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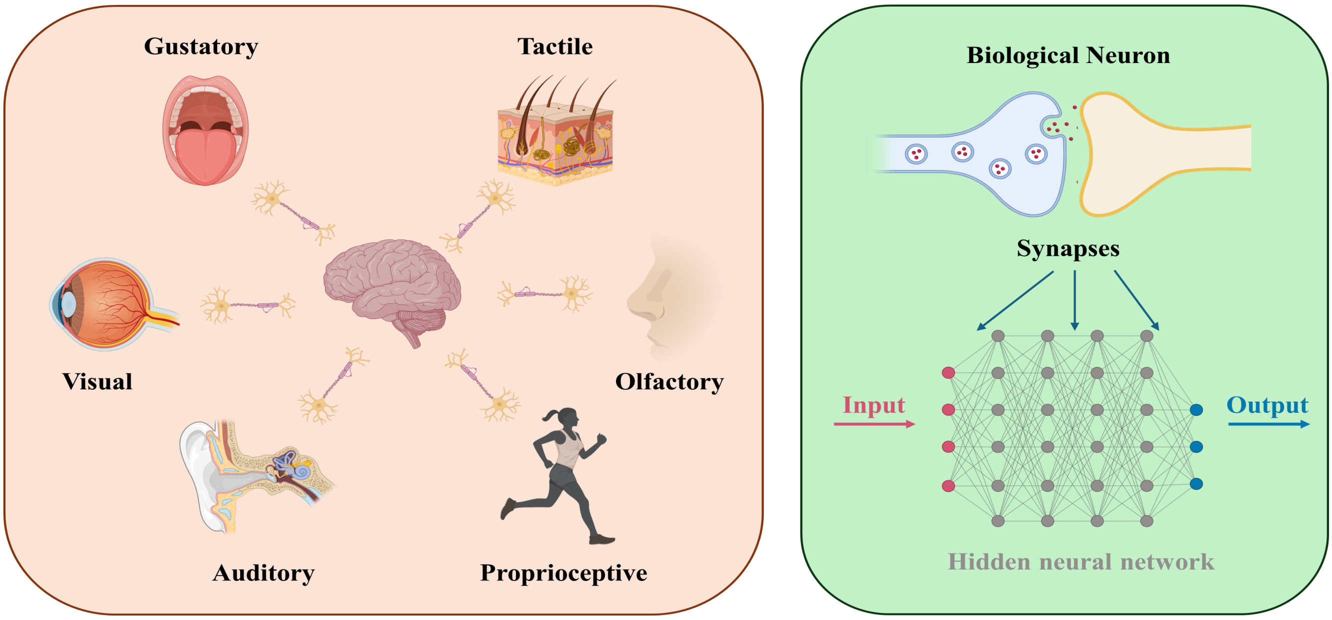
Neuromorphic Computing in Sensory Systems: A Review

Weijia Yan[1] Jingjing Qiu[1,*]

1 Department of Mechanical Engineering, Texas A&M University, College Station, TX, USA
** Corresponding author: jennyqiu@tamu.edu*

Neuromorphic Computing in Sensory Systems



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ABSTRACT

Unlike traditional sensor architectures that often generate an excess of redundant data and suffer from high power consumption, neuromorphic sensors offer a streamlined approach, providing energy-efficient data processing by leveraging the mechanisms of spiking neural networks. This work reviews the latest advancements in neuromorphic visual, auditory, gustatory, olfactory, haptic and proprioceptive sensors, drawing parallels with their biological analogs and discussing their integration with neuromorphic computing frameworks. By converging neuroscience, materials science, and microelectronics, neuromorphic sensors potentially enhance human sensory capabilities, promising profound impacts on robotics and artificial intelligence.

Keywords: ***Neuromorphic computing, Neuromorphic engineering, Bio-sensor, Wearable devices***

1. INTRODUCTION

Neuromorphic computing derives from a paper published by Professor Carver Mead at the California Institute of Technology in 1990. It emphasizes the emulation of the principles of neurons and synapses in the human brain for data processing. Unlike the frame-based continuous data processing of traditional machine learning approaches, such a brain-inspired machine learning technique uses “spikes” to compute in response to changes or events in the input and thus convey information about the temporal dynamics of the input. Neuromorphic computing can be more effective than traditional machine learning approaches due to their brain-inspired nature, especially when the input data are ill-conditioned. In neuromorphic computing, only a small amount of charge is released during the transmission of neural impulses. The signal passes only when the accumulated charge exceeds a set threshold. Neuromorphic chips process information in a parallel and event-driven manner, making localized real-time data processing feasible and quicker in applications that require quick responses and low power consumption even to multiple inputs simultaneously, such as robotics, autonomous systems, Internet of Things (IoT), and multiplex sensing.

In recent years, increasing efforts have been made to incorporate neuromorphic computing for processing diverse sensory information, leading to the development of intelligent and adaptive sensing systems inspired by biological principles. These systems aim to mimic the complex selective attention operations performed by biological organisms, allowing for quick determination of motor actions in response to subsets of sensory inputs, while suppressing non-salient signals. The synergy between neuromorphic principles and learning algorithms further enabled sensors with enhanced adaptability, improved efficiency, and low latency, such as reduced data redundancy. The integration of neuromorphic computing at the edge, in closer proximity to sensors, has emerged as highly intelligent and adaptive sensing platforms, which makes them promising for applications in robotics and computational neuroscience. However, the design and development of hardware architectures capable of efficiently supporting multiplex neuromorphic sensing is still challenging. Research in this field spans from single-chip sensors to multi sensory modalities, with a focus on enhanced adaptabilities under different environment and operation conditions.

