Embedded Silicon-Organic Integrated Neuromorphic System

Shengjie Zheng\textsuperscript{1,2,+}, Ling Liu\textsuperscript{1,2,+}, Junjie Yang\textsuperscript{1,2}, Jianwei Zhang\textsuperscript{2,3}, Tao Su\textsuperscript{2}, Bin Yue\textsuperscript{1,2}, and Xiaojian Li\textsuperscript{2,*}

\textsuperscript{1}University of Chinese Academy of Sciences, Beijing, China
\textsuperscript{2}CAS Key Laboratory of Brain Connectome and Manipulation, the Brain Cognition and Brain Disease Institute (BCBDI), Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences; Shenzhen-Hong Kong Institute of Brain Science-Shenzhen Fundamental Research Institutions, Shenzhen, China
\textsuperscript{3}Southern University of Science and Technology, Shenzhen, China

\textit{xj.li@siat.ac.cn}
\textit{+}these authors contributed equally to this work

ABSTRACT

The development of artificial intelligence (AI) and robotics are both based on the tenet of “science and technology are people-oriented”, and both need to achieve efficient communication with the human brain. Based on multi-disciplinary research in systems neuroscience, computer architecture, and functional organic materials, we proposed the concept of using AI to simulate the operating principles and materials of the brain in hardware to develop brain-inspired intelligence technology, and realized the preparation of neuromorphic computing devices and basic materials. We simulated neurons and neural networks in terms of material and morphology, using a variety of organic polymers as the base materials for neuroelectronic devices, for building neural interfaces as well as organic neural devices and silicon neural computational modules. We assemble organic artificial synapses with simulated neurons from silicon-based Field-Programmable Gate Array (FPGA) into organic artificial neurons, the basic components of neural networks, and later construct biological neural network models based on the interpreted neural circuits. Finally, we also discuss how to further build neuromorphic devices based on these organic artificial neurons, which have both a neural interface friendly to nervous tissue and interact with information from real biological neural networks.

Introduction

With the advent of the era of AI, technologies such as deep learning have been subjected to higher requirements in the face of increasing usage demands\textsuperscript{1}. While traditional computers demonstrate efficiency and precision when dealing with simple logical problems, the human brain is often superior when dealing with complex spatio-temporal problems while demonstrating low energy consumption\textsuperscript{2}, which has inspired researchers. As a result, neuromorphic engineering that mimics human central and peripheral neural functional architectures, computational principles, and information transfer and processing mechanisms has developed rapidly\textsuperscript{3,4}. Meanwhile, in order to meet the application needs of next-generation Internet of Things (IoT) smart terminals for deep human-machine interaction, it will be important to study low-power, ultra-sensitive, and human-machine integrated artificial neural systems with integrated signal sensing and brain-inspired intelligent information processing technologies. However, nervous tissue and traditional electronic devices are fundamentally different in principle and material. Biological neural systems are based on bio-organic materials and perform large-scale information processing through chemical reactions and ion flows\textsuperscript{5,6}. In contrast, electronic computers are based on silicon-based semiconductor materials and perform serial information processing through gated electron flow\textsuperscript{7,8}. Therefore, how to achieve direct information interaction between AI-based devices and biological nervous systems is the key problem that needs to be solved.

