

Enhancing learning of spiking neural networks with lifetime-tunable optical neuron devices

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Research Article

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Abstract

Temporal heterogeneity is a defining feature of biological neural systems, where neurons with distinct membrane time constants support complementary information-processing functions. However, most hardware spiking neural networks (SNNs) still rely on artificial neurons with fixed membrane dynamics, limiting the ability to reproduce the adaptive temporal processing of the brain. Here, we demonstrate a

CMOS-compatible lifetime-tunable optical neuron device based on a TiN/Hf_{0.5}Zr_{0.5}O₂/TiO₂/ITO heterostructure. Under optical excitation, read-voltage-regulated photocarrier dynamics enable physical modulation of the photocurrent decay lifetime, providing a direct device-level analogue of a tunable neuronal membrane time constant. Incorporating the lifetime tunability into SNNs enables adaptive temporal heterogeneity with coexisting fast and slow membrane-potential dynamics. Simulation results on CIFAR-10, CIFAR-100, Tiny-ImageNet, Caltech101, and CIFAR10-DVS show that this architecture achieves faster convergence and higher classification accuracy than fixed-lifetime neuronal counterparts. This work opens a route toward adaptive SNNs with tunable membrane time constants, providing a promising strategy for biologically inspired, temporally adaptive, and hardware-oriented neuromorphic computing systems.

Introduction

The brain, one of the most complex organs in biological systems, relies on a highly diverse network of neurons to fulfill its myriad functions. Neurons differ not only in morphology but also in electrophysiological properties, including membrane time constants, ion-channel compositions, and synaptic coupling patterns [1][2][3]. Among these parameters, the membrane time constant is particularly important because it defines the temporal window over which synaptic inputs are integrated and therefore determines how neurons respond to signals occurring at different time scales [4][5][6]. Fast-spiking (FS) interneurons and low-threshold spiking (LTS) neurons provide representative examples of this temporal diversity. Fast-spiking interneurons, such as parvalbumin-containing basket cells [7], are widely distributed in the hippocampus and cerebral cortex and can sustain high-frequency firing through Kv3-family potassium channels, including Kv3.1b and Kv3.2 [8][9]. Their short effective membrane time constants and rapid repolarization dynamics enable precise responses to synaptic inputs and support gamma-band oscillations associated with information processing, memory formation, and spatial navigation [10][11]. In contrast, LTS neurons [12][13] exhibit slower membrane dynamics governed by low-threshold calcium conductance and potassium-mediated afterhyperpolarization [14][15],

allowing them to participate in low-frequency oscillatory activity and network modulation, particularly during slow-wave sleep [16][17][18]. This coexistence of neurons with distinct temporal integration windows highlights a central principle of neural computation: biological networks process information through heterogeneous, rather than uniform, membrane dynamics [19][20].

However, despite substantial progress in neuromorphic engineering, this form of temporal heterogeneity remains difficult to implement in hardware spiking neural networks (SNNs). Algorithmic SNN models can introduce neuron diversity by assigning different membrane parameters in software [21][22][23], but most hardware implementations still rely on artificial neurons with fixed or only weakly configurable membrane dynamics. Such fixed-lifetime neurons cannot fully capture state-dependent oscillatory synchronization, hierarchical temporal integration across cortical layers, or other time-scale-dependent functions observed in biological neural systems [24] [25]. Therefore, a hardware SNN platform that can directly tune the membrane time constant at the device level is highly desirable for building more biologically faithful and computationally flexible neuromorphic systems.

In this work, we propose a neuromorphic SNN computing architecture in which optoelectronic neuronal functionality and tunable membrane time constants are integrated within a single device. By rationally engineering a $\text{TiN}/\text{Hf}_{0.5}\text{Zr}_{0.5}\text{O}_2(\text{HZO})/\text{TiO}_2/\text{ITO}$ heterostructure, we demonstrate a CMOS-compatible lifetime-tunable optical neuron whose photoresponse decay dynamics can be modulated to emulate variable neuronal membrane time constants. Under all-optical modulation, the device emulates essential neuronal and synaptic behaviors, including leaky integration, paired-pulse facilitation (PPF), excitatory postsynaptic current (EPSC), and the transition from short-term memory (STM) to long-term memory (LTM), while exhibiting stable tunability of the membrane time constant. Leveraging this device-level lifetime tunability, we further construct an SNN with adaptive lifetime dynamics and evaluate its performance on CIFAR-10, CIFAR-100 and other benchmark datasets, demonstrating the advantages of the lifetime-tunable mode over conventional fixed-lifetime operation.