Significant advances have been made in the development of neuromorphic sensory materials. Typically, two-dimensional materials, optoelectronic materials, ionic liquids/gels, ferroelectric materials, phase-change materials, and biological materials have all been studied in the fabrication of neuromorphic devices, enabling the simulation of basic biological synaptic functions and laying the hardware foundation for artificial perception systems. The major focus is to seek novel functional materials with high sensitivity and selectivity through materials synthesis, micro-nano fabrication, device physics, and circuit design.

This literature review provides a comprehensive overview of the current state of research on neuromorphic sensing, their applications and challenges.

2. NEUROMORPHIC VISUAL SENSORS

Vision is a primary method of perception and is vital due to its capacity for comprehensive information gathering on the surrounding environment with a high level of detail and accuracy. Inspired by the architecture of the human retina and the principles of the brain-inspired machine learning, neuromorphic vision sensors can simulate the pulse firing mechanism of the biological retina and efficiently capture and process visual information[1, 2]. By leveraging in-sensor computing, visual data is detected, converted into electrical signals, and processed within the neuromorphic visual sensor devices. The ultimate goal is to simulate the structure and mechanisms of biological vision perception, scene reconstruction, object recognition, texture analysis, motion tracking and spatial data extraction in a timely and energy-efficient manner.

Neuromorphic visual sensors emulate the characteristics of the biological visual system to operate, offering a promising and efficient approach for achieving low power consumption and high-performance image processing capabilities of vision sensors[3-5]. The human visual system is a complex integration of the eyes, optic nerves, and the visual cortex of the brain. The retina within the human eye is responsible for perceiving and preprocessing visual information, which is then transmitted to the visual cortex of the brain through the visual nerves for further processing[6, 7]. The retina, as the site of visual information acquisition and initial processing, consists of three main layers: the photoreceptor layer, the outer plexiform layer, and the inner plexiform layer. The retina converts the spatiotemporal information contained in incoming light from the visual scene into spike trains and patterns, capable of preprocessing the information carried by these spikes, which discards redundant visual data, significantly accelerating further information processing in the human brain[1, 8].

Based on the simulation of the human visual system, neuromorphic vision devices, also known as silicon retinas, have been developed over the past three decades. Mahowald and Mead et al. firstly introduced the silicon retinas in 1991[9]. Silicon retinas represent neuromorphic vision sensors that are modeled after the human retinas, sometimes also called event cameras. In the past decades, various integrated circuit-based visual sensors have been developed including temporal contrast vision sensors, gradient-based sensors, edge-orientation sensitive sensors, and optical flow sensors[3, 10, 11]. Currently, vision sensors based on biological principles are continuously being developed. Relative to integrated circuit-based visual sensors, they overcome drawbacks such as high noise levels and complex circuitry. Common neuromorphic vision sensors include Dynamic Vision Sensors (DVS), Asynchronous Time-based Image Sensors (ATIS), and Dynamic and Active-pixel Vision Sensors (DAVIS).

DVS is a benchmark neuromorphic sensor based on event-driven or Address-Event Representation (AER) [12, 13]. It features sub-millisecond precision, >120 dB dynamic range, and low power consumption of 23 mW. This approach was first proposed by Delbruck et al., who reported an event-driven vision sensor with 64x64 pixels recording brightness changes at each pixel [14]. In a typical DVS pixel, it includes a photoreceptor, differencing circuit, and comparators,which simplify and simulate the three-layer structure of the retina in the eye[15].

This type of vision sensor is sensitive to dynamic information provided by the scene, but it has significant limitations in perceiving sustained information. Posch et al. developed ATIS, a time-based asynchronous image sensor, which demonstrated for the first time the possibility of simultaneously acquiring static and dynamic image information[16, 17]. ATIS has the capability to simultaneously capture static and dynamic image information, offering a high degree of flexibility due to the combination of two sub-pixels within each pixel. In comparison to DVS, ATIS can measure the absolute pixel intensity in addition to the detection of brightness changes. By combining DVS and APS, another method, DAVIS, has been developed to integrate dynamic and static information into a single pixel[18, 19]. The advantages of DAVIS include high temporal resolution, high dynamic range, low power consumption, and absence of motion blur [105]. These traditional neuromorphic vision sensors have been widely applied in various computer vision and robotics applications[20, 21]. However, they still suffer from drawbacks such as complex circuitry, high latency, low integration, and high power consumption.