On the other hand, neurological disorders, neurodegenerative diseases, psychiatric disorders, and neuromuscular diseases cause a huge social and economic burden worldwide. The traditional combination of medication and surgery is associated with high side effects and significant surgical risks for patients. The advent of implantable neuroelectrodes has brought hope to the majority of patients\textsuperscript{9}. The ideal neuroelectrode can diagnose and treat the corresponding neurological diseases by recording the electrical signals of nerves and electrical stimulation without destroying the nervous tissues. While the neural interface is an important component of various bioelectronic applications, the performance of neural electrodes and their stability depends mainly on the stability of the neural interface\textsuperscript{10}. Despite the rapid development of neuroelectrode technologies, their functionality has so far been reliable only in short-term and controlled laboratory environments. Therefore, how to establish a safe, long-term stable, and high-performance interface between neural electrodes and nervous tissues is an important issue.
that needs to be addressed to achieve clinical applications of neural electrodes. To address the above issues, we propose to achieve deep human-machine interaction capabilities by performing hardware simulations of the nervous system to prepare brain-inspired neural devices. Field Programmable Gate Arrays (FPGA) have the capability of field setup in logic gates and data flow setup through routing matrices, which can collect biological neural signals (e.g., electrophysiological signals in the mouse brain) and convert them into mechanical electrical signals. In combination with this technology, neurons, and neural networks are simulated in terms of material and morphology, i.e., organic neuromorphic, with a view to solving the interface articulation between brain-inspired neural devices and the nervous tissue. The nature of neuronal activity is based on the electrochemical reactions of bio-organic materials. Inspired by biological neurons, artificial synaptic devices can be constructed to realize the conversion of electrical signals to bio-neural signals to electrical signals that can be processed by the devices\(^1\)\(^\text{-}^\text{13}\). Organic semiconductor materials are similar in structure to the biomolecules that make up biological neurons and have natural biological adaptability, and organic materials have flexible and easily moldable qualities that make them easy to wear and implant\(^1\)\(^\text{-}^\text{14}\),\(^\text{15}\), thus building artificial synaptic transistors prepared from organic semiconductors is more conducive to achieving direct information interaction with nervous tissue.

By simulating the structure, construction materials and operation mechanisms of natural intelligent systems, i.e., hardware simulation of the nervous system to facilitate the learning of brain intelligence and to improve the information interaction with existing electronic devices. Specific research includes three areas.

- **Artificial simulation of neural synapses based on organic materials, i.e., organic neuromorphic.**

  The nature of neuronal activity is based on the electrochemical reactions of bio-organic materials based on a variety of organic semiconductor polymers as the base materials for neuroelectronic devices. Organic semiconductor materials are similar in structure to the proteins, sugars, and nucleic acids that make up neurons and have natural biocompatibility. They are also biodegradable, flexible, and easy to mold, making them relatively easy to process. They support both electron and ion transport in conductor function and are an excellent choice for communicating electronic and neurophysiological signals. At the same time, organic semiconductor polymers are used to build organic neural network computing modules, in which neurons process and transmit information through electrochemical reactions that occur in and out of the body, making them a kind of ”electrochemical computer”. The organic semiconductor base materials we have developed are processed and molded into “artificial synapses” that simulate synaptic morphology and perform synaptic computational functions such as spike time-dependent plasticity\(^1\)\(^6\), spike frequency-dependent plasticity, and short- and long-term synaptic plasticity.

- **Computational simulation of the nervous tissue at the neuronal and neural circuit levels, i.e., silicon neuromorphic.**

  Brain-inspired neurocomputing modules are prepared using FPGA devices and hardware description languages to implement specific neural computational functions. First, FPGA are used to prepare artificial neuronal computational modules based on neuronal computational models abstracted from neurophysiological data. Then, based on the neural network simulation and event-driven computation, we realize the spiking neural network architecture that simulates specific neural circuits\(^1\)\(^7\)\(^,^\text{18}\) by the time and frequency encoding information of spikes and constructs the brain-inspired neural network computation module to realize the specific neural computation function.

- **Development of neural electrodes with high biocompatibility, i.e., neural matrix-like sensors.**

  Polyindole derivatives with good electrical properties and abundant functional groups were used as adhesion layer materials to improve the adhesion performance without affecting the electrochemical properties of the neural electrodes. In addition, the neural electrodes with good electrical conductivity and biocompatibility were prepared by a new process method of electropolymerization and electrical grafting, and the electrochemical properties of the electrode materials and their stability were verified. Finally, the prepared devices were used for mouse brain electrical signal acquisition applications for performance verification.