Results

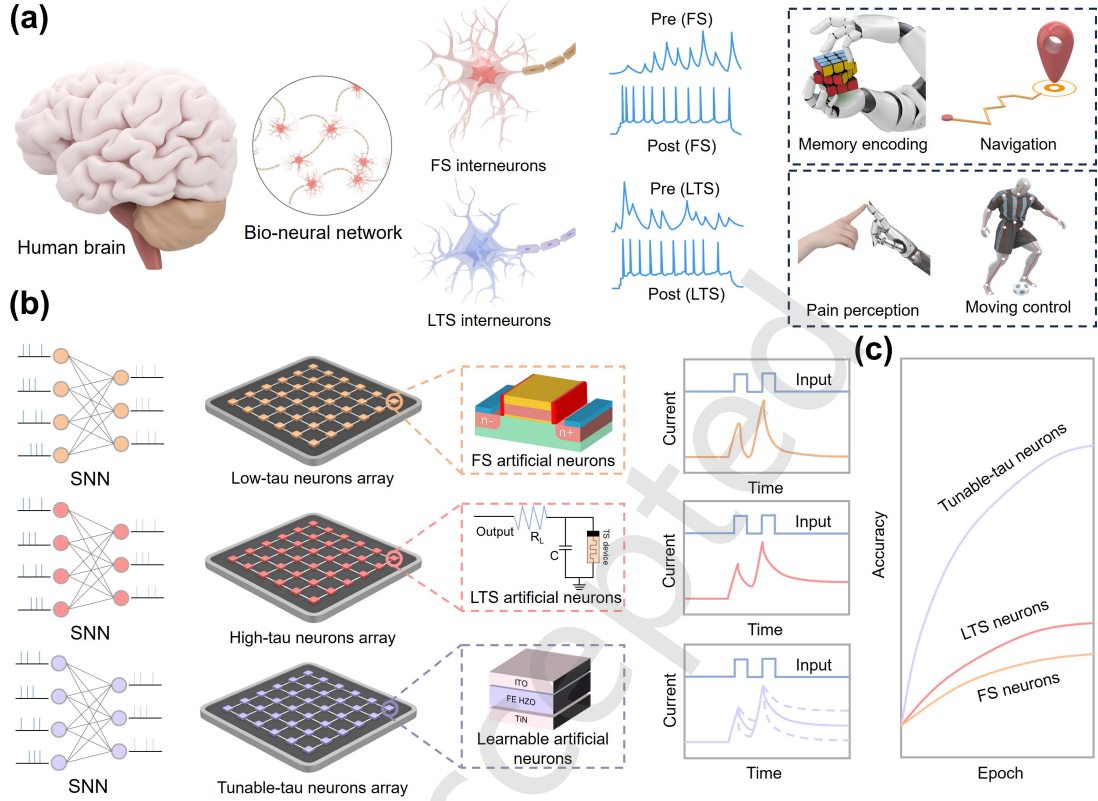


Figure 1. Concept of the HZO-based tunable- τ neuron device. (a) Schematic illustration of fast-spiking interneurons and low-threshold spiking neurons. (b) Schematic comparison between existing artificial neuron devices and the HZO-based tunable- τ neuron device. (c) Comparison of recognition results in SNNs.

Figure 1a schematically illustrates two representative neuronal populations with markedly different membrane time constants: fast-spiking (FS) interneurons and low-threshold spiking (LTS) neurons. By operating over different temporal windows, these neurons support distinct network functions associated with memory encoding, spatial navigation, pain perception, and motor control. As summarized in Fig. 1b, previous device-level implementations have reproduced the dynamics of FS- and LTS-like neurons through separate hardware strategies. For FS-like behavior with a short effective τ , transistor cells using an antiferroelectric gate dielectric exploit gradual polarization reversal and intrinsic polarization/depolarization dynamics to generate rapidly decaying neuronal responses. In contrast, LTS-like behavior with a longer τ

has been obtained by coupling a threshold-switching (TS) memristor device with an external RC circuit module, which extends the relaxation time of the neuronal response. Although these approaches capture specific neuronal time scales, the architecture lack device-level dynamic τ tunability, particularly the ability to reversibly switch between short-lived volatile responses and long-lived nonvolatile states within the same hardware unit. To address this limitation, we design a CMOS-compatible Tunable- τ optoelectronic neuron based on a ferroelectric $\text{Hf}_{0.5}\text{Zr}_{0.5}\text{O}_2$ (HZO)/ TiO_2 heterostructure, in which the temporal response is governed by read-voltage-regulated photocarrier dynamics. Under optical excitation, the read voltage modulates the lifetime of photogenerated carriers, thereby physically tuning the membrane time constant and enabling a single device to emulate both FS and LTS neuronal dynamics. As shown in Fig. 1c, the SNNs constructed with tunable- τ neurons achieve higher training accuracy than their fixed- τ counterparts by adapting neuronal dynamics to different temporal-processing demands.

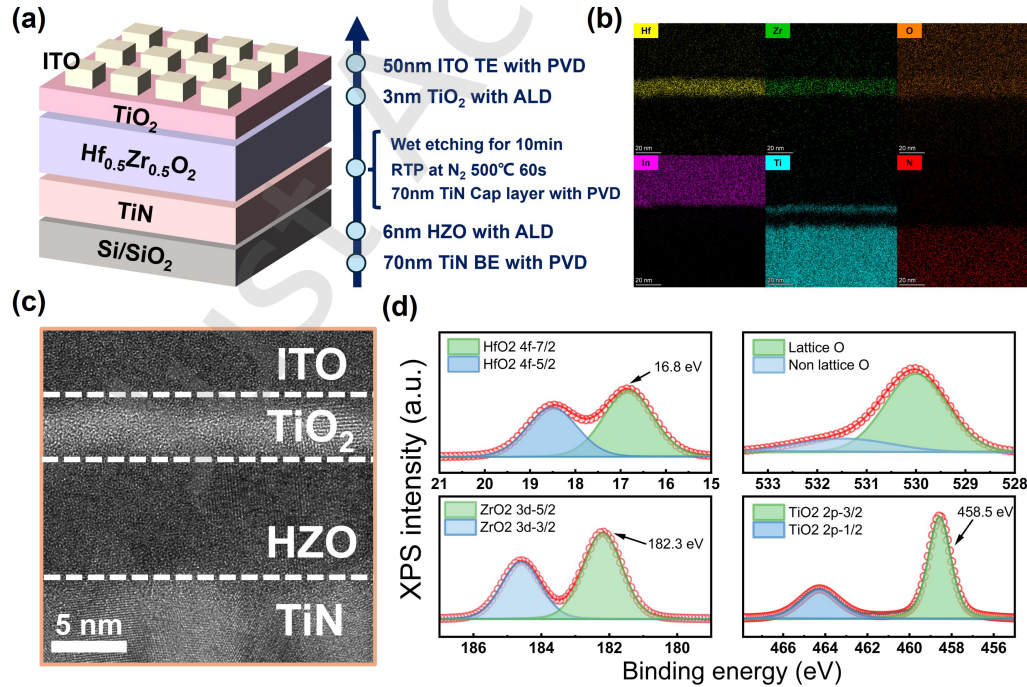


Figure 2. Device Characterization. (a) Schematic image of the proposed device structure and Fabrication process flow. (b) The EDS distribution mapping diagrams of all the elements along the corresponding position. (c) Cross-sectional TEM images of HZO/ TiO_2 stack capacitor. (d) The Hf 4f, O 1s, Zr 3d, and Ti 2p core-level spectra of the grown HZO and TiO_2 films.

