
High-order dynamics in an ultra-adaptive neuromorphic vision device

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High-Order Dynamics in An Ultra-Adaptive Neuromorphic Vision Device

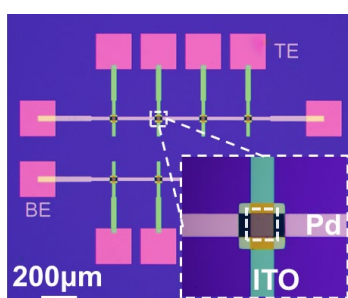
Jiayi Xu^{1#}, Biyi Jiang^{1,2#}, Weizhen Wang^{2#}, Zhifeng Guo¹, Junsen Gao¹, Xinyan Hu¹, Jingkai Qin³, Liang Ran⁴, Longyang Lin¹, Songhua Cai^{2*}, Yida Li^{1*}, and Feichi Zhou^{1*}

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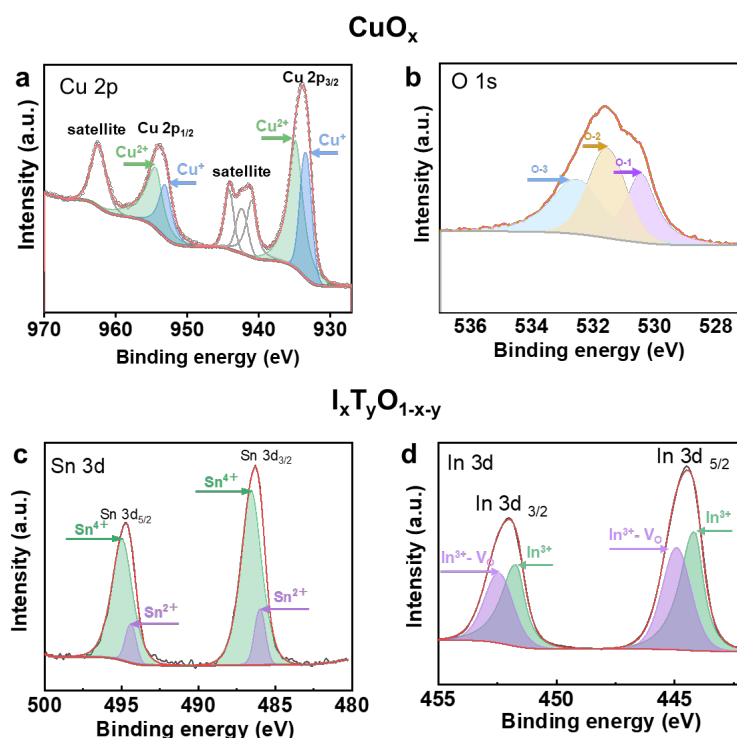
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Supplementary Table 1 | Performance metrics of each dynamic of a UANV device.

	RSN dynamic	RGN dynamic	CS dynamic	CN dynamic
Programming voltage	0 V	0.04 V	0.1 V	> 1.3 V
Read voltage	0 V	0.04 V	10 mV	> 1.3 V
Energy consumption	0 J	42.5 fJ	14 fJ	0.35 nJ
Power consumption	0 W	8.5 pW	0.7 pW	0.38 μ W

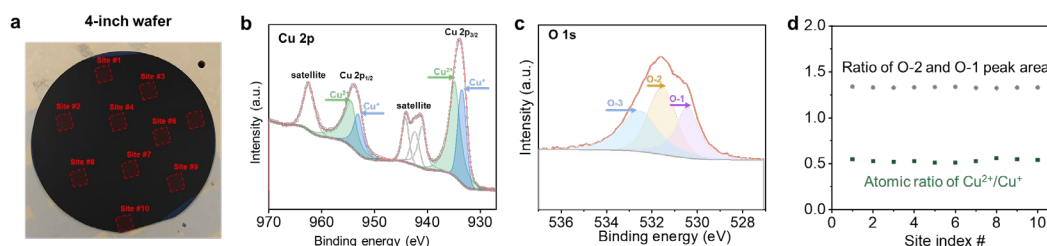


Supplementary Fig. 1 | Optical microscopy image of the two-terminal cross-point structure of $I_xT_yO_{1-x-y}/CuO_x/Pd$ (30 nm/ 40 nm/ 30 nm) UANV device with an effective area of $25 \mu m \times 25 \mu m$.