**The System Design**

This section focuses on how to integrate artificial synapse devices, FPGA devices that simulate electrophysiological kinetic properties of neurons, and neural matrix-like sensors into a brain and brain-inspired technology integration system. The organic artificial synapse device can receive electrical spike sequence input and perform neuroplastic computation and simulated signal output, while the FPGA device implemented in silicon-based neurons can realize the simulation of the electrophysiological properties of eight different types of biological neuron cells, while a variety of connection modes with brain-inspired computational properties are realized through the simulation of different real neural circuits and the interconnection between silicon-based neurons. The artificial synapse integration board and the FPGA device development board are connected by a
The neural electrodes acquire neural signals from the mouse brain along (1), and the signal acquisition processes the neural signals and transmits them to the FPGA as input along (2). The FPGA can accept exogenous inputs along (3). The two layers of silicon-based neurons are connected through artificial synapses. The presynaptic silicon-based neurons transmit the spike signals to the postsynaptic neurons through the artificial synapses along (4) and (5), and the spike signals are transmitted and processed by the signal stimulator along (6), and then the mouse brain is stimulated by the neural electrodes along (7).

The Logic Structure of Integrated Neuromorphic System

The logical structure of the system consists of three parts: a silicon-based neuron implemented in FPGA devices, an artificial synapse based on organic/inorganic materials, and a biocompatible neural interface. The silicon-based neuron and the artificial synapse together form a neuromorphic system, which in turn communicates with the nervous tissue through the neural interface sensor in both directions. The overall logic structure of this system is shown in Figure 1. (b).

The Physical Structure Integrated Neuromorphic System

The system contains five layers in the physical structure from top to bottom, and the overall structure is shown in Figure 2. The second layer is the input FPGA device, which is mainly responsible for simulating biological neurons, generating electrophysiological signals similar to biological neurons, and transmitting the spike signals to the artificial synapse integration board through the physical connection with the adapter board of the first layer; the third layer is the output FPGA device, which is mainly responsible for receiving the processed signal from the artificial synapse integration board in the first layer, converting the received analog signal into a binary digital signal through the analog-to-digital converter (ADC) module, and feeding this signal as an input to the current stimulus to the artificial neuron based on the hardware description language implementation. In this layer, a spiking neural network model is implemented in the FPGA device, which contains two layers: an input layer and an output layer. The input layer contains 8 leaky integrate-and-fire (LIF) neurons, and the output layer contains 16 LIF neurons. The neurons in the input layer and the neurons in the output layer are connected by a variety of connection patterns, enabling the simulation of many types of neural microcircuits. The fourth and fifth layers are identical, and both contain an FPGA development board of the same model. This FPGA development has the function of signal acquisition and stimulation in one. This FPGA device development board converts the spike signals from the third layer of the system into microcurrent stimulation as an external input to the nervous tissue and then collects the electrophysiological signals from the nervous tissue and transmits them back to the neuromorphic system through the neural interface sensors connected to the front-end board. A demonstration of the entire system is shown in Figure 1.

Layer 1 - Artificial synaptic integration board and adapter board

The first layer of this system contains the artificial synapse integration board and the supporting adapter board, as shown in Figure 3. The artificial synaptic integrated board consists of a base board and 15 artificial synaptic devices encapsulated on the baseboard. The integrated board is connected to a matching adapter board through its edge connectors and slots. The adapter board provides 32 pins, 15 of which are spike input pins, and the input side FPGA device is connected to these pins to
Artificial synaptic integration board and adapter board

The FPGA as the input

Acquisition and stimulation integrated board

The FPGA as the output

Acquisition and stimulation integrated board

Figure 2. The physical structure of integrated Neuromorphic system.

(input the spike signal to the integrated board; the other 15 pins are the output pins of the signal to be measured, through which the integrated board is connected to the output side FPGA device development board to send the analog signal output from the integrated board to the output side FPGA device. There are two adapter boards, which can be used with two integrated boards and can provide 30 channels of artificial synaptic computing capability; one is a 5 V/3.3 V power supply port and one is a ground port.

Figure 3. (a) Artificial synaptic integration board. (b) Adapter board.

Layer 2 - The FPGA as the input

The second layer of this system is the input-side FPGA device development board, as shown in Figure 4. (a). The input-side FPGA device development board is model National Instruments (NI) myRIO-1950, which includes 8 analog inputs, 4 analog outputs, 32 digital I/O lines, Xilinx FPGA and dual-core ARM Cortex-A9 processor, and the myRIO-1950 can be programmed using LabVIEW. The input FPGA board sends the spike signal to the artificial synapse integration board located at the first layer through the digital output port. The input FPGA board can output 16 channels of spiking signals. Specifically, the input FPGA device simulates biological neurons in real time by implementing a spiking neuron model with a total of 8 neurons, each outputting two spiking signals. The spiking neuron model used is the Izhikevich model\(^1\). The host computer software that works with the FPGA board at the input is shown in Figure 4 (b). With this upper computer software, the following functions can be implemented.