In order to address the drawbacks of traditional neuromorphic vision sensors implemented based on CMOS, neuromorphic vision sensors based on emerging devices have been developed. Based on recently developed various novel functional materials, some neuromorphic vision architectures mimicking the low power consumption and high-resolution characteristics of the eye have been developed, including hemispherical vision sensors, Optoelectronic Resistive Radom Access Memory (ORAM) vision sensors, and Neural Network (NN) vision sensors[22]. The hemispherical structure of the human retina is advantageous for high-sensitivity image acquisition, visual information preprocessing, and transmission. Hemispherical vision sensors aim to simulate this characteristic of the human eye, making them suitable for applications in humanoid robots which require a wide field of view[23]. Long et al. demonstrated a hemispherical neuromorphic retina of a bionic eye with achromatic vision, which possesses capabilities of color perception, optical adaptability, and energy efficiency that were missing in previous studies[24]. Currently, the limitation of hemispherical image sensors lies in the fact that their pixels are composed of photodetectors, which lack the capabilities for information storage and preprocessing. ORAM employs an alternative approach using optical excitation modulation, which enables the integration of optical sensing and preprocessing capabilities, simplifying the circuitry of neuromorphic vision sensors and reducing power consumption. Zhou et al. proposed a novel multimodal ORAM device array based on modified silk fibroin protein (MSFP), which allows for complete optical SET and optical RESET operations along with further multiple image preprocessing functionalities[25]. NN visual sensors are a type of neural network visual sensor with in-sensor computing capabilities, designed to address the issues of latency and high power consumption in traditional visual systems. Wang et al. reported on an image sensor based on van der Waals (vdW) heterostructures, which achieved a reconfigurable visual sensor capable of simultaneous image sensing and processing[26]. Neural network image sensors based on two-dimensional materials have demonstrated great potential in ultrafast machine vision applications. However, these visual sensors are not easily compatible with large-scale integration, limiting their further applications. In the future, how to fully utilize optoelectronic devices and novel functional materials to compost large-scale hemispherical neural network image sensors remains an important research direction. Researchers continue to strive for the realization of low-power, real-time, highly biomimetic machine vision systems.

Recently, more and more in-vehicle cameras (i.e. Unmanned aerial vehicle) with onboard processors provide automatic driver assistance, navigation, lane departure warning, obstacle avoidance, and surveillance functionality. In medical imaging devices, such as X-ray or ultrasound machines, neuromorphic computing enhances their real-time image process and analysis capability. In mobile devices, facial recognition, augmented reality, and image enhancement all become broadly used. For instance, the focal plane sensor-processor (FPSP)[27], an in-sensor visual computing device, has been developed for more than 20 years with in-chip perception, memory, and processing architectures altogether. In comparison with conventional computer vision systems, the FPSP allows for decreased system complexity, reduced power consumption, enhanced information processing efficiency and security.

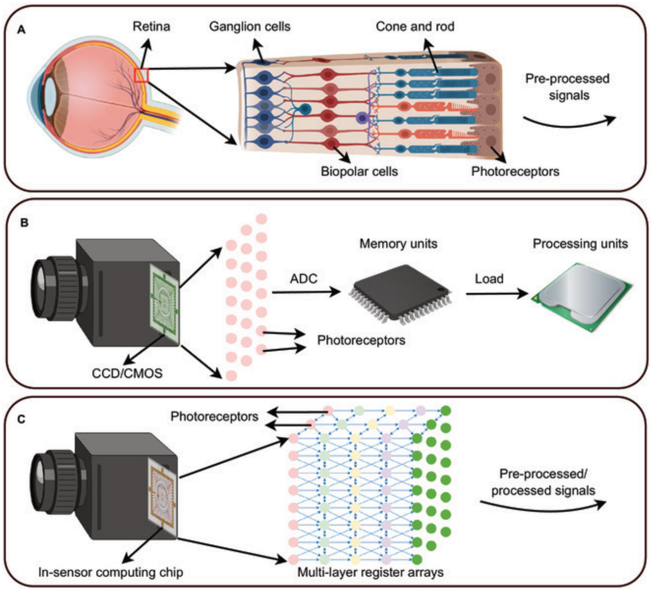

Figure 1. The principle of neuromorphic vision sensor. Adapted from Liu, Y., et al., 2023[28] The Authors, published by Intelligent Computing, under a Creative Commons Attribution License 4.0 (CC BY 4.0). Reprinted with permission.

Despite a range of materials have been studied in their photo-electric synaptic plasticity, such as metal oxide (i.e. MoOx, ZnO, Al2O3 used as dielectrics or charge trapping layers), Si nanocrystals, perovskites, and two-dimensional (2D) semiconductors (i.e. MoS2, WSe2, WS2, MoSe2, graphene, hexagonal boron nitride (h-BN), etc.), it is still challenging to fabricate bionic eyes due to poor reliability and limited functionality. For instance, the range of typical optical bandgap is still limited to their applications including robotics, computer vision, and surveillance.

3. NEUROMORPHIC TACTILE AND HAPTIC SENSORS

The sense of touch enables robots and artificial systems to perceive and respond to touch in a manner similar to human skin. It is critical in human-robot interaction. Tactile sensing involves complex physical interactions and plays a key role in estimating physical properties such as surface texture, hardness, material, shape, etc. The ability to discern through touch enables systems to differentiate between themselves and surrounding objects, and the rich physical interactions among real-world objects can be better understood. In biological systems, tactile sensing exhibits superior performance and robustness: human reflexes can respond rapidly within 65 milliseconds when processing signals from the brain[29, 30]. Due to the unique parallel processing and memory of synapses distributed within the brain, biological systems exhibit extremely low energy consumption and high speed responses. Consequently, researchers are attempting to replicate this efficient functionality through neuromorphic systems.

