8], whole-body tactile sensing [7], large area tactile skins [18] and so on. By contrast, this paper presents a thorough review of the techniques in biomimetic tactile sensing, including emulating the properties of mechanoreceptors using artificial tactile sensors and biomimetic tactile signal processing with spike trains. Fig. 2 depicts the organization of the somatic sensory system in human beings, the biomimetic sensing system to reproduce the human sense of touch and the relationship between Section 2 and 3.

2. 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 the neurophysiology of tactile stimulus perception.

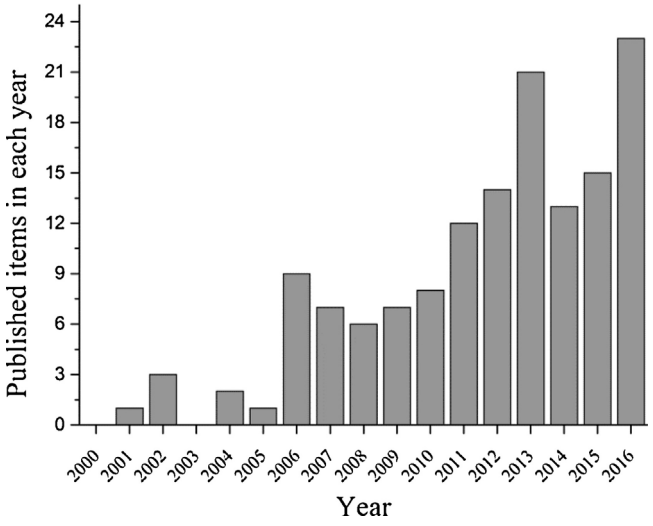

Fig. 1. Number of publications in Web of Science with topic keywords "biomimetic tactile" or "biomimetic touch" and "spike".

2.1. Human mechanoreceptors

Thanks to the microneurography technology in the late 1960′s [21], the tactile afferents have been intensely investigated. There are four main types of mechanoreceptors embedded in the human skin throughout the body [9], 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 [22]. 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. Table 1 summarizes the characteristics of each mechanoreceptor [23]. Fig. 3 illustrates the characteristics of human mechanoreceptors.