- With the neuron editing function, using the Izhikevich model, the neuron type is edited by changing the parameters affecting the kinetic properties of the neuron, and the membrane potential change corresponding to that neuron type can be observed.
- The host software interacts with the FPGA development board to select the neuron type to be simulated in the upper
computer, to realize the parallel simulation of 8 neurons, and to output the spike time series output of 16 channels (each neuron corresponds to 2 channels).

- The type of each neuron to be simulated can be controlled, and the type can either be preset or added after editing.

![Figure 4](image1.png)

**Figure 4.** (a) The FPGA development board. (b) The host computer software

**Layer 3 - The FPGA as the output**

The third layer of this system is the output-side FPGA device development board, as shown in Figure 5. (a). The output FPGA device development board is also NI myRIO-1950, and the output FPGA board receives the analog signals from the first layer of artificial synapse integration board through the analog input port. The output FPGA board can output 32 channels of spiking signals. Specifically, the output FPGA device simulates biological neurons in real time by implementing a spiking neuron model and connecting the neurons to form a spiking neural network. The network contains 32 neurons, of which 8 neuron groups are input neurons responsible for processing the external input analog signals and 16 neurons are output neurons, each of which outputs two channels of spiking signals. The spiking neuron model used is the LIF model\(^{20}\). The upper computer software that works with the FPGA board at the output is shown in Figure 5. (b). With this upper computer software, the following functions can be implemented.

- With the neuron editing function, the module uses the LIF model to enable the editing of neuron types by changing the parameters that affect the kinetic properties of the neuron, and enables the observation of the membrane potential changes corresponding to that neuron type.

- The upper computer software interacts with the FPGA development board, where the topology of the spiking neural network to be simulated is selected. In the network, the input layer contains 8 neurons, each neuron corresponds to a channel of the analog-to-digital converter (ADC); the output layer contains 16 neurons; the neurons in the output layer and the neurons in the input layer can be fully connected, or recurrent connected to each other.

- Realize the parallel simulation of 16 neurons and output the spike time series output of 32 channels (each neuron corresponds to two channels).

![Figure 5](image2.png)

**Figure 5.** (a) The FPGA development board. (b) The upper computer software
Layer 4 and 5 - Acquisition and stimulation integrated board

The fourth and fifth layers of this system are the integrated development board for acquisition and stimulation, as shown in Figure 6. The acquisition and stimulation integrated development board consist of a core board on the upper layer and an expansion board on the lower layer. The core board is the XEM6010 module from OpalKelly, and the FPGA in the module is the Spartan-6 from Xilinx. The expansion board is designed independently and is responsible for extending the input and output interfaces for the core board, receiving the incoming signal from the electrode and output current stimulation. It can be used for 16-channel electrophysiological signal acquisition or 16-channel constant current stimulation via Serial Peripheral Interface (SPI) protocol.

![Figure 6](image.png)

**Figure 6.** (a) Acquisition and stimulation integrated board. (b) Acquisition and stimulation integrated board with the analog front-end circuit board. (c) The analog front-end circuit board.

Neural Simulation based on FPGA

This section investigates how FPGA devices can be used to process input signals and output spiking spatio-temporal signals. In the considered model, the input can be either an external analog and digital signal or a preset fixed value, and the output is a spiking spatio-temporal signal. Specifically, the FPGA device needs to achieve the simulation of the electrophysiological properties of a real biological neuron. The electrophysiological properties of the biological neuron is first abstracted into a concrete mathematical model, generally referred to as the spiking neuron model, in the form of a differential equation for the time-dependent variation of the cell membrane potential. The iterative solution of the differential equation yields a discrete value of the membrane potential change in time, and a spike is fired when the membrane potential value exceeds a threshold value, while the membrane potential returns to the resting potential value. Since there are several spiking neuron models, the computational complexity and biological interpretability of the model must be considered, and the spiking neuron model suitable for this system must be selected.