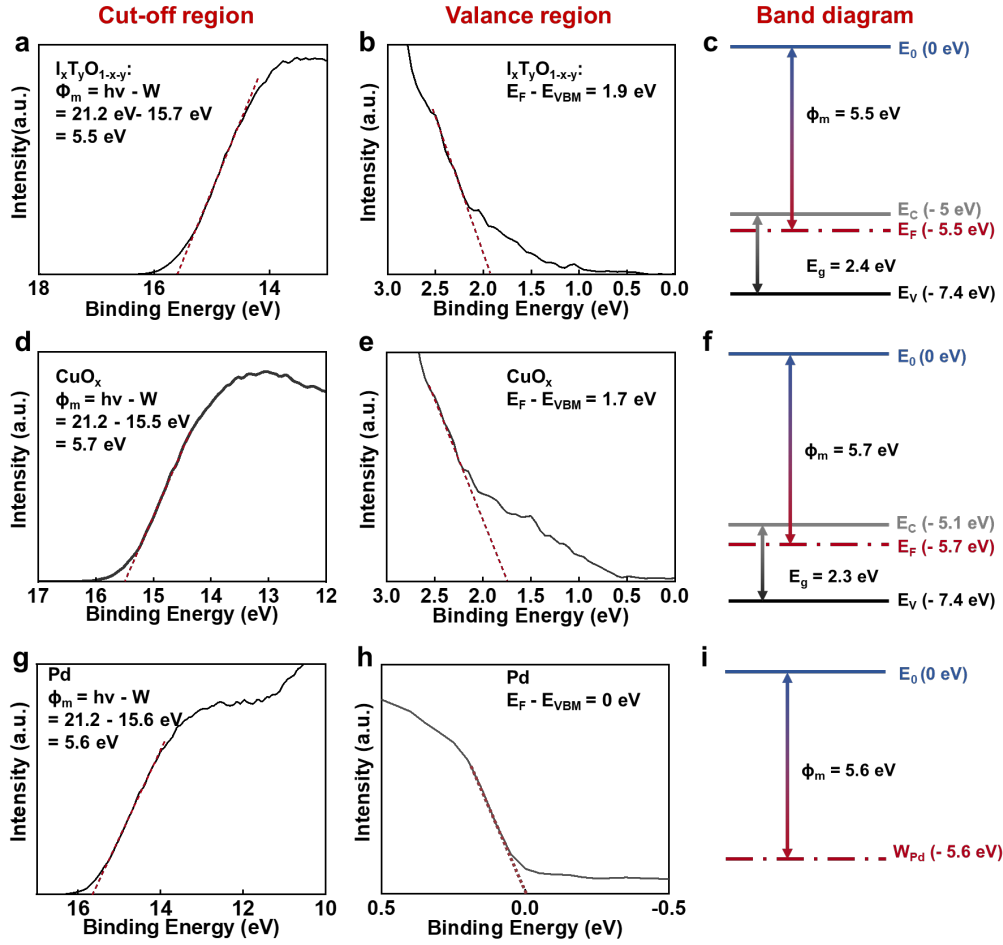


Supplementary Fig. 2 | XPS spectra of the CuO_x and $I_xT_yO_{1-x-y}$ thin films. (a) Narrow scan of Cu 2p. Cu 2p spectrum is deconvoluted into four peaks: $Cu^+ 2p_{1/2}$ (953.1 eV), $Cu^{2+} 2p_{1/2}$ (954.4 eV), $Cu^+ 2p_{2/3}$ (933.4 eV), $Cu^{2+} 2p_{2/3}$ (934.9 eV). (b) Narrow