2.1.1. 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

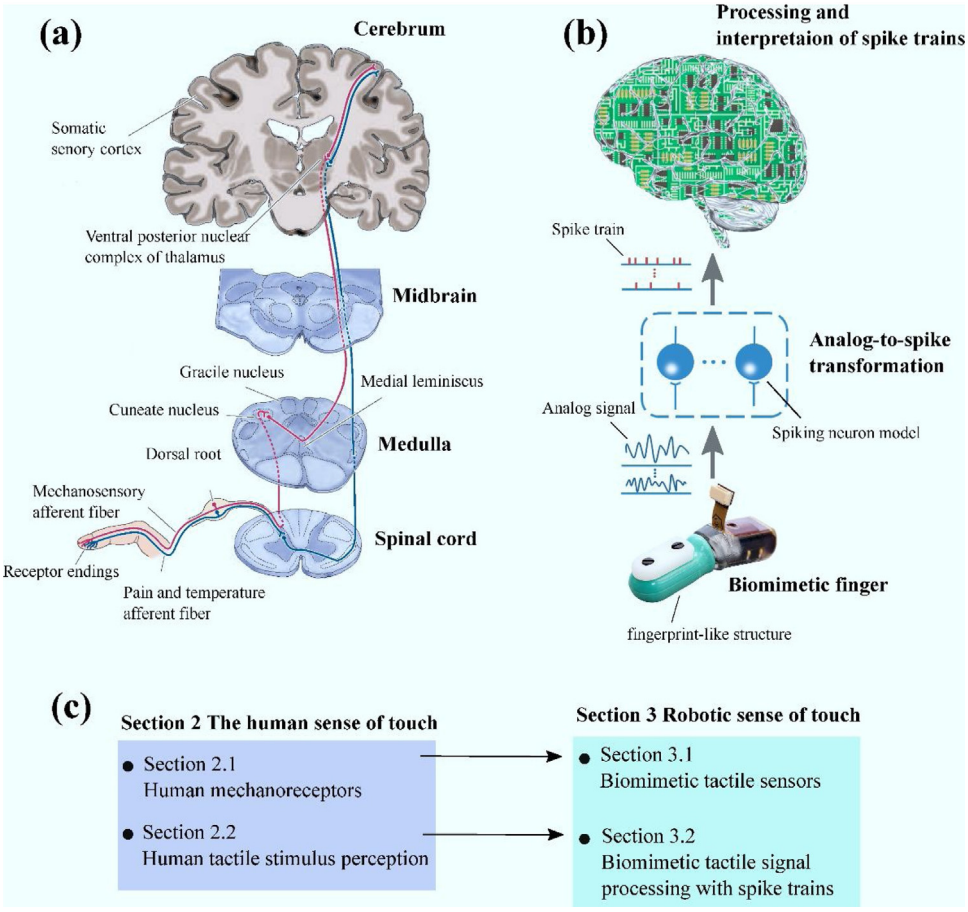

Fig. 2. (a) Mechanosensory information transmitted from the fingertip to the brain [19]. (b) A biomimetic sensing system to mimic the human sense of touch including a biomimetic finger (The BioTac sensor from SynTouch [20,21]) with fingerprint-like structure, analog-to-spike transformation, and processing and interpretation of spike trains. (c) The relationship between Section 2 and Section 3.

Table 1
Characteristics of human mechanoreceptors.

Mechanoreceptors	Field diameter (mm)	Frequency range (Hz)	Detected parameters
Merkel discs (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

Pacinian corpuscles are oval shaped and are approximately 1 mm in length and 0.6 mm in diameter.

2.1.2. 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.

2.1.3. 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 capsulated, as are the two previous ones.

2.1.4. 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°, 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.

2.2. Human tactile stimulus perception

2.2.1. Shape perception

Humans are able to 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. 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 [24]. A series of flat

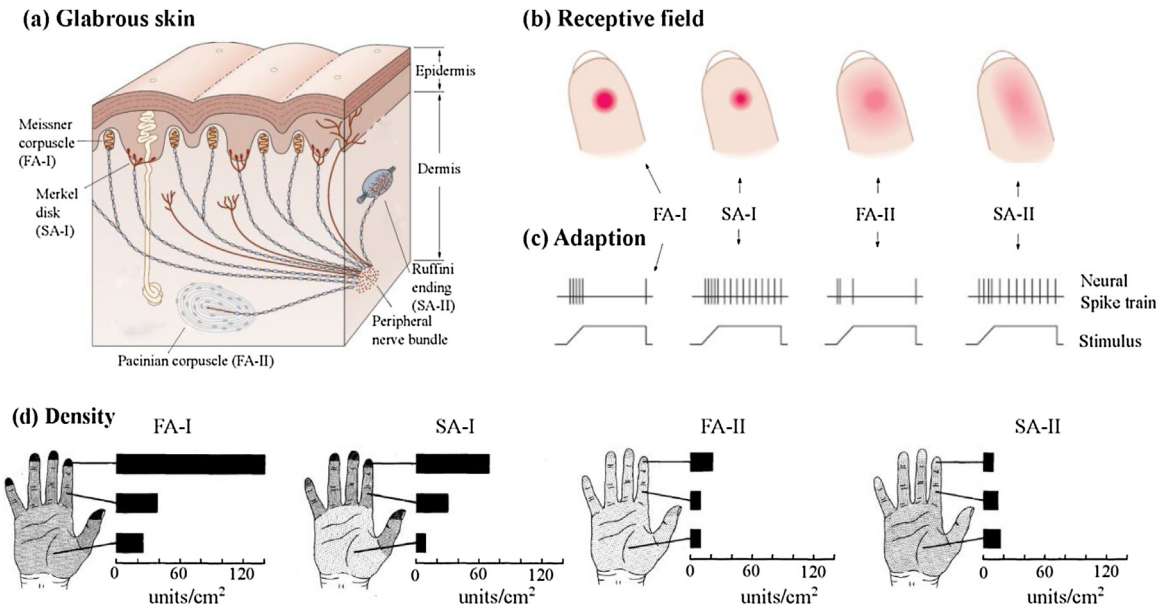

Fig. 3. Human mechanoreceptors. (a) A cross section of the glabrous skin [6]. (b) The receptive field of each type of mechanoreceptors [6]. (c) The Spike trains of each type of mechanoreceptors in response to a specific stimulus [6]. (d) The density of each type of mechanoreceptors [20].