The device architecture and fabrication process are illustrated in Figure 2a, with detailed processing parameters provided in Note S1 of the Supporting Information. Energy-dispersive X-ray spectroscopy (EDS) mapping confirms the elemental distributions across the TiN, HZO, and TiO₂ functional layers (Figure 2b), while cross-sectional high-resolution transmission electron microscopy (HR-TEM) reveals the device morphology (Figure 2c). The thicknesses of the functional layers were precisely controlled by the number of plasma-enhanced atomic layer deposition (PEALD) cycles, yielding two oxide layers with thicknesses of 3 and 6 nm, respectively. Figure 2d presents the X-ray photoelectron spectroscopy (XPS) core-level spectra of the as-fabricated HZO and TiO₂ films, including Hf 4f, O 1s, Zr 3d, and Ti 2p regions. In the Hf 4f, the Hf 4f-7/2 peak at 16.8 eV can be attributed to Hf–O bond. The Zr 3d-5/2 peak at 182.3 eV refers to Zr–O bond. For the Ti 2p spectrum, the Ti 2p-3/2 located at 458.5 eV refers to Ti–O bond.

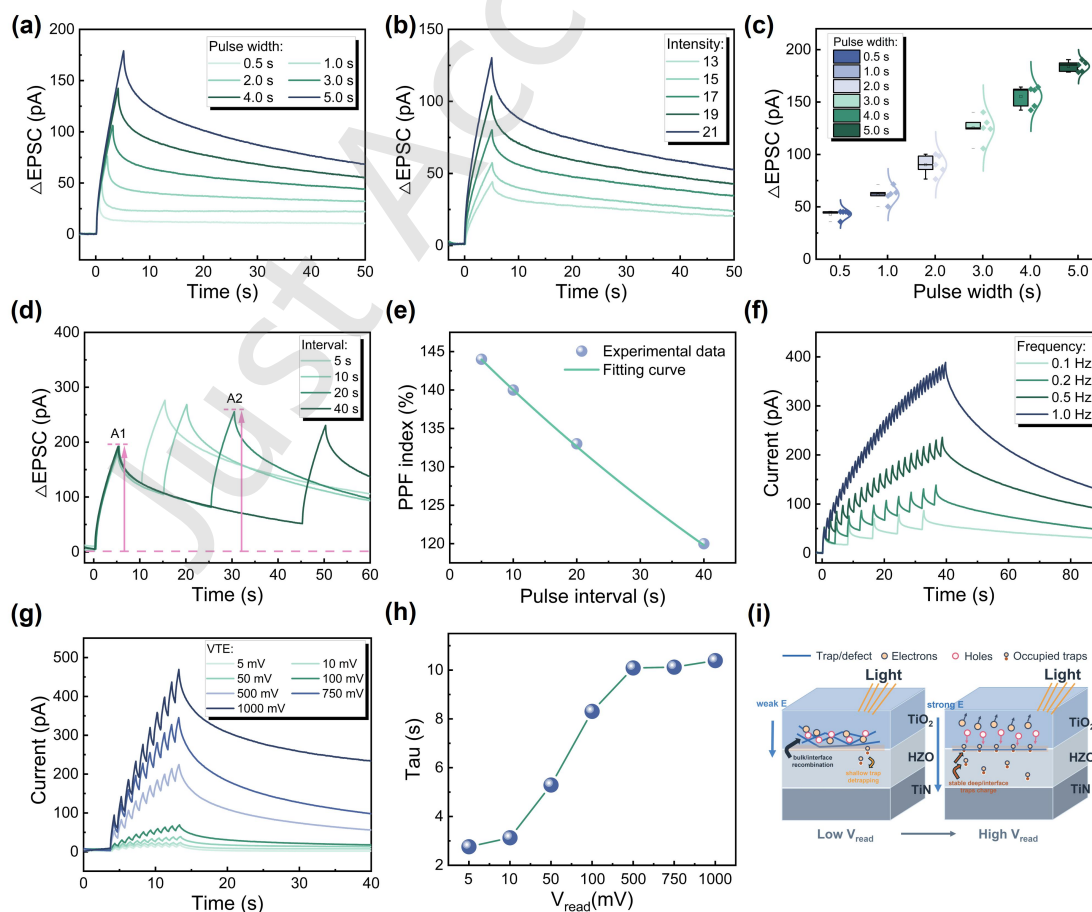


Figure 3. Optical synaptic plasticity and read-voltage-modulated carrier lifetime of the lifetime-

tunable optical neuron device. (a) EPSC response induced by optical pulses with different pulse widths (0.5, 1, 2, 3, 4, and 5 s) at a fixed intensity of 21 mW/cm². (b) Device-to-device variation statistics of the photocurrent response under different optical pulse widths. (c) EPSC response induced by optical pulses with different light intensities (13, 15, 17, 19, and 21 mW/cm²) at a fixed pulse width of 5 s. (d) Paired-pulse facilitation (PPF) behavior induced by paired optical pulses with different intervals (5, 10, 20, and 40 s). (e) Dependence of the PPF index on the pulse interval. (f) Transition from short-term plasticity to long-term plasticity induced by increasing the optical pulse frequency (0.1, 0.2, 0.5, and 1 Hz) at a fixed pulse width of 0.5 s. (g) EPSC response induced by different V_{read} (5, 10, 50, 100, 500, 750, and 1000 mV) under a fixed optical pulse sequence (pw = 1 s, 1 Hz, 21 mW/cm²). (h) Effective lifetime of photogenerated carriers under different V_{read} . (i) Schematic mechanism of the read-voltage-modulated photogenerated carrier lifetime.