Based on the advancements in micro-neuroimaging techniques, the sense of touch was extensively explored by researchers in the 1960s[31, 32]. Humans are capable of recognizing various shapes through touch due to the presence of mechanoreceptors. Mechanoreceptors can be divided into two categories: slow adapting (SA) mechanoreceptors and fast adapting (FA) mechanoreceptors[33, 34]. The sensitivity of human tactile perception can be quantified by three attributes: spatial resolution, temporal resolution, and pressure resolution. Suresh et al. confirmed that the temporal patterns in the afferent responses of macaques encoded shape information[35]. Alessandro et al. investigated the ability of humans to discriminate 3D force directions by applying force stimuli to the palmar surface of the index fingertip[36]. Knill et al. found that human perceptual computation is achieved in an optimal Bayesian manner[37]. Based on these studies of human tactile perception, biomimetic tactile sensors have been developed. Various tactile sensing technologies have been developed, including resistive, piezoelectric, capacitive, optical, and magnetic types[38-45].

To emulate the tactile capabilities of human mechanoreceptors, various types of tactile sensors have been developed based on diverse transduction technologies and the utilization of spiking neuron models. Spiking neuron models are expressed in the form of ordinary differential equations (ODEs), which translate the signals generated by artificial tactile sensors into induced spikes. This includes models such as the leaky integrate-and-fire model, the quadratic integrate-and-fire model, the Izhikevich model, and the Hodgkin-Huxley model[46]. Among these, the leaky integrate-and-fire model is the most basic and simple model. Its drawback is that due to the fixed threshold, the generated spikes lack variability in timing or delay[46, 47]. The quadratic integrate-and-fire model incorporates spike latency and activity-dependent thresholds[48]. The Izhikevich mode is capable of eliciting all known firing patterns present in various cortical neurons[49]. Hodgkin et al. proposed the Hodgkin-Huxley model which consists of a set of four ordinary differential equations that explain the ionic mechanisms underlying the initiation and propagation of action potentials in the squid giant axon[50].

Table 1. Comparison of biomimetic tactile stimulus sensing with spike trains. Adapted with permission [31]. Copyright 2018, Elsevier.

YEAR	AUTHOR	TACTILE SENSOR	ANALOG-TO-SPIKE	SPIKE TRAIN DECODING	APPLICATION	REF.
2012	Spigler et.al	A 2 × 2 piezoresistive tactile sensor array	The Izhikevich model	Spike frequency domain analysis	Grating discrimination	[51]
2013	Bologna et.al	A 4 × 6 capacitive square tactile sensor array	The integrate-and-fire model	Naïve Bayesian classifier	Braille letter recognition	[52]
2013	Lee et.al	A fabric based binary tactile sensor array	The Izhikevich model	Tempotron	Curvature discrimination	[53]
2014	Lee et.al	A low-cost, foot pressure sensor	The Izhikevich model	The synaptic kernel inverse method (SKIM)	Gait event detection	[54]
2015	Rongala et.al	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	[55]
2015	Chou et. al	An interactive, tactile neurorobot with a 9-by-8 matrix of trackballs	The Izhikevich model	STDP	Learning touch preferences	[56]
2017	Yi and Zhang	A biomimetic fingertip with PVDF films	The Izhikevich model	A unified framework of spike train distance based kNN	Roughness discrimination	[57]

Advancements in spike-based sensor models have enabled the development of biomimetic tactile signal processing methods that encode tactile signals into spikes[58, 59]. Recently, biomimetic tactile sensing with spikes has increasingly garnered attention by researchers. Lee et al. adopted the Izhikevich model to convert tactile signals into spike signals. Inspired by the way tactile data is processed in the brain, they used time rather than intensity as the feature for event detection, achieving exceptional temporal resolution[53, 54, 60]. Rongala et al. implemented a decoding process that includes spike-feature-based and Victor-Purpura distance-based methodologies[55, 61]. The generated neuromorphic spike sequences were able to classify a variety of natural textures. Spigler et al. proposed an artificial mechanotransduction system based on a 2×2 MEMS array touch sensor. The results indicated that core tactile information is retained in the neural representation, and modulation generated through spiking can be utilized for surface discrimination tasks[51]. The summary of research papers related to spike-based biomimetic tactile stimulus perception is as shown in Table 1.

While the generation of spike signals for biomimetic tactile stimulus perception is receiving increasing attention, there remains significant room for improvement. With the development of advanced tactile sensors, it is possible to generate spike signals directly through the tactile sensors without the need for spiking neuron models. Another potential direction is the use of tactile sensor arrays and spiking neural networks to simulate population spike activity. Deep learning and Insights gained from deep learning and research in biomimetic tactile sensors and signal processing could also play a role in future applications of tactile sensing.

4.NEUROMORPHIC AUDITORY SENSORS

Neuromorphic auditory sensors capture sound feathers relevant to human hearing, including speech recognition, sound localization, and audio processing. The essence of neuromorphic auditory sensors lies in their biomimetic design, drawing inspiration from the human cochlea and auditory cortex. This approach enables the sensors to capture and interpret auditory signals with remarkable efficiency, paving the way for advancements in hearing aids, environmental monitoring, and even interactive computing systems. At the heart of these sensors' functionality is advanced signal processing, often facilitated by spiking neural networks (SNNs). These networks emulate the neural processing of the human brain, allowing for the efficient and accurate classification of a vast array of sounds, from environmental noises to human speech.

Traditional methods for sensing auditory signals rely on the continuous sampling of auditory inputs at a specific Nyquist frequency tailored for the application[62]. After undergoing Analog-to-Digital Conversion (ADC) and subsequent digital processing, this data is transformed into auditory frames. The utilization of high-resolution ADCs and the digital processing of auditory frames result in significant power consumption. Although dynamically varying the sampling rate can reduce power consumption, there is a risk of losing critical information due to lower sampling rates.