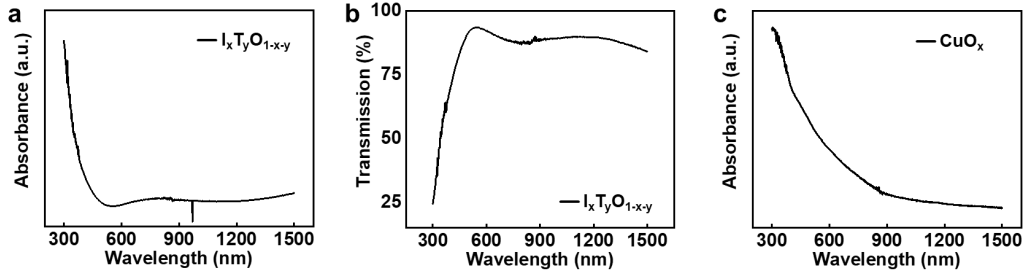
scan of O 1s. O 1s spectrum is deconvoluted into three peaks: O-1 (Lattice Oxygen, 530.5 eV), O-2 (Chemisorbed Oxygen, 531.6 eV) and O-3 (Physically Adsorbed Oxygen, 532.6 eV), indicating the existence of oxygen vacancies. (c) Narrow scan of Sn 3d. Sn 3d spectrum is deconvoluted into four peaks: Sn^{2+} 3d_{3/2} (485.9 eV), Sn^{2+} 3d_{5/2} (494.5 eV), Sn^{4+} 3d_{3/2} (486.6 eV) and Sn^{4+} 3d_{5/2} (495.0 eV). (d) Narrow scan of In 3d. In 3d spectrum is deconvoluted into four peaks: In^{3+} - V_O 3d_{3/2} (452.4 eV), In^{3+} 3d_{3/2} (451.8 eV), In^{3+} - V_O 3d_{5/2} (444.9 eV), In^{3+} 3d_{5/2} (444.3 eV).



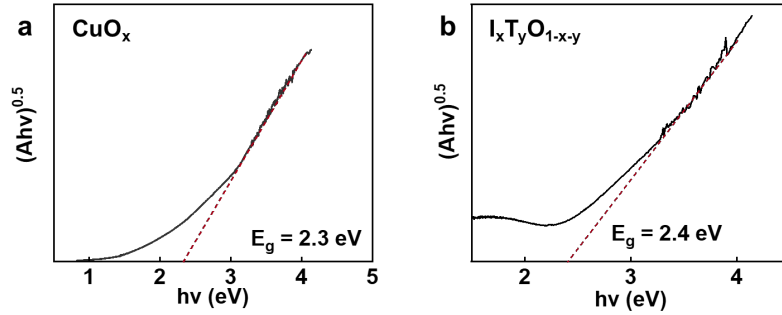
Supplementary Fig. 3 | Defect uniformity in large-area CuO_x thin film. (a) Photo of CuO_x thin film deposited on a 4-inch wafer, with randomly selected areas indicated in red boxes, followed by X-ray photoelectron spectroscopy (XPS) measurements for validating large-area defect uniformity. (b) Narrow scan of Cu 2p. Cu 2p spectrum is deconvoluted into four peaks: Cu⁺ 2p_{1/2} (953.1 eV), Cu²⁺ 2p_{1/2} (954.4 eV), Cu⁺ 2p_{2/3} (933.4 eV), Cu²⁺ 2p_{2/3} (934.9 eV). (c) Narrow scan of O 1s. O 1s spectrum is deconvoluted into three peaks: O-1 (Lattice Oxygen, 530.5 eV), O-2 (Chemisorbed Oxygen, 531.6 eV) and O-3 (Physically Adsorbed Oxygen, 532.6 eV). (d) Distribution of Cu²⁺/Cu⁺ atomic ratio and O-2 and O-1 peak area ratio in the deposited CuO_x film at the 10 sites, displaying high uniformity.