Spiking Neural Model

The structure of a biological neuron consists of three main parts: the dendrite, the soma, and the axon. The function of the dendrite is to collect signals from other neurons and transmit them to the soma, which is responsible for computational processing and generates neural spikes when the accumulation of received currents causes the neuronal membrane potential to exceed a specific threshold, and the spikes propagate along the axon, which then transmits the signals to other neurons through the synapse located at the end of the axon. Neurophysiologists have developed many theoretical models for the dynamics of neuronal membrane potentials, and these models are the basic units that form spiking neural networks. Here we focus on the leaky integrate-and-fire (LIF) model\(^2\) and the Izhikevich model\(^{19,21}\).

**The Leaky Integrate-and-Fire (LIF) Neuron Model**

The leaky integrate-and-fire (LIF) model, as a simplified version of the neuronal model, has been widely used as the basic unit of spiking neural networks due to its relatively small computational effort. In 1907, Lapicque proposed the integrate-and-fire (LIF) model\(^2\), and since the mechanism of action potential generation was not clear at that time, the process of action potential was described in a simplified way as follows: the neuron will excite a spike when the membrane potential reaches the threshold, and the membrane potential subsequently falls back to the resting value. The LIF neuron model retains these features while simplifying the action potential generation process, i.e., reducing the computational complexity while providing considerable biological interpretability, the LIF model is represented by the following equation (1).

\[
\tau \frac{du}{dt} = -(u - u_{rest}) + R \cdot I(t)
\]
In the LIF model, $\tau$ is expressed as the time constant of the differential equation, $u$ is the membrane potential, and $u_{\text{rest}}$ is a constant parameter expressed as the resting potential of the cell membrane. $I(t)$ is the input current, and $R$ is the cell membrane resistance.

The Izhikevich Neuron Model
The Izhikevich model\(^{19}\) was proposed by Eugene M. Izhikevich in 2003, and it can simulate all known types of cortical neurons. The model combines the biological soundness of the Hodgkin-Huxley model\(^{23}\) dynamics and the computational efficiency of the LIF neuron model, which allows the model to support the simulation of networks of larger neuron numbers. The Izhikevich model is described by two differential equations\(^2\).

\[
\frac{dV}{dt} = 0.04V^2 + 5V + 140 - u + I(t) \\
\frac{du}{dt} = a(bV - u)
\]

where $u$ is the membrane recovery variable to describe the effect of ion current on membrane potential; $a$, $b$ are used to adjust the time scale of $u$ and the sensitivity about membrane potential $V$, respectively. $I(t)$ is the stimulation current as a function of time. By the choice of parameters, the Izhikevich model can demonstrate the firing patterns of different neurons.

Neural Circuit
Neurons do not exist independently within the brain but are highly interconnected in synapses to form circuits that work together to process information, and this connectivity pattern provides the basis for neuronal populations to perform specific functions\(^{24}\). For example, specific circuits are associated with short-term and long-term memory storage and the extent of the feature receptive fields\(^{25}\), and this cluster of neurons, which processes information in a similar way to individual neurons, integrates incoming information and then decides whether to perform the output of the information. Also, circuits are modulated by the type of synaptic input they receive, including excitability as well as inhibition. Neural circuits can be briefly summarized into several types\(^{26}\), including feedforward excitation, feedforward inhibition, lateral inhibition, feedback/recurrent inhibition, mutual inhibition, feedback/recurrent excitation, and mutual excitation, as shown in the Figure 7.

![Figure 7](image-source)

**Figure 7.** (a) Feedforward excitation, (b) Feedback/Recurrent excitation, (c) Mutual excitation, (d) Feed-forward inhibition, (e) Feedback/Recurrent inhibition, (f) Lateral inhibition and (g) Mutual inhibition. The image sources from Zheng, S. et al\(^{27}\)
Neurons and Neural Circuits Parallel Simulation
Simulation of neurons and neural circuits starts with determining the spiking neuron model. Based on the computational complexity and biological rationality of the model, we choose the Izhikevich model in the neuron parallel simulation part and the LIF model in the neural circuit parallel simulation part.