Since HZO is an insulating layer with no optical response, the photocurrent (PC) of this heterostructure is primarily governed by the bandgap of TiO₂. As shown in Figure S1, the photocurrent emerges at an incident wavelength of 270 nm and reaches its maximum at 310 nm, corresponding to a photon energy of 4.0 eV. Synaptic plasticity is emulated by applying 310nm optical pulses to the lifetime-tunable optoelectronic neuron under a bias voltage of 0.1 V. Figure 3a and 3b show that the excitatory postsynaptic current (EPSC) increases with both optical intensity and pulse duration. Specifically, the photocurrent increases as the light intensity is raised from 13 to 21 mW/cm² and the pulse duration is extended from 0.5 to 5 s. Figure 3c compares the photocurrent responses of different devices under single optical pulses with varied durations, demonstrating excellent device-to-device uniformity of the HZO-based lifetime-tunable optoelectronic neurons. Paired-pulse facilitation (PPF) is further characterized using two consecutive optical pulses, as shown in Figure 3d. Here, the pulse-induced EPSC increments triggered by the first and second pulses were respectively denoted as A1 and A2. The ratio A2/A1 was defined as the PPF index. The PPF index increases as the inter-pulse interval decreases, confirming the capability of this artificial neuromorphic system to emulate synaptic plasticity with

optical signals. As shown in Figure 3e, the experimental data are well fitted by a double-exponential decay function, $PPF\ index = C_0 + C_1e^{-\Delta t/\tau_1} + C_2e^{-\Delta t/\tau_2}$. Figure 3f examines the frequency-dependent EPSC under consecutive optical stimulation. As the pulse frequency increases from 0.1 to 1 Hz, current accumulation during the pulse train becomes more pronounced, leading to a higher steady-state current and an EPSC increase from 86.3 to 388.7 pA. This frequency-dependent neuromorphic response reproduces the transition from short-term plasticity to long-term potentiation (STP to LTP), exhibiting temporal accumulation and relaxation characteristics analogous to biological synapses. Neurons convert continuous analog inputs into discrete spike events, enabling event-driven information transmission. Here, the carrier lifetime τ of photogenerated carriers is precisely modulated by tuning the Read Voltage V_{read} during photocurrent readout. As shown in Figure 3g, increasing V_{read} from 5 to 1000 mV markedly enhances the peak photocurrent and slows the post-illumination decay. Under the low V_{read} , the photocurrent rapidly returns to the baseline, indicating pronounced volatility. Under the high V_{read} , the current persists for a longer period, indicating a more nonvolatile photoconductive state. In Figure 3h, τ is extracted by fitting the post-illumination decay current with $\Delta I(t) = I_{dark} + \Delta I_0 \exp(-t/\tau)$. The extracted τ increases monotonically with V_{read} and gradually saturates high-bias region, demonstrating continuous voltage control over the carrier lifetime. Notably, as shown in Figure S2, the carrier lifetime can reach over 776 s under a read voltage of 1500 mV, showing its wide range tunability. The photoresponse mechanism is analyzed based on the device structure, as shown in Figure 3i. V_{read} regulates carrier recombination and trap occupation by modulating the internal band bending and electric-field distribution. At low V_{read} , the weak internal electric field leads to strong spatial overlap between electrons and holes generated in TiO_2 , making them prone to recombination within the TiO_2 layer or near the HZO/TiO_2 and TiO_2/ITO interfaces. Meanwhile, carriers trapped in shallow states are readily detrapped after illumination is turned off, resulting in rapid decay of the photoinduced conductance and a short τ . As V_{read} increases, the enhanced external electric field drives photogenerated electrons and holes to drift in opposite directions, reducing their spatial overlap and suppressing

recombination. Meanwhile, field-assisted trapping and effective barrier lowering increase the occupation probability of deep traps or interfacial traps. After illumination is turned off, these stably trapped space charges can continuously modulate the local potential and injection barrier near the HZO/TiO₂ interface, allowing the photoconductive state to persist for a longer time. As a result, τ increases monotonically and the device exhibits stronger nonvolatility. When deep traps gradually approach their filling limit and both carrier-separation efficiency and barrier modulation become saturated, further increasing V_{read} produces a weaker enhancement in τ , eventually leading to saturation.