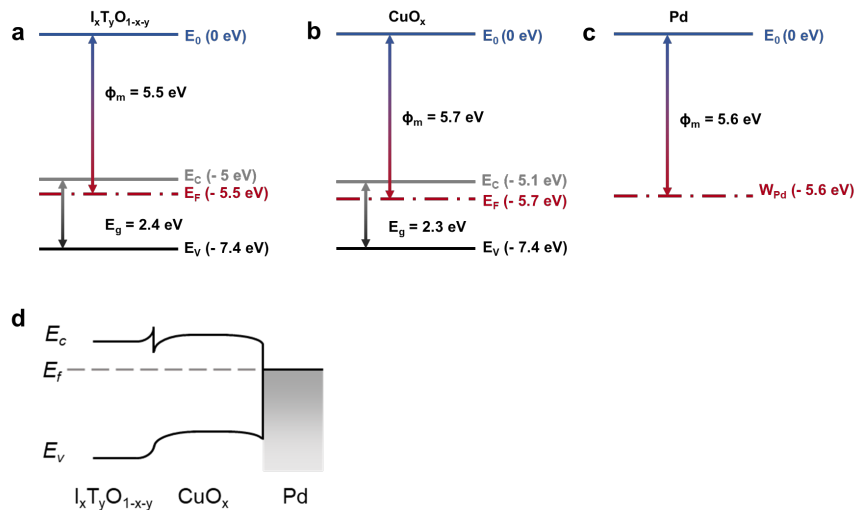
Supplementary Fig. 4 | Ultraviolet photoelectron spectroscopy (UPS) tests of as-prepared $I_xT_yO_{1-x-y}$, CuO_x , Pd thin films on the SiO_2 substrate. (a) Cut-off region of $I_xT_yO_{1-x-y}$. The work function is extracted as 5.5 eV. (b) Valence region of $I_xT_yO_{1-x-y}$. The difference between the Fermi level and valence band maximum is extracted as 1.9 eV. (c) Band diagram of the as-prepared $I_xT_yO_{1-x-y}$ film. (d) Cut-off region of CuO_x . The work function is extracted as 5.7 eV. (e) Valence region of CuO_x . The difference between the Fermi level and valence band maximum is extracted as 1.7 eV. (f) Band diagram of the as-prepared CuO_x film. (g) Cut-off region of Pd . The work function is extracted as 5.6 eV. (h) Valence region of Pd . The difference between the Fermi level and valence band maximum is extracted as 0 eV. (i) Band diagram of as-prepared Pd film.



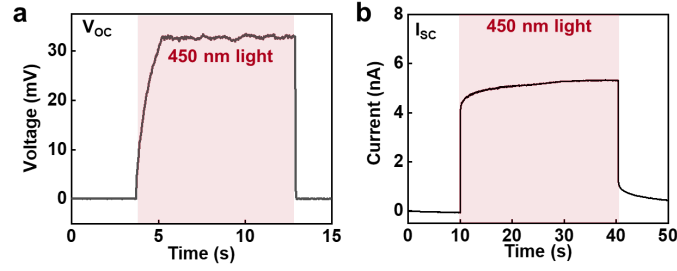
Supplementary Fig. 5 | Ultraviolet-visible (UV-Vis) spectra of the as-prepared $I_xT_yO_{1-x-y}$ and CuO_x layers on the quartz substrates at the wavelengths from 300 to 1500 nm. (a) absorption spectrum and (b) transmission spectrum of the $I_xT_yO_{1-x-y}$ layer, suggesting a maximum transmission at the wavelength of 540 nm. (c) The absorption spectrum of the CuO_x thin film.