plates were employed to study the tactile discrimination of shape [25,26]. Each plate has a step in the middle with fixed height and varying widths from 0 to 3.13 mm. SA-I mechanoreceptors offer more information in terms of spatial features of a shape [25]. In comparison, FA-I mechanoreceptors play an important role in the discrimination of fine differences in sharpness [26]. The perception of edge orientation in human vision is well understood. Suresh et al. [27] investigated the encoding of edge orientation signals in tactile afferents of macaques, and confirmed that the temporal patterns in the afferent responses of Rhesus monkeys encode the edge information.

The question of how a stimulus such as object shape is encoded in sensory system is remarkably critical in sensory neuroscience [28]. The recent progress in understanding how the brain perceives the unknown state of the world and forms decisions is reviewed in [29]. An increasing body of evidence shows that human perceptual computation is realized in an optimal Bayesian way [30], 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 [29].

2.2.2. Fingertip force perception

Goodwin and Wheat [31] studied the magnitude estimation of contact force with 4 spherically curved surfaces of different curvatures. The authors 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 [32], investigated the human ability to discriminate the 3D force direction by applying the force stimuli to the volar surface of the index fingertip. The applied force had a magnitude of 5 N and dynamics less than 2 Hz. It 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. The authors showed that the difference of 3D force direction as small as 7.1° could be discriminated by humans. A following up work [33] 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. [34], 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 in five distinct directions. Five force directions consist of normal force and forces at a 20° from the normal in the proximal, ulnar, distal, or radial directions. A flat stimulus surface was employed to deliver forces. 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.

2.2.3. Slip detection

Srinivasan et al. [35], investigated the influence of surface microgeometry on tactile slip detection and the underlying peripheral neural codes. Both the psychophysical experiments on human finger pad and neurophysiological experiments on monkey finger pad 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 finger pad. 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. Johansson and Westling [36] delivered weak electrical cutaneous stimulation on six subjects through the surfaces of the object and observed that FA-I, FA-II and SA-I afferents could reliably signal slips with different sensitivity.

2.2.4. Hardness perception

Srinivasan and Lamotte [37] 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 specimen independent 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 [38] 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. [39], 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. Friedman et al. [40] conducted psychophysical study of hardness estimation. The surfaces both harder and softer than the finger pad. The experimental results suggested that the hardness classification depends on whether the object conforms to the body. More specifically, an object is considered as soft if it conforms to the body, while an object is considered as hard if the body conforms to the object.

2.2.5. Texture perception

Human beings possess the capability to sensitively perceive different materials [41], 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 [42–44]. Connor et al. [43], 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 mm. Yoshioka et al. [44] 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 [42]. 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. Unlike previous work on artificial textured surfaces, Manfredi et al. [45] focused on the natural scenes of texture perception. There are 55 textures explored in total, including a variety of everyday fabrics such as foam, vinyl, and leather. The authors suggested that characterizing the skin vibrations is the first step to understand the mechanisms underlying texture perception.

3. Biomimetic sense of touch

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 present the approaches of biomimetic tactile signal processing with spike trains and various applications in stimulus perception.

3.1. Biomimetic tactile sensors

3.1.1. Tactile transduction mechanisms

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 [1]. 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.

3.1.1.1. 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 mainly fall into four categories: strain gauges, piezoresistors, percolative composites, and composites. A detailed review of piezoresistive tactile sensors can be found in the paper [46].

3.1.1.2. 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 [47]. 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 [48,49]. The mechanical property of strain gauges are considered to be comparable to that of slow-adapting mechanoreceptors [50].

3.1.1.3. 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 [51].

3.1.1.4. Percolative composites. percolative composites are formed by dispersed conductive fillers such as carbon black (CB) [52,53], graphite [54,55] and carbon nanotubes (CNTs) [56,57] 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, and the lower density results 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.

3.1.1.5. Quantum tunneling composites (QTCs). quantum tunneling composites [58,59] 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 [60]. 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.