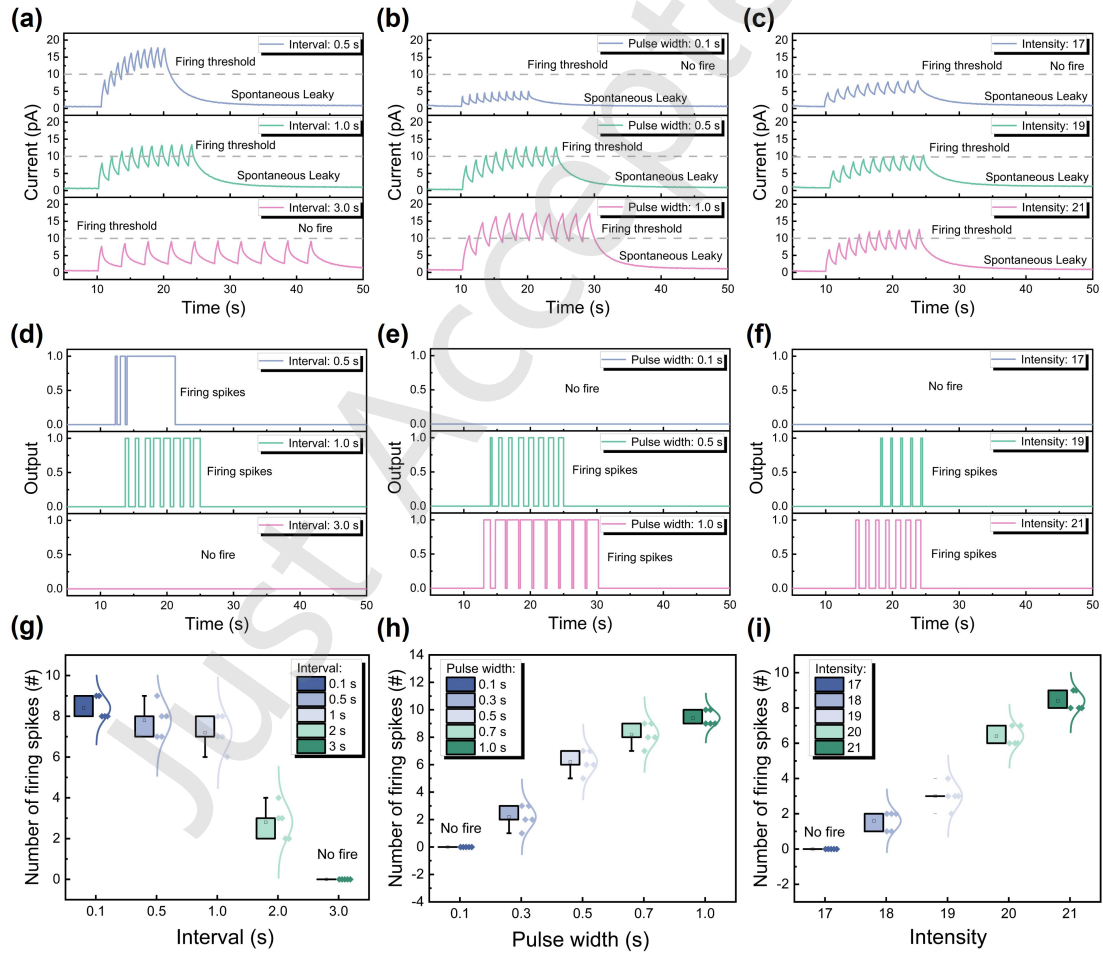


Figure 4. Optical modulation of LIF neuronal firing in the lifetime tunable optical neuron device. Photocurrent responses of the device to different (a) optical pulse interval, (b) pulse width, and (c) light intensity at a fixed read voltage. Temporal evolution of neuronal firing behaviors after analog-to-digital conversion under different (d) optical pulse interval, (e) pulse width, and (f) light intensity. Device-to-device variation statistics of the neuronal firing counts under different (g)

optical pulse interval, (h) pulse width, and (i) light intensity.

Based on the read-voltage-modulated effective lifetime of the device photocurrent, we further evaluated the LIF neuronal characteristics of the device in the optical mode, with a fixed read voltage of 5 mV and a firing threshold of 10 pA. Figure 4a-c show the temporal photocurrent responses of the device under different pulse interval, pulse width, and light intensity, respectively. By feeding the device output currents under different illumination conditions into an analog-to-digital converter (ADC), Figure 4d-f present the temporal evolution of neuronal firing under different conditions, demonstrating that the input spike trains in the neuronal mode can be effectively modulated by tuning the incident-light parameters to enable sparse coding and event-driven information transmission. Figure 4a and 4d show that the neuronal firing frequency decreases with increasing pulse interval, indicating that shorter pulse intervals induce more frequent firing events. Figure 4b and 4e reveal the effect of pulse width on neuronal firing. At a pulse width of 0.1 s, no firing event is triggered, whereas the number of firing events increases markedly as the pulse width increases. Figure 4c and 4f show the neuronal firing characteristics under different light intensities. At low incident light intensity, no firing event is triggered; as the light intensity increases, the firing frequency increases significantly, indicating enhanced triggering sensitivity. Figure 4g-i summarize the firing-event statistics of multiple devices under different conditions, further revealing the effects of pulse interval, pulse width, and light intensity on the neuronal firing frequency. Figure 4g shows that the number of firing events progressively decreases with increasing pulse interval. Conversely, Figure 4h reveals an increase in firing events as the pulse width is extended. These trends indicate that rapid photocurrent recombination imposes a stringent temporal requirement on optical stimulation: shorter pulse intervals reduce inter-pulse decay, whereas longer pulse widths enhance carrier accumulation, both of which promote higher firing frequencies. Figure 4i shows that the number of firing events increases significantly with light intensity because of the enhanced generation rate of photogenerated carriers. These results demonstrate that the firing behavior of

the lifetime-tunable optical neuron device can be reliably regulated by tuning the optical-pulse parameters.