Early electronic cochlea has been built in CXIOS VLSI technology using micropower techniques to achieve this goal of usefulness via realism. Lyon et al. proposed an analog electronic cochlea that models the human cochlea using aVLSI[63]. Upon this foundation, Watts et al. address issues related to device mismatch, stability, and dynamic range, thereby enhancing the performance of subthreshold analog VLSI systems[64]. This was achieved despite the limited accuracy of individual devices, allowing for effective control over the behavior of higher-level systems. Sarpeshkar et al. developed a low-power wide-dynamic-range analog VLSI Cochlea, achieved through the use of transconductance amplifiers with a wide linear range, low-noise filter topologies, Automatic Gain Control (AGC), and an overlapping cascaded structure[65]. These early efforts laid the groundwork for further research into the design of artificial electronic cochleae.

Based on the developmental experiences of artificial cochleae, auditory processors suitable for silicon cochleae have also been developed[66-68]. Sarpeshkar et al. reported an ultra-low-power auditory processor that significantly enhances efficiency by delaying digitization through initial analog preprocessing, which can be utilized in bionic ears[69]. They claimed that it is suitable for use in fully implanted cochlear-implant systems of the future and may also be used as an ultra-low-power spectrum-analysis front end in portable speech-recognition systems.

Silicon cochleae are widely used in auditory scene analysis. The Address Event Representation (AER) is incorporated into silicon cochlea chips for general neuromorphic applications such as sound localization and audio-visual sensor fusion. Chan et al. developed an analog integrated circuit containing a matched pair of silicon cochleae with AER and demonstrated the cochleae's capability in sound localization in both ideal and reverberant environments[70]. Liu et al. proposes an integrated event-based binaural silicon cochlea system aimed at efficient spatial audition and auditory scene analysis[71]. They claimed that the computational cost of an event-driven source localization application can be up to 40 times lower when compared to a conventional cross-correlation approach.

Currently, neuromorphic devices have also been proposed to achieve sound localization. Two primary mechanisms for sound localization have been identified: coincidence detection through Interaural Time Difference (ITD) and Interaural Level Difference (ILD) [72]. Sun et al. detected an interaural time difference by suppressing sound intensity- or frequency-dependent synaptic connectivity. A circuit with our tunable excitatory and inhibitory synaptic devices demonstrates a key function for realizing the most precise temporal computation in the human brain[73].

These developments underscore the transformative potential of neuromorphic auditory sensors, leveraging biological principles and advanced computational models to create more efficient, accurate, and versatile auditory sensing technologies. As research progresses, these sensors are poised to revolutionize the field of auditory processing, offering new possibilities for both human and machine auditory systems.

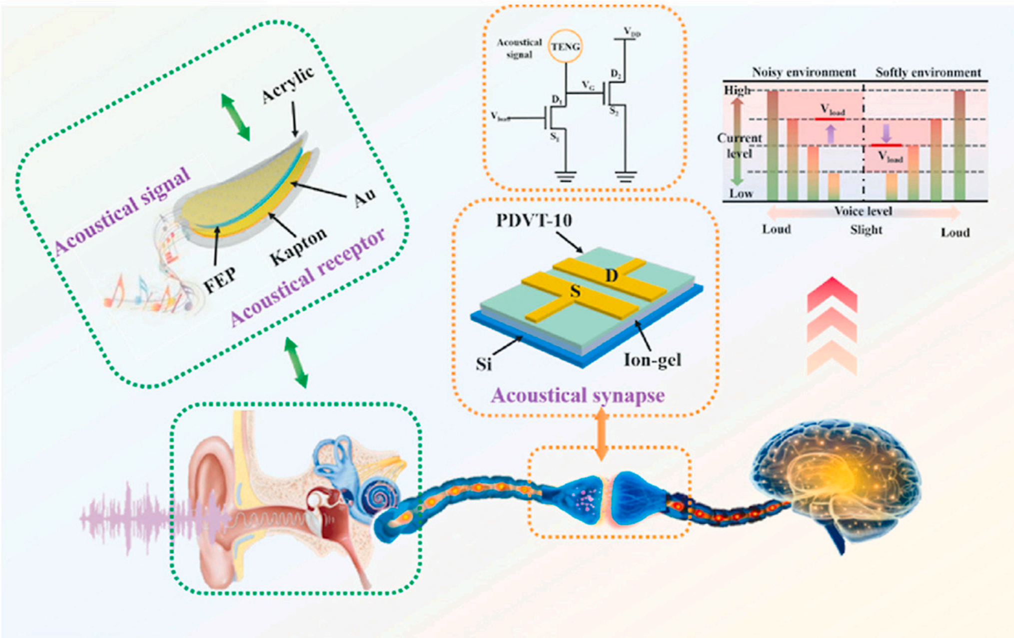

Figure 2. A schematic representation of the human auditory pathway and acoustic processing with neuromorphic functionalities. Adapted with permission[38]. Copyright 2020, Elsevier.