3.1.1.6. Piezoelectric sensors. Piezoelectric materials will produce electrical charges when they are deformed or subjected to mechanical force [61,62], and correspondingly a voltage is developed if the surfaces are electroded. A variety of tactile sensors have been developed based on the piezoelectric effect [63–68]. In contract 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 [69–73]. The mechanical property of PVDF films are considered to be comparable to that of fast-adapting mechanoreceptors [50]. 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 [74]. Both PVDF and PZT have been incorporated into robotic hand for slip detection [72,75].

3.1.1.7. 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 [76–78]. 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, the 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 [79–81].

3.1.1.8. 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 (EML) and have a wide sensing range. However, they have some disadvantages such as bulky sizes. The optical sensor called the TacTip [82] 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 [83], identify objects [84], and detect slip [85].

3.1.1.9. Magnetic sensors. Magnetic tactile sensors modulate the tactile stimuli in the magnetic mode. For example, based on the principle of electromagnetic induction, Takenawa [86], 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 [87] 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 [86,88].

3.1.2. Biomimetic tactile sensors to mimic the properties of mechanoreceptors

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. Fig. 4 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) [92], 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 [92,93]. 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 [92]. A simple neural dynamics model was proposed by Izhikevich [94], which can fire all the patterns which exist in kinds of cortical neurons. The quadratic-integrate-and-fire model [95] 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 [96], also called as conductance-based model, was proposed by Alan Lloyd Hodgkin and Andrew Huxley in 1952, which 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 observations.

Piezoresistive (e.g., strain gauges) and piezoelectric (e.g., PVDF) materials are regarded as to be equivalent to SA and FA mechanoreceptors respectively [50,97]. 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 [98]. With a pulse modulation algorithm [99], 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 [100–102], 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 [91,103], 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 [104], but no direct comparison with biological recordings are demonstrated. Yi and Zhang [105] 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. [90], 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 compares the related works on mimicking the properties of mechanoreceptors based on artificial tactile sensors.

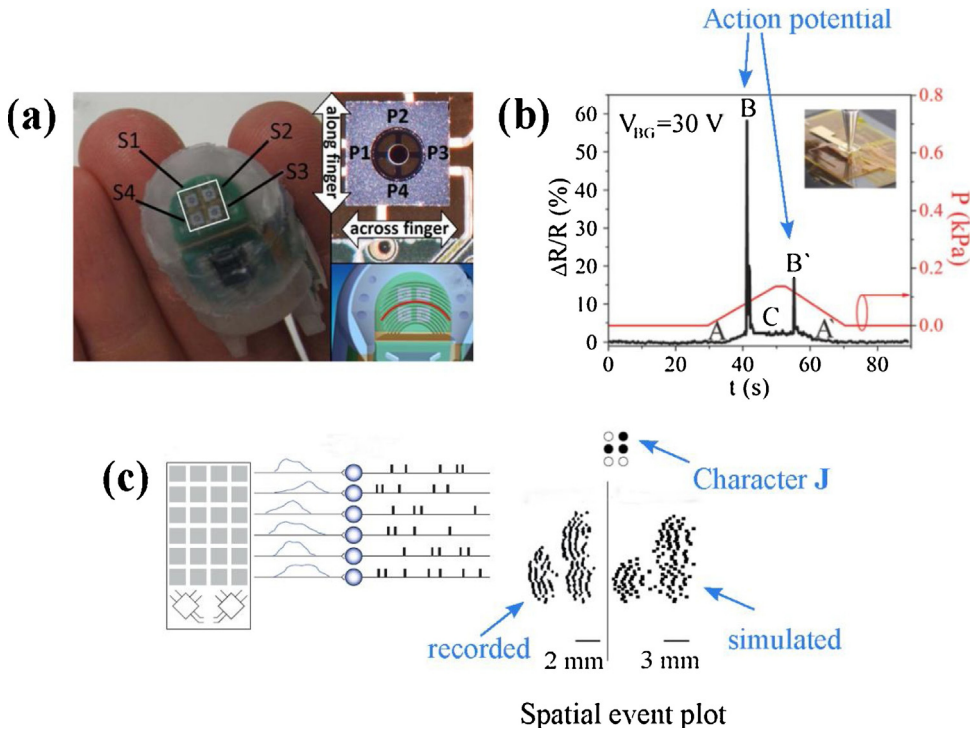

Fig. 4. Artificial tactile sensors to mimic the properties of mechanoreceptors. (a) A sensor density of 72 units/cm^2 is achieved by aid of MEMS techniques, which mimics the density of SA-I mechanoreceptors [89]. (b) The action potential generation of FA mechanoreceptors is emulated by the single-layer graphene [90]. (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 [91].