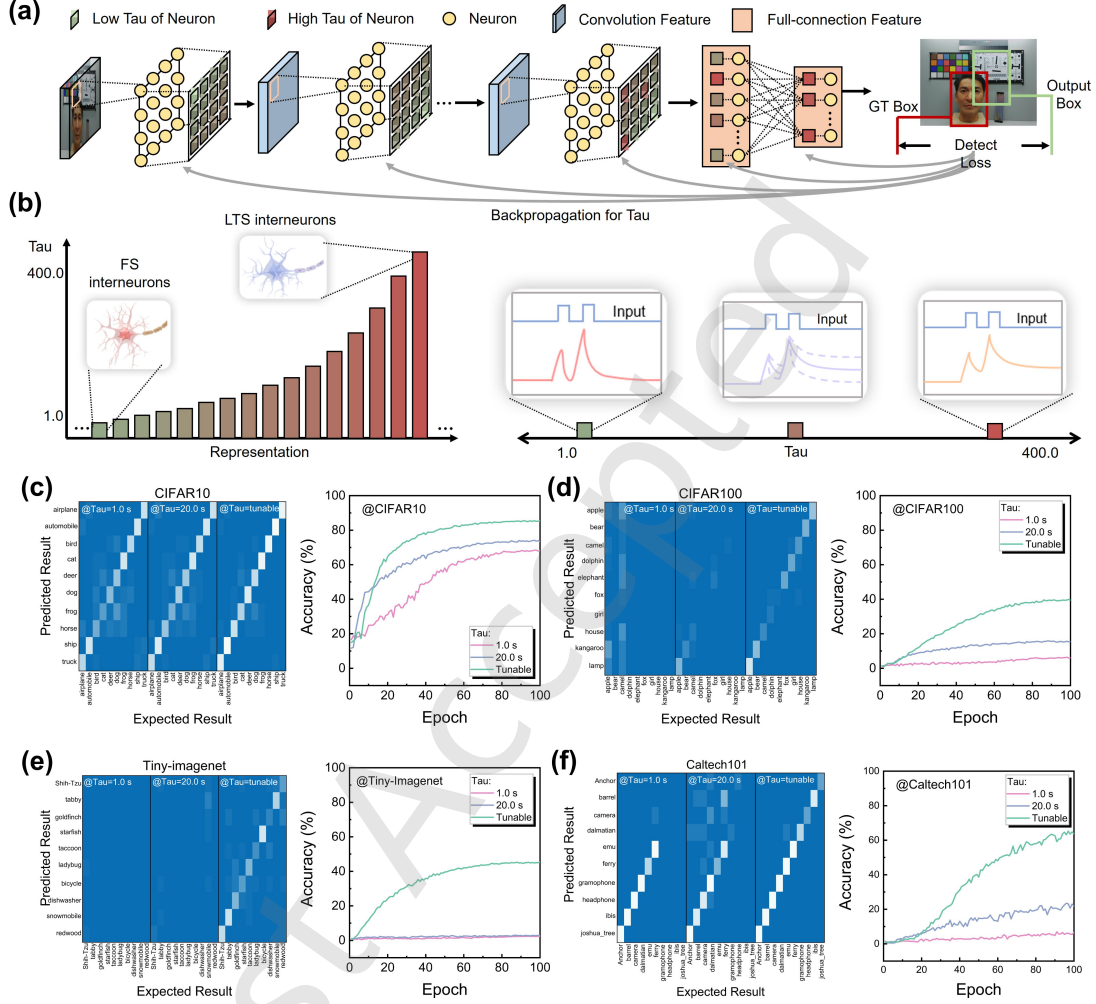


Figure 5. SNN implementation based on lifetime-tunable neuron device. (a) Architecture of the proposed SNN for validating the lifetime-tunable neuron device. (b) Schematic comparison of membrane time constants among FS, LTS, and lifetime-tunable optical neuron. (c–f) Training dynamics and classification performance of SNNs constructed with lifetime-tunable neurons on the CIFAR-10, CIFAR-100, Tiny-ImageNet, and Caltech101 datasets.

Here, we constructed an SNN comprising multiple LIF layers and treated the neuronal time constant(τ) as a trainable parameter extracted from the device, providing a functional counterpart to the lifetime tunability of the proposed neuron device. This configuration was used to evaluate the potential performance advantages of lifetime-tunable neurons. And the network was trained and evaluated across

multiple datasets. Figure 5a shows the architecture of the proposed SNN. After spike encoding, the input images are fed into convolutional modules for feature extraction, followed by a spatiotemporal feature layer composed of LIF neurons, and finally classified through fully connected layers. Notably, the LIF layer contains neuronal populations with different τ , and τ is updated through backpropagation. In the discrete-time LIF model, the membrane potential follows $V(t+1) = \exp(-\Delta t/\tau)V(t) + I(t)$, indicating that τ directly determines the integration–leakage window of neuronal inputs. Therefore, τ is set as a trainable parameter and updated through backpropagation, allowing the network to adaptively select suitable τ values in different layers to match the spatiotemporal integration requirements of different tasks. Because early convolutional layers require stable image feature extraction, neurons in the preceding feature layers are more suited to smaller τ values. In contrast, higher layers require longer-term integration of temporal statistics and semantic cues, making larger τ values more favorable. Overall, making τ trainable allows the network to develop multilevel temporal heterogeneity, in which fast and slow membrane dynamics coexist to support complementary information-processing functions. This adaptive temporal organization overcomes the intrinsic trade-off in conventional fixed- τ SNNs: excessively fast dynamics limit information accumulation, whereas excessively slow dynamics introduce redundant temporal integration and degrade temporal resolution. Figures 5b illustrate the τ characteristics of FS, LTS, and tunable- τ neurons. Figure 5c–f present the confusion matrices and recognition results after 100 training epochs on CIFAR-10, CIFAR-100, Tiny-ImageNet, and Caltech101, respectively. The distinct diagonal features in the trained confusion matrices indicate successful image recognition. Each dataset was trained under three modes: fixed low- τ mode ($\tau = 1s$), fixed high- τ mode ($\tau = 20s$), and tunable- τ mode ($\tau = \text{tunable}$). For the relatively simple CIFAR-10 dataset, all three modes achieve reasonable recognition accuracy, whereas the tunable- τ mode shows a clear performance advantage (85.21%), as shown in Figure 5c. For the more complex and challenging CIFAR-100, Tiny-ImageNet, and Caltech101 datasets, the training results show that

the tunable- τ mode yields the highest recognition accuracy (39.47%, 45.33% and 63.80%, respectively) and faster training efficiency, as shown in Figures 5d–f. Detailed recognition results are provided in Table S1. In addition, we evaluated the training and recognition capability of the SNNs on the dynamic CIFAR10-DVS dataset. After 100 training epochs, the tunable mode achieves a recognition accuracy of 76.31%, outperforming the two fixed modes with accuracies of 73.08% and 50.6%, as shown in Figure S3. In addition, Table S2 summarizes the performance results of the proposed SNN, BA-LIF [22] and PLIF [23], indicating that the proposed SNN achieves promising performance. We further evaluated the capability of the SNNs for static object detection, and Figure S4 presents the predicted images for static objects under the three modes. The two fixed modes suffer from missed detections and misclassification, whereas the tunable mode enables more accurate detection. Figure S5 shows the average precision (AP) of the SNNs under different IoU thresholds (0.5, 0.5:0.95, and 0.75) after 80 training epoch. The simulation results show that the tunable mode achieves the highest AP values of 93.1%, 63.3%, and 57.7%, respectively. Collectively, these results demonstrate that the proposed lifetime-tunable optical neuron enhances the spatiotemporal feature extraction and learning capabilities of SNNs by introducing device-level temporal heterogeneity, underscoring its promise for in-memory, event-driven, and temporally adaptive neuromorphic computing.