5. NEUROMORPHIC OLFACTORY SENSORS

Neuromorphic olfactory sensors, including electronic noses, aim to replicate the sense of smell and identify various scents. During the Industrial Revolution, the need to detect the presence of hazardous volatile organic compounds (VOCs) first emerged, sparking research into gas sensing technology[74]. Moncreiff developed the first artificial mechanical olfactory device, utilizing inorganic adsorbents to adsorb odor molecules onto a membrane, achieving a sensitivity slightly lower than that of the human nose[75]. With growing demand for gas sensors, gas sensing systems have evolved towards miniaturization, real-time operation, compactness, and affordability[76, 77]. As the application of gas sensors continues to expand, more complex electronic sensing systems are being incorporated into the development of artificial noses[78].

Gardner et al. formally defined the electronic nose and described it as a device composed of analog sensing units and digital processing units, capable of recognizing simple or complex odours[79, 80]. They developed an intelligent olfactory system integrating a CMOS gas sensor array and processing units on a single chip. The typical characteristics and functions of integrated smart sensors in electronic noses were emphasized, along with the challenges of applying them in real-world environments[76]. With the introduction of semiconductor gas sensors, new methods for signal preprocessing, dimensionality reduction, classification, and regression were introduced to handle the multivariate data output[81, 82].

Electronic noses benefit from complementary metal oxide semiconductor(CMOS) and microelectro mechanical systems(MEMS) technologies, advanced pattern matching methods, and novel sensing materials[84]. Persaud et al. adopted a biomimetic olfactory approach, constructing an electronic nose with semiconductor transducers. It was demonstrated that stimulating this process using some pattern classification principles from artificial intelligence research should be feasible[85]. Koickal et al. developed the analog circuit design and implementation of the components of an adaptive neuromorphic olfaction chip[86, 87]. They implemented a neuromorphic architecture with chemical sensors, converting chemical sensing signals into spike sequences. This spiking neural structure formed the signal processing stage of the olfactory bulb model. On-chip spike timing-dependent plasticity learning circuits were integrated, allowing for dynamic adjustment of weights for odor detection and classification. Bermark et al[88-94]. proposed a hardware/software co-design approach using the Zynq platform, aimed at implementing an electronic nose system based on Principal Component Analysis as an alternative to pure software or hardware implementations for the processing part of gas identification systems. This approach reduces the computational challenges involved in pattern matching.

The sensing front-end of electronic nose systems typically employs chemiresistive sensors, including either metal oxide sensors or conductive polymer sensors[77]. Recently, advancements in materials science and nanotechnology have facilitated the development of novel sensing technologies, such as Multi-Walled Carbon Nanotubes (MWNTs) and gold nanoparticles. These sensing front-ends exhibit improved sensitivity characteristics, making them suitable for integration with spike-based processing[95, 96]. The increasing application of carbon nanotubes in electronic sensing is primarily due to their superior electrical conductivity compared to carbon black. Research indicates that

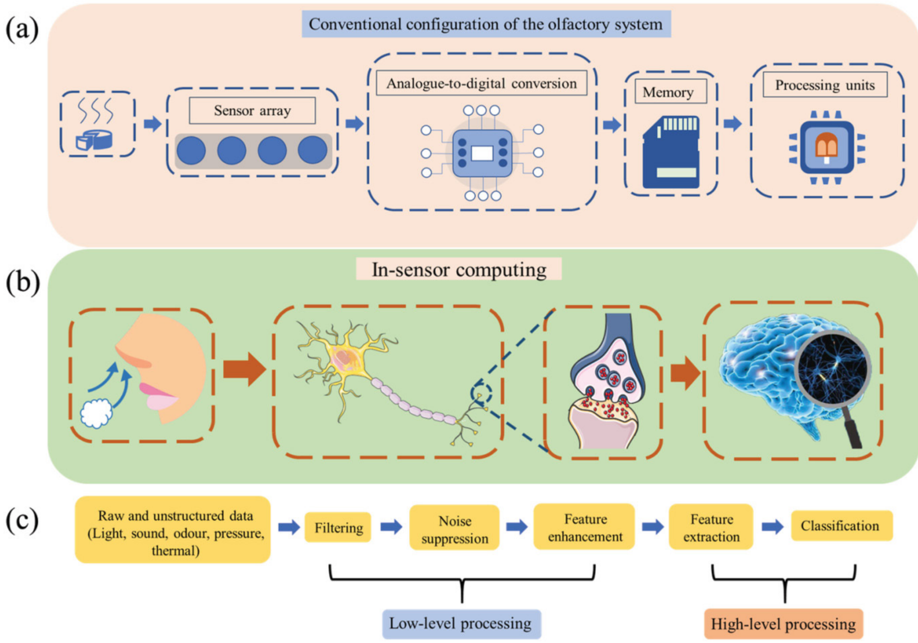

Figure 3. The origin of in-sensor olfactory computing. Adapted with permission[83]. Copyright 2023, John Wiley and Sons.

neuromorphic olfactory systems can greatly benefit from the remarkable characteristics of carbon nanotube-polymer composite sensors, such as ultra-high sensitivity, rapid response times, repeatability, and long-term stable output[97-99].

Recent advancements in neuromorphic engineering have led to the development of a new generation of electronic noses, aiming to mimic the biological olfactory pathways. Applying neuromorphic approaches to artificial olfactory systems has advantages such as reducing processing overhead and mitigating signal drift and noise through the implementation of learning algorithms[90, 100]. Artificial sensory systems based on smart sensing neuromorphic devices have emerged as a new direction in the field of electronic noses. Artificial sensory systems based on synaptic or neuronal devices can more efficiently transmit external information to the brain than traditional sensors used in building neuromorphic systems[83].