Table 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. [50]	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. [89]	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. [98]	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. [91]	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. [98]
2013	Lee et al. [104]	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. [98]. The difference is that the spiking neuron are two Izhikevich neurons.
2016	Yi and Zhang [105]	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. [98]
2016	Sul et al. [90]	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

3.2. Biomimetic tactile signal processing with spike trains

In this section, the biomimetic methods to process tactile signals and their applications are reviewed.

3.2.1. Biomimetic tactile signal processing methods

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. Spikes carry information for high-level perception, known as neural codes, including rate codes and spike codes [93,106,107].

3.2.1.1. Rate codes. Rate code is assumed to be the neuronal representation of stimuli [111]. 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 [93]. Rate codes are commonly served as a benchmark for decoding the tactile stimulus [100,112].

3.2.1.2. Spike codes. 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

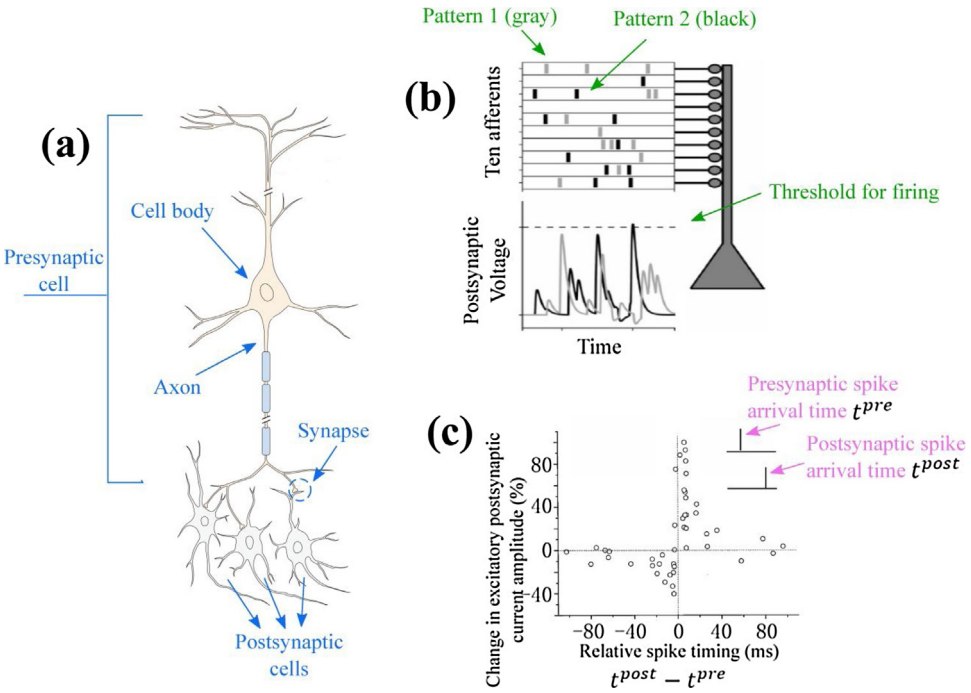

Fig. 5. (a) The structure of neuron and synapse [6]. (b) Classification of two different patterns based on the tempotron [127]. (c) The unsupervised learning STDP observed in hippocampal glutamatergic synapses [131].

visual, auditory, and somatosensory system [113–116]. 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 [117]. 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 [118].

Multiple neurons, connected through synapses, form a network, which inspires the development of the third generation of neural network called spiking neural networks [108–110]. 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 [119,120]. A large body of electrophysiological experiments [121–123] shows that the changes of synaptic strength can be induced by following patterned stimuli. Fig. 5 shows the structure of neuron and synapse as well as the learning rules in spiking neural networks. Learning in spiking neural network includes supervised learning and unsupervised learning.