Conclusion

In summary, we demonstrate a CMOS-compatible lifetime-tunable optical neuron device based on a TiN/HZO/TiO₂/ITO heterostructure. Under all-optical control, the device reproduces key neuronal and synaptic behaviors, including leaky integration, PPF, EPSC, and STM-to-LTM transition, while enabling physical modulation of the lifetime constant. By incorporating this device-level lifetime tunability into SNNs, the network develops adaptive temporal heterogeneity with coexisting fast and slow membrane dynamics, leading to improved classification accuracy and faster convergence on CIFAR-10 and other benchmark datasets. These results establish

lifetime-tunable optical neurons as a promising hardware building block for biologically inspired, in-memory, event-driven, and temporally adaptive neuromorphic computing.

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Electronic Supplementary Material

Enhancing learning of spiking neural networks with lifetime-tunable optical neuron devices

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Note S1 Detailed information of the device fabrication process.

The TiN/TiO₂/HZO/TiO₂/ITO device was fabricated as follows. First, a 70nm TiN bottom electrode was deposited on a cleaned SiO₂/Si substrate by sputtering. A 6nm ferroelectric Hf_{0.5}Zr_{0.5}O₂ (HZO) film was then grown by plasma-enhanced atomic layer deposition (PEALD) at 270 °C. Tetrakis dimethylamido hafnium (TDMAHf), tetrakis dimethylamido zirconium (TDMAZr), and oxygen plasma were used as the

Hf precursor, Zr precursor, and oxygen source, respectively. The HZO composition was controlled by alternately depositing one HfO_2 cycle and one ZrO_2 cycle. Subsequently, a 70nm TiN capping layer was deposited by DC sputtering. To crystallize the ferroelectric phase in HZO, rapid thermal annealing was performed at 500 °C for 60 s in an N_2 ambient. The TiN capping layer was removed by wet etching in an $\text{NH}_4\text{OH}/\text{H}_2\text{O}_2/\text{H}_2\text{O}$ solution with a volume ratio of 1:2:5 for 10 min. A 3nm TiO_2 layer was subsequently deposited by PEALD at 270 °C. After UV photolithography, an indium tin oxide (ITO) top electrode was deposited by dc sputtering.

Note S2 Device characterization.

Elemental analysis was performed using an in situ X-ray photoelectron spectroscopy system (XPS, PHI 5000C, PerkinElmer). Electrical characterization was conducted with the Agilent B1500 semiconductor parameter analyzer in the atmosphere at room temperature.

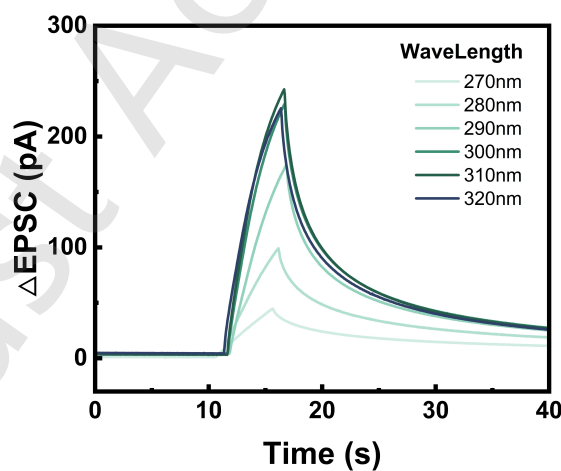


Figure S1. EPSC response induced by optical pulses with different wavelengths (270, 280, 290, 300, 310, and 320 nm) under fixed conditions (pw = 5 s, 21 mW/cm²).

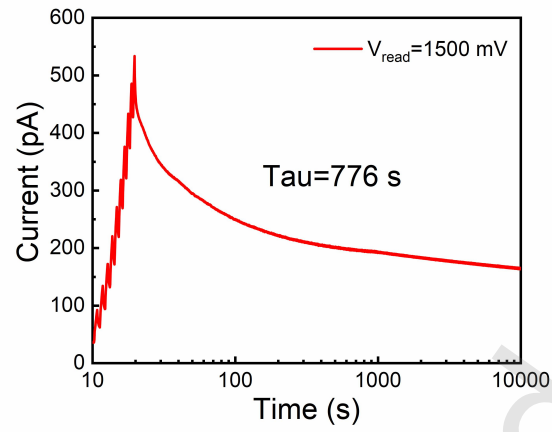


Figure S2. EPSC response induced by $V_{\text{read}}=1500$ mV under a fixed optical pulse sequence (pw = 1 s, 1 Hz, 21 mW/cm²), showing a Tau=776 s.

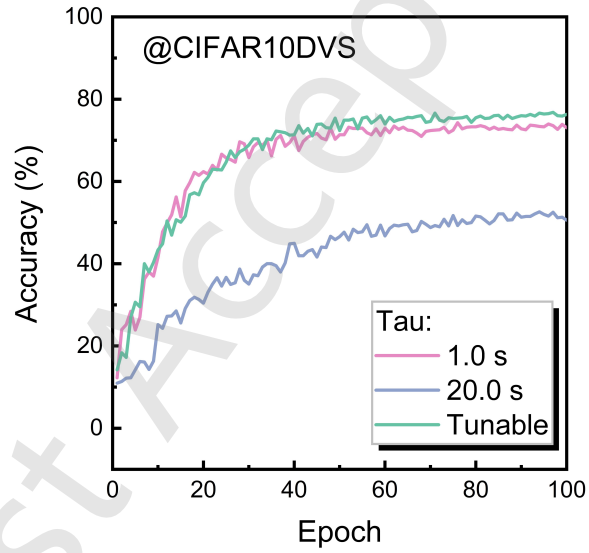


Figure S3. Recognition accuracy of the SNNs on the dynamic CIFAR10DVS dataset.