Currently, electronic nose systems based on neural networks still face several unresolved issues. Firstly, there is a need to reduce power consumption when developing artificial sensory systems based on synaptic and neuronal devices[101]. There is a significant difference in power consumption between current artificial olfactory systems and biological systems. Therefore, advancements in various aspects such as materials and structural design are needed to promote more effective compatibility between artificial synaptic devices and biological synapses. Secondly, enhancing system stability and durability is crucial for achieving high-performance artificial synaptic devices.

6. NEUROMORPHIC GUSTATORY SENSORS

Gustatory sensing refers to mimicking the sense of taste. Due to the growing demand for liquid analysis systems to assess process quality in industries such as food, beverages, and chemical manufacturing, the industrial sector has propelled the development of automated systems for monitoring the physicochemical properties of products throughout the manufacturing cycle. In this context, the use of chemical multi sensor arrays as an “electronic tongue” stands out for its ability to recognize both quantitative and qualitative components of complex solutions[102].

Similar to neuromorphic olfactory processing[103], artificial tongues employ an array of chemical sensors (i.e., artificial taste buds), followed by the reading of multivariate sensor responses in the electrical domain, which are then modeled through appropriate machine learning methods. Artificial tongues also benefit from CMOS and MEMS technologies, as well as novel sensing materials[104].Microsensors fabricated using semiconductor technology possess advantages such as miniaturization, robustness, high reproducibility, scalability in manufacturing, and ease of integration with readout electronic circuits. Subsequently, fusion algorithms can be applied to multi-sensor readings to achieve automated analysis.

Over the past few decades, various fundamental principles for liquid sensing have been reported[106]. Currently, sensor arrays used for liquid sensing are based on electrochemical methods such as potentiometry, as well as voltammetry. Other techniques, such as surface acoustic wave sensors and optical chemical sensors, have also been reported[107-110]. Similar to the electronic nose, the fundamental principle behind the electronic tongue is the combination of signals from nonspecific and overlapping sensors with pattern recognition routines. The use of multivariate analysis methods in

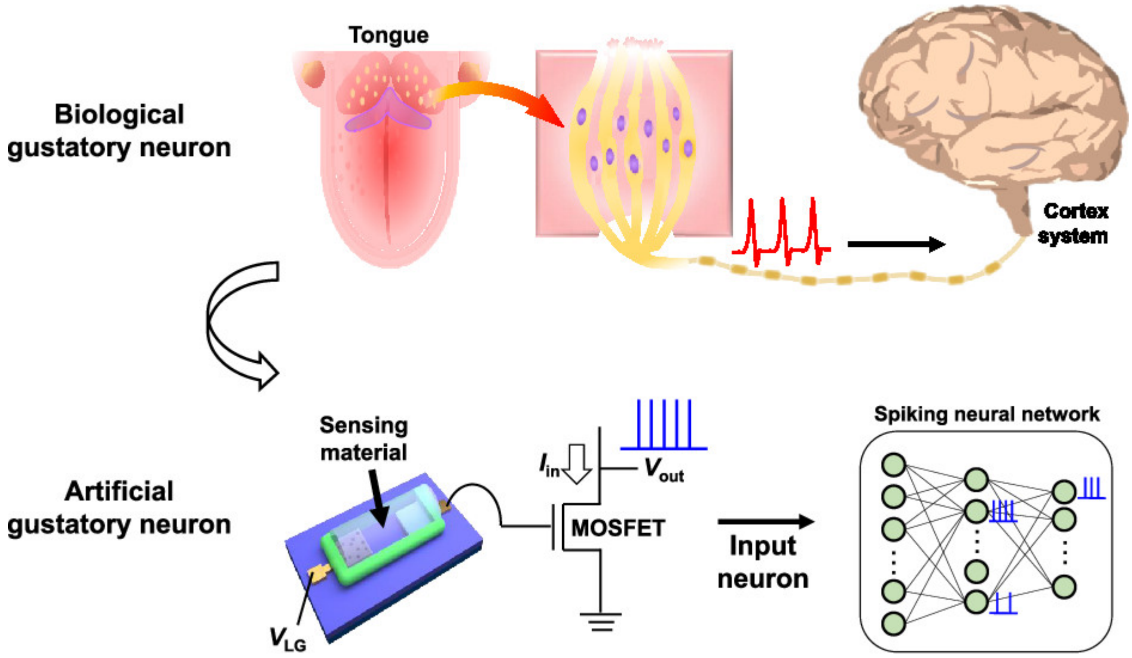

Figure 4. Neuromorphic E-tongue system with artificial gustatory neuron. Reprinted (adapted) with permission[105]. Copyright 2024 American Chemical Society.

conjunction with sensor arrays has been proven to be very powerful.

Multivariate analysis identifies structures and correlations within data or builds models from a calibration dataset, which are then used to make predictions based on test data[111]. To establish models based on the calibration dataset, various techniques can be employed, such as Partial Least Squares (PLS) and Artificial Neural Networks (ANN)[112]. Recently, Han and colleagues developed a device capable of simultaneously detecting ion concentrations and generating spike signals for an electronic tongue, integrating sensing and neuronal functions. Using Metal Oxide Semiconductor Field Effect Transistors to simulate gustatory neurons in two taste modalities, the sensors achieved synchronized sensing and spike encoding, with spike frequency varying according to the concentrations of hydrogen and sodium ions[105]. Yang et al. developed a neuromorphic gustatory system capable of simulating taste perception, information processing, and providing warnings for excessive intake[113]. This system exhibits sensitivity several orders of magnitude beyond the biological level, offering a promising strategy for the development of biomimetic and bio-integrated electronics.