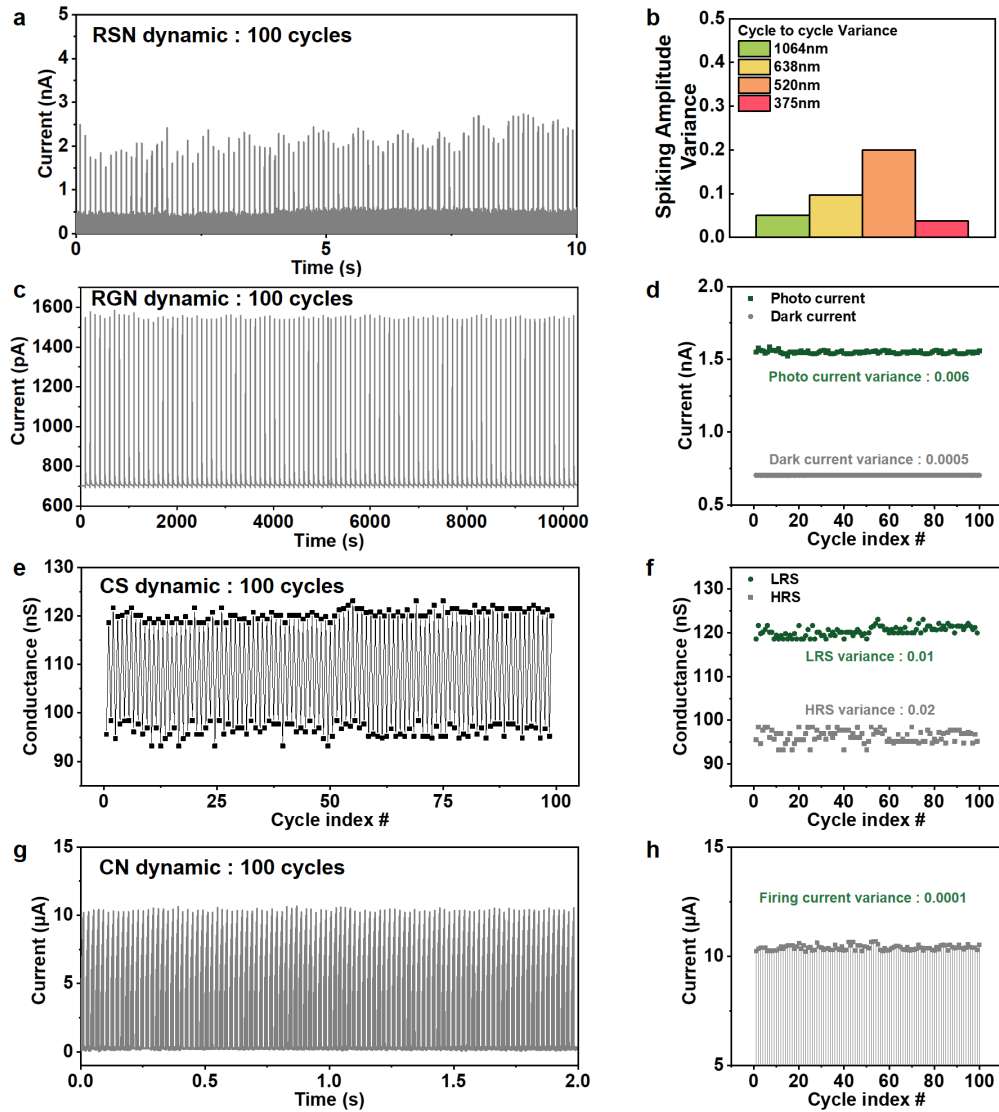
Supplementary Fig. 6 | Tauc plots for as-prepared CuO_x and $I_xT_yO_{1-x-y}$ thin films. The band gap of (a) CuO_x is extracted as 2.3 eV and the band gap of (b) $I_xT_yO_{1-x-y}$ is extracted as 2.4 eV according to the Tauc's equation $(\alpha h\nu)^{\frac{1}{n}} = B(h\nu - E_g)^{1-3}$.