3.2.1.3. 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 [124–126]. One typical example for the supervised learning rule is the tempotron. The tempotron [127] 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 fails 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. The tempotron could only specify the firing status i.e., firing or not firing. In contrast, Remote Supervised Method (ReSuMe) [128] is another supervised method that is able to generate desired spike trains in response to a given input class. The synaptic efficacy of ReSuMe is determined by both the correlation between the presynaptic and postsynaptic spike arrival times and the correlation between the presynaptic and desired spike arrival times. However, one disadvantage of ReSuMe is the low learning efficiency and high computational complexity. Therefore, Xu et al. [129] proposed a new supervised learning method for spiking neurons, which is more suitable to solve real-time problems.

3.2.1.4. Unsupervised learning. As opposed to supervised learning rule, the incoming spike patterns come with not any supervisory signals. Associated with memory formation [134], spike timing-dependent plasticity (STDP) is a spiking generalization of Hebbian learning [130,131]. The standard 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. There are also many other STDP learning rules [132], where synaptic changes are determined by the presynaptic spike arrival time and the postsynaptic membrane potential. The plasticity model is successfully demonstrated to discover the connectivity patterns associated with the neural code. Feldman [133] provided a review of the broad view of plasticity including various forms of STDP.

Table 3
Comparison of biomimetic tactile stimulus sensing with spike trains.

Year	Author	Tactile Sensor	Analog-to-spike transformation	Spike train decoding	Application
2012	Spigler et al. [102]	A 2 × 2 piezoresistive tactile sensor array	The Izhikevich model	Spike frequency domain analysis	Grating discrimination
2013	Bologna et al. [91]	A 4 × 6 capacitive square tactile sensor array	The integrate-and-fire model	Naïve Bayesian classifier	Braille letter recognition
2013	Lee et al. [104]	A fabric based binary tactile sensor array	The Izhikevich model	Tempotron	Curvature discrimination
2014	Lee et al. [135]	A low-cost, foot pressure sensor	The Izhikevich model	The synaptic kernel inverse method (SKIM)	Gait event detection
2015	Rongala et al. [100]	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
2015	Chou et al. [136]	An interactive, tactile neurorobot with a 9-by-8 matrix of trackballs	The Izhikevich model	STDP	Learning touch preferences
2017	Yi and Zhang [112]	A biomimetic fingertip with PVDFfilms	The Izhikevich model	A unified framework of spike train distance based *k*NN	Roughness discrimination

3.2.2. Biomimetic tactile sensing with spike trains

Biomimetic tactile perception with spikes has attracted increasing attentions in the past decade. Lee et al. [104], 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 [127] was employed to distinguish between the 105 mm indenter and 65 mm indenter based on the relative timings of first spikes. Lee et al. [135], 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. [91] 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 naive 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. [100], 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. Yi and Zhang [112] extended Rongala et al.'s work by proposing a unified framework of spike train distance based *k*NN (STD-*k*NN), where various spike train distances were explored. One work on surface roughness discrimination in a soft neuromorphic fashion was reported by Spigler et al. [102], 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 3 summarizes the relevant papers of biomimetic tactile stimulus perception with spikes.

4. Future direction

Although tremendous progress has been made in biomimetic tactile perception, there is still much space to improve. While the spike-like signal generation for biomimetic tactile stimulus perception receives an increasing attention, the emphasis has remained on utilizing spike neuron models to do the analog-to-spike conversion. The recent work by Sul et al. [90] provided the possibility to generate artificial action potentials without any spike neuron models. The developed graphene-based pressure sensor momentarily released spikes in response to the pressurization. However, the biological spiking neurons behave much richer and more complicated, for instance, tonic spiking and bursting, phasic spiking and bursting, rebound spiking and bursting, inhibition-induced spiking and bursting, etc [92]. How to realize biologically plausible replication of neuronal spiking activities is still an open question.