Currently, the research on neuromorphic gustatory systems is still relatively limited compared to fields such as vision, hearing, and olfaction. Artificial tongues have considerable potential for applications in industries such as food, beverage, and chemical manufacturing, though some technologies and applications remain underdeveloped[102, 114].In the future, the integration of sensor technologies based on diverse techniques and the development of neural algorithms that are more long-term stable and resistant to drift will be potential directions for advancement.

7. NEUROMORPHIC PROPRIOCEPTIVE SENSORS

Proprioceptive sensors may provide information about the position and movement of body parts. They also benefit from neuromorphic computing. In the human brain, the activity in the hippocampus and entorhinal cortex regions enables individuals to easily orient themselves within environmental maps[115]. Additionally, they support path integration for autonomous navigation. Based on motion cues such as the individual's direction and speed over time, path integration can estimate their position within the scene map[116]. This is due to the mammalian nervous system encoding map-like spatial representations. When navigating using path integration, the brain needs to encode spatial positions and update this information with the direction and speed of movement[117, 118]. Spatial navigation models help us better understand the workings of the brain. In mammals, proprioceptive information is transmitted from Golgi tendon organs and muscle spindle organs to the central nervous system. Particularly, muscle spindles are the primary source of proprioceptive feedback for spinal sensory-motor regulation and servo control. These sensory organs play crucial roles in monitoring and regulating the positions and movements of the body's muscles and joints. Currently, various models of afferent activity from muscle spindles have been developed. These models aim to accurately simulate the dynamic responses of muscle spindles to changes[119-122]. These significant advancements in neuroscience have built the foundation for research on Neuromorphic Proprioceptive Sensors.

Proprioceptive feedback is crucial for robots during motion because it allows them to perceive the position, velocity, and acceleration of their own parts. This type of sensory feedback is essential for precise control and coordinated movement, enabling robots to interact more effectively with their environment and perform complex tasks with higher accuracy[123].

Currently, the developed solutions for generating spike activity from proprioceptive information in closed loops can be categorized into two types: custom translation and biologically-inspired translation[124]. The former typically refers to custom information translation specifically tailored for the task. Bouganis et al. proposed a spiking neural network architecture capable of autonomously learning to control a 4-degrees-of-freedom(DOF) robotic arm. The neural network consists of approximately 12,000 Izhikevich neurons and features a feedforward architecture[125]. Stewart et al. demonstrated a hybrid neuromorphic learning paradigm, which learns complex sensorimotor mappings based on a small set of hard-coded reflex behaviors. All control is implemented through spiking neurons simulated on neuromorphic hardware (SpiNNaker)[126].

The biology inspired proprioceptive information generation method attempts to emulate the true topological neural networks found in physiology. Screenivasa et al. developed a neuromuscular skeletal model of the human arm stretch reflex based on a real spiking neural network[127]. This model identifies neuromuscular parameters at the motor unit level, which integrates the effects of skeletal movement, neural and mechanical feedback. Based on the model of Mileusnic[128], Vannucci et.al proposed a proprioceptive feedback transmission mechanism that can be fully integrated into spiking neural network simulations and neuromorphic hardware[124]. Chen et al. reported a self-powered Artificial Motion Sensing System (AMSS) that achieves multimodal information recognition, including angles and digits, within a Spike Correlated Neural Network (SCNN). They demonstrated the significant potential of the AMSS, based on simulated vision and vestibular collaboration, in the fields of neural robotics, prosthetics, and soft electronics[129]. In the future, the advantages of spike algorithms for proprioception inspired by the brain will increasingly be combined with the benefits derived from robotic technology. Event-based sensor approaches can provide an innovative method for effective biomimetic autonomous robotics.

8. DISCUSSION AND CONCLUSION

One notable advantage of neuromorphic sensors is that they can chemically communicate with real neurons and the brain in the form of implanted microelectronics[130]. Neuromorphic sensors are generally based on the understanding and emulation of biological sensation and neural activity in humans; therefore, further interdisciplinary research is crucial. This includes overcoming challenges such as integration complexity, energy efficiency, and the ability to process multimodal sensory information in real-time. The discovery of various materials has also led to significant advancements in the development of flexible electronic technologies. Using materials with stretchable properties for the fabrication of stretchable synaptic devices is very appealing for neuromorphic systems used in artificial intelligence. By increasing the collaboration across fields such as neuroscience, materials science, and microelectronics, the development of neuromorphic technologies can not only emulate human sensory capabilities but also has the potential to enhance them. The future development of neuromorphic sensing should focus on the relevance of different sensor inputs and efficient preprocessing. Future research directions should also target neuromorphic sensing for parameters such as pressure, vibration, temperature, and magnetic fields, as well as the associated sensor fusion functionalities that integrate these various inputs, which can be widely used in bionic robots[131]. Neuromorphic emulation has accelerated scientific advancements in neuroscience and robotics. We can expect these emerging studies to provide additional inspiration and momentum for development in the field.

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