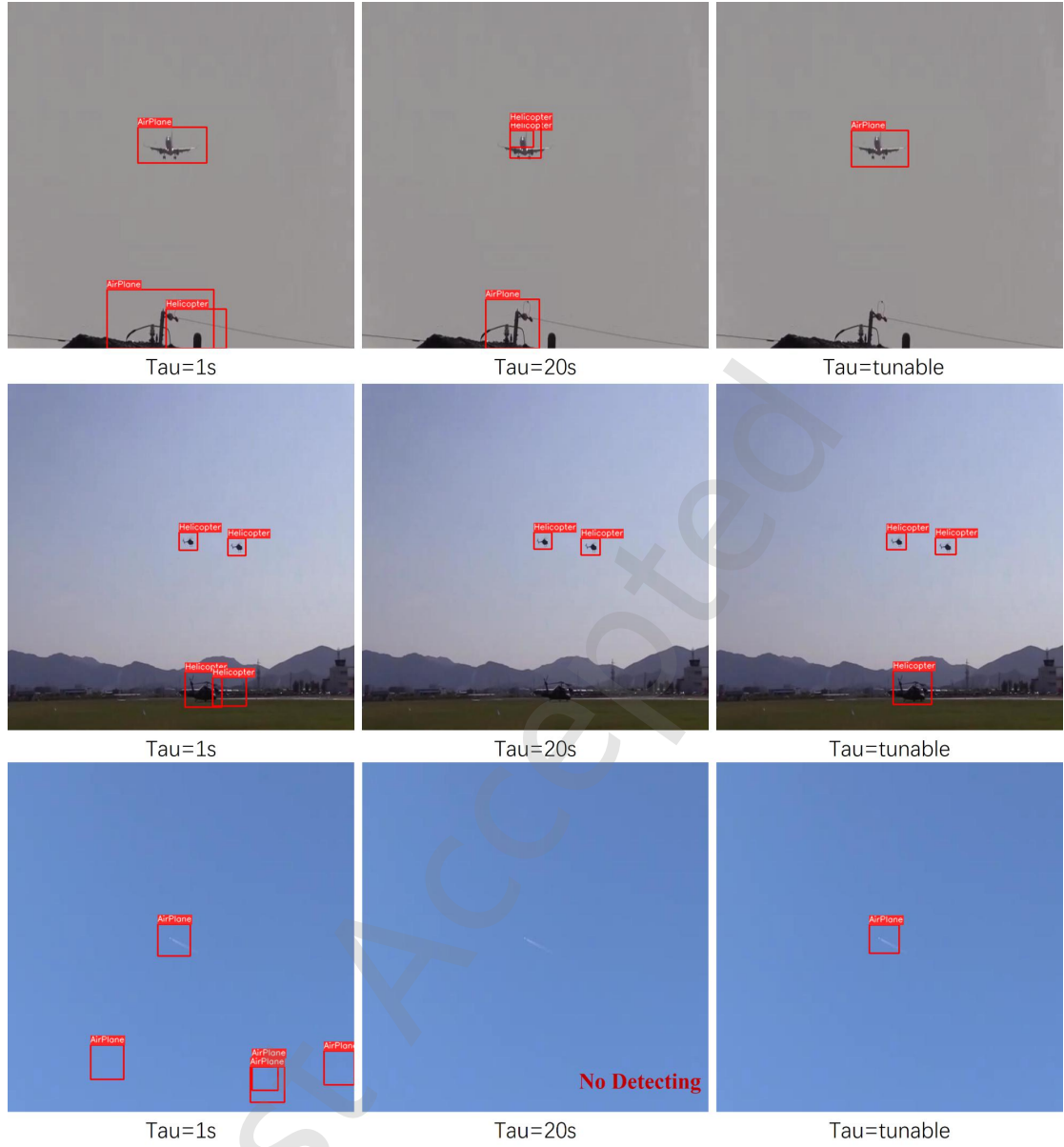


Figure S4. Predicted images of static objects by the SNNs under the three modes.

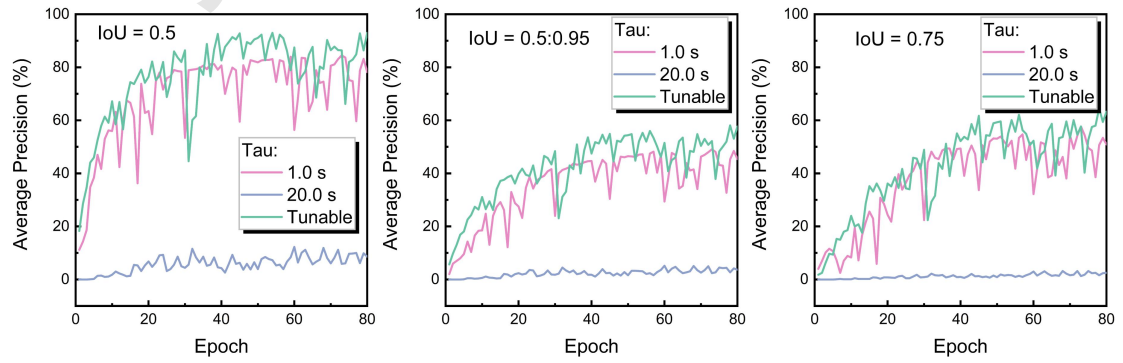


Figure S5. Average precision of the SNN under different IoU thresholds (0.5, 0.5:0.95,

and 0.75) after 80 training epoch.

Table S1. Recognition results of SNNs based on tunable-time-constant neurons on different datasets after 100 epochs.

Accuracy	$\tau=1s$	$\tau=20s$	$\tau=tunable$
CIFAR-10	68.12%	73.42%	85.21%
CIFAR-100	6.09%	15.52%	39.47%
Tiny-ImageNET	2.42%	2.88%	45.33%
Caltech101	6.59%	21.89%	63.80%
CIFAR10DVS	73.08%	50.60%	76.31%

Table S2. Performance comparison among different SNN models.

Method	Adaptation mechanism	Dataset/task	Reported performance
Proposed tunable- τ software SNN	Trainable membrane time constant	CIFAR-10	85.21%
PLIF [23]	Learnable membrane time constant	CIFAR-10	93.50%
Proposed tunable- τ software SNN	Trainable membrane time constant	CIFAR10-DVS	76.31%
PLIF [23]	Learnable membrane time constant	CIFAR10-DVS	74.80%
BA-LIF [22]	Input-dependent adaptive membrane time constant	N-Caltech101	92.1%