The neuron parallel simulation
The neuron parallel simulation specifically requires the implementation of a spiking neuron model and its deployment into an FPGA device, i.e., neuron computation in an FPGA development board. The developed upper computer software is shown in Figure 8. (a). The upper computer software is responsible for interacting with the FPGA development board, selecting the type of neuron to be simulated in the upper computer, and adjusting parameters such as time step, input stimulus current magnitude, and initial value of membrane potential related to neuron simulation.

The neural circuit parallel simulation
The neural circuit parallel simulation specifically requires the implementation of the spiking neuron model and the circuit model and the deployment into the FPGA device. The developed upper computer software is shown in Figure 8. (b). The upper computer software is responsible for interacting with the FPGA development board and controlling the start and end of the simulation at the upper computer.

![Figure 8. (a) The neuron parallel simulation software interface. (b) The neural circuit simulation software interface.](image)

Organic Neuromorphic Device
This section describes the study of artificial synaptic devices based on different materials and the study of how to integrate artificial synaptic devices at scale and interconnect them with FPGA device ends for communication. Different artificial synaptic devices based on:

- two-end artificial synaptic electronics based on organic/inorganic hybrid chalcogenides;
- synaptic transistors based on Poly(3-hexylthiophene) (P3HT) nanowire films;
- synaptic transistors based on SnO₂ nanoparticle films, and SnO₂ synaptic transistor arrays

The research on the integration of artificial synaptic devices focuses on the design of synaptic integrated circuit boards, and the integration of 15-channel synaptic devices is achieved by packaging the synaptic devices on the integrated circuit boards. For the interconnection and communication with the FPGA device side, the main research is on how to design the adapter board. Through this adapter board, the synaptic device integrated circuit board and the FPGA device input are connected, and furthermore, the artificial synaptic devices are implemented to simulate the input signal of the FPGA device end. At the same time, the synaptic integrated board and the FPGA device output are connected, and the calculated analog signal is input to the FPGA device output.

Synaptic Device Integration
Based on the fact that SnO₂ nanoparticle thin film synaptic electronic devices exhibit good synaptic plasticity modulation ability, and the devices have good air stability, they can be organically combined with silicon-based integrated circuits to make the integration neuromorphic system work stably. Therefore, this project chooses to develop an array of artificial synaptic devices by combining SnO₂ nanoparticle thin film synaptic electronics as artificial synapses with integrated circuit (IC) development boards. In this system, SnO₂ artificial synaptic devices were prepared on Polyethylene Naphthalate Two Formic Acid Glycol Ester (PEN) substrate, cut into suitable size individual synaptic devices, and fixed on a development board.
capable of carrying 15 artificial synaptic devices. The devices are then connected to the development board through conductive silver paste to form an effective pathway, as shown in Figure 9. Finally, the array of artificial synaptic devices is encapsulated using Polydimethylsiloxane (PDMS) to realize the organic combination of synaptic devices and the IC development board. The synaptic array can receive FPGA electrical spikes, which can generate 15 channels of output after simulating synaptic plasticity.

The synaptic device IC board is combined with an adapter board, and the ports are divided into stimulus and output ports, except for the power and ground ports. The digital output port of the FPGA device on the input side is connected to the stimulus port of the adapter board, and the output port is connected to the analog input port of the FPGA device on the output side. With this adapter board, in Figure 3. (b), the reception and processing of the spike signal from the organic neuromorphic device to the FPGA are realized and the output of 15 channels is generated.

**Figure 9.** The synaptic electronic devices based on SnO$_2$ nanoparticle thin film.

**Flexible Neural Interface**

The neural interface is based on polyindole derivatives, a class of conducting polymers with different functional groups, which have attracted much attention in recent years for applications in energy devices, electrocatalysis and biosensors. We hypothesized that polyindole derivatives with good electrical properties and abundant functional groups might serve as adhesion-promoting layers for Poly(3,4-ethylenedioxythiophene) (PEDOT) without weakening the electrochemical properties of the neural electrode. After systematically investigating the adhesion and electrochemical properties of various polyindole derivatives, we found that poly(5-nitroindole) (PIN-5NO$_2$) was the most promising candidate as a PEDOT adhesion promoter$^{29}$. The PIN-5NO$_2$ films were first prepared by a new process method of electropolymerization and electrografting as a conductive, adhesive and biocompatible interfacial layer, followed by the electropolymerization deposition of conformal PEDOT to construct a solid Au/PIN-5NO$_2$/PEDOT electrode interface, as shown in Figure 10. Then the macroporous grid array electrodes were designed and prepared, and the electrodes of Au/PIN-5NO$_2$/PEDOT were combined with them to verify the electrochemical properties of the electrode materials and their stability. Finally, the prepared devices were used for mouse brain cortex electrical signal acquisition applications for performance verification.