Current research regarding the biomimetic mechanoreceptor primarily focuses on mimicking individual mechanoreceptor, for example, using piezoresistive sensor to mimic SA-I mechanoreceptors and utilizing piezoelectric sensor to mimic FA-I mechanoreceptors. Given the fact that population response across neuronal networks better accounts for the neural coding of various stimuli [28], it is desirable to extend the research scope to integrate a population of biomimetic mechanoreceptors in the case of robotic applications, particularly, in the robotic fingertip based on mechanically compliant and compact tactile sensors.

Another interesting direction could be deep learning for biomimetic tactile sensing. Compared to the revolution in audio and image processing, deep learning has less been applied in tactile sensing due to the unavailability of big data set. However, a recent work [137] on material classification may provide the new insights in employing deep learning for tactile sensing applications. In this work, the raw tactile signals with 24,000 dimensions are directly fed into a convolutional deep learning network architecture. The classification accuracy can reach 97.3%.

The sense of touch in human beings motivates the development of biomimetic sensors and systems. On the other way around, the biomimetic system may even yield insight into the study of neuroscience as well. For example, the question remains as to how human beings encode the surface roughness during the physical finger-surface interactions. Specifically, it is still an open question as to which mechanoreceptor play a significant role in surface roughness discrimination. Yi and Zhang [105] provided an approach to investigate surface roughness recognition with a biomimetic fingertip, which is able to mimic the mechanical properties of FA-I mechanoreceptors. This platform may shed light on the neurophysiological study. In addition, Methods in computational neuroscience [138] are important tools for understanding what the mechanoreceptors do and how the nervous systems function. The computational and mathematical modeling of the neural systems encourages the crosstalk among the various disciplines ranging from the study of neuroscience on the molecular and cellular level to human psychophysics and psychology [139].

5. Conclusion

This paper provides a review of biomimetic tactile sensors and signal processing with spike trains. Parallel to the review of the human sense of touch with an emphasis on the properties of human mechanoreceptors and human tactile stimulus perception, the current techniques to mimic the properties of human mechanoreceptors and biomimetic tactile signal processing with spike trains for various applications were also reviewed. With the development of advanced tactile sensors, spike-like signal could be generated directly via the tactile sensors without any employment of spiking neuron models. Another interesting direction could be mimicking the population spiking activities using tactile sensor array and spiking neural networks. Deep learning may also play a role in the future tactile sensing applications. The insights gained in the study of biomimetic tactile sensors and signal processing may shed light on the research in the neuroscience as well.

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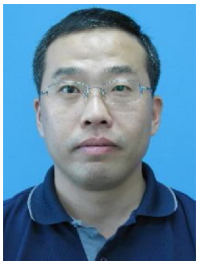
Biographies

Zhengkun Yi received his B.S. degree from University of Science and Technology of China (USTC) and M.E. degree from Chinese Academy of Sciences (CAS). He is currently a PhD student in the joint PhD degree programme between Nanyang Technological University (NTU) and Technische Universitaet Darmstadt (TUD). His research interests include biomimetic tactile sensing and exploration, sensor fabrication techniques, machine learning, and computational neuroscience.



Yilei Zhang received his Ph.D degree (2007) from Iowa State University in mechanical engineering and electrical engineering. Before joining Nanyang Technological University in 2012, he served as a senior research engineer in the Goodyear Tire and Rubber Company. His research interests include neuroengineering, bioinspired sensors, etc.

Jan Peters is a Full Professor (W3) for Intelligent Autonomous Systems at the Computer Science Department of the Technische Universitaet Darmstadt and at the same time a senior research scientist and group leader at the Max-Planck Institute for Intelligent Systems, where he heads the interdepartmental Robot Learning Group. Jan Peters has received the Dick Volz Best 2007 US Ph.D. Thesis Runner-Up Award, the 2012 Robotics: Science & Systems – Early Career Spotlight, the 2013 INNS Young Investigator Award, and the IEEE Robotics & Automation Society's 2013 Early Career Award. In 2015, he was awarded an ERC Starting Grant. Jan Peters has studied Computer Science, Electrical, Mechanical and Control Engineering at TU Munich and FernUni Hagen in Germany, at the National University of Singapore (NUS) and the University of Southern California (USC), and been an visiting researcher at the ATR Telecommunications Research Center in Japan. He has received four Master's degrees in these disciplines as well as a Computer Science PhD from USC.