**Discussion**

In the long run, having an effective and efficient hardware tool to simulate and generate realistic spikes has great possibilities. This could pave the way for synthetic neuronal components to be connected to nervous tissues. Neuromorphic systems based on this type can be used to generate realistic biological signals for stimulating biological neural networks thus enabling closed-circuit systems in which biology and hardware can be stimulated with each other.

Despite further attempts in the work reported in this paper, considerable challenges remain in this area. For example, the research on spiking neural networks is relatively immature, especially the lack of effective training and learning algorithm. The problems of how to better involve SNN$^{30,31}$ in hardware for signal processing and online learning mechanisms to solve complex problems are currently difficult to overcome. However, in biological brains, even nematodes with only a few hundred neurons exhibit extremely rich emergent intelligence. How to implement biological neural networks based on hardware and to implement brain-inspired algorithms will be the key to progress in this field. At the same time, the technologies used in today’s traditional computing systems are not well suited to simulate biological neural networks, and today’s neuromorphic chips represent a promising development.

At the same time, the soft mechanical and biocompatible nature of organic materials makes organic protomers as well as arrays well suited to interact with living organisms, and the points of low energy conversion, tunability, low cost, and biocompatibility make organic material-based artificial synapses a potential for successful development in neuromorphic
computing. Despite the current success of artificial synapses, more research is needed to overcome the current limitations. For example, further increases in state retention are needed, especially for long-term operation, and encapsulation needs to enhance stability and cyclic durability during the period. We hypothesize that such neuromorphic devices incorporating organic artificial synapses could be used to enhance biological intelligence, such as intracortical brain-machine interfaces and adaptive control of prostheses.

Such combined organic and silicon-based neuromorphic systems in the future may also enable part of a bio-hybrid system for brain repair, coupling brain-inspired devices to neurons in vitro or to the brain in vivo and communicating bi-directionally through a closed-circuit architecture. The key to the implementation of such closed-circuit systems is the ability to process and decode neural signals in real-time to drive actuators for brain function modulation or replacement. Thus, a physiologically sound interaction between biological neural networks and brain-inspired devices can be achieved. Moreover, such neuromorphic systems can enhance biohybrid systems with hardware intelligence and distributed computing, allowing the brain to achieve unprecedented computational power, dynamic learning, and adaptivity, accompanied by extremely low power consumption and miniaturization.

Nevertheless, great progress has been made in artificial synaptic materials and hardware simulations of biological neurons. However, these are structurally simple biosensors that are far from the complexity of neuromorphic systems. Therefore, the implementation of novel neuromorphic systems requires parallel efforts from different disciplines to address the numerous challenges associated with them. Advances in hardware architecture design, online learning algorithms, and biocompatible materials bode well for the extreme controllability and safety of such neuromorphic systems in the future, and for the realization of a new paradigm for brain-machine integration, from interaction to integration.

Conclusion

This paper describes an embedded silicon-based organic neuromorphic system based on FPGA to build the basic computational unit of brain-inspired neural networks combined with artificial synapses that achieve signal conversion, thus realizing specific neural computational functions, and then combined with biocompatible neural electrodes to interact with nervous tissue for information. In this paper, an artificial neural system with integrated signal sensing and brain-inspired intelligent information processing technology is realized, and in-depth research is conducted on artificial synaptic devices, neural matrix-like sensors, and artificial neuronal computation as well as system integration of biological brain and brain-inspired technology, which further demonstrates the feasibility of the integration system, and the system also lays the technical foundation for the development of next-generation brain-machine interface with brain-machine integration.
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