Supplementary Fig. 7 | Band diagram for the as-prepared (a) $I_xT_yO_{1-x-y}$, (b) CuO_x and (c) Pd thin films before contact and (d) band alignment for $I_xT_yO_{1-x-y} / CuO_x / Pd$ after contact.

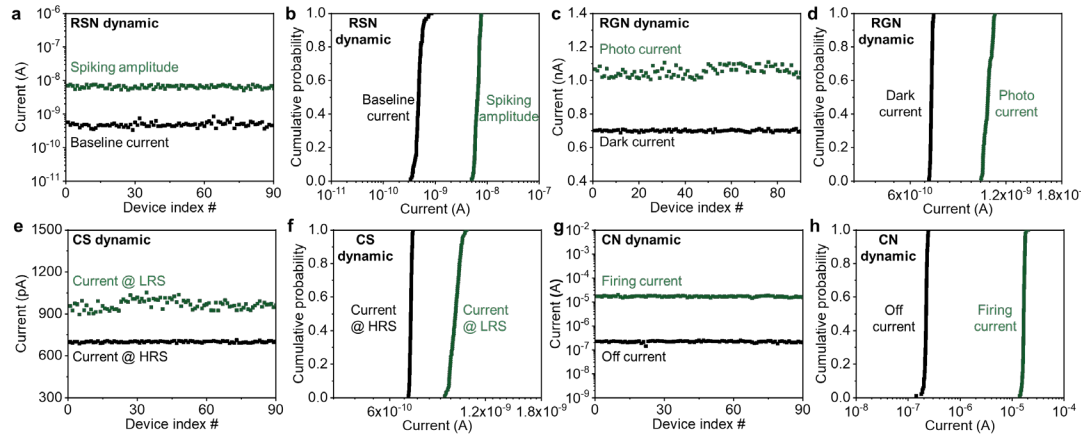


Supplementary Fig. 8 | Photovoltaic characteristics of the UANV device. (a) Open-circuit voltage (V_{oc}) of 32 mV under $0.37 \mu\text{W}/\mu\text{m}^2$ 450 nm light illumination. (b) Short-circuit current (I_{sc}) of 5 nA under $0.37 \mu\text{W}/\mu\text{m}^2$ 450 nm light illumination.

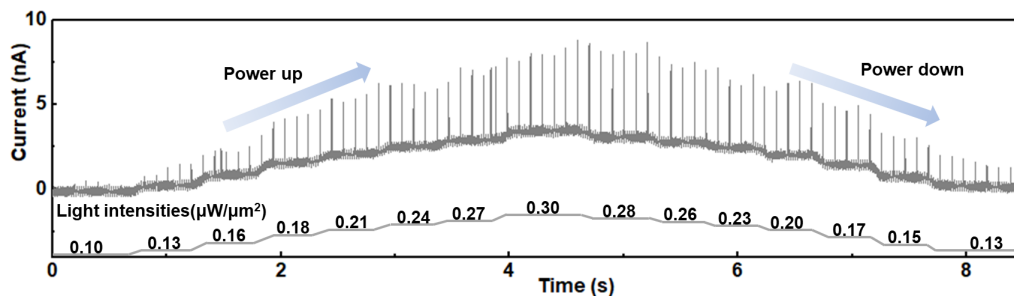


Supplementary Fig. 9 | Cycle-to-cycle endurance of UANV device in four dynamics. (a) Cyclic photoresponsive spiking characteristics in RSN dynamics under 375nm light with an intensity of $0.14 \mu\text{W}/\mu\text{m}^2$ for 100 cycles. (b) Spiking amplitude variances at different wavelengths. (c) Cycle-to-cycle endurance of the UANV device in RGN dynamic under 450 nm light pulse illumination ($0.22 \mu\text{W}/\mu\text{m}^2$, pulse width of 2 s) for 100 cycles. (d) Cyclic photo current and dark current, exhibiting low cycle-to-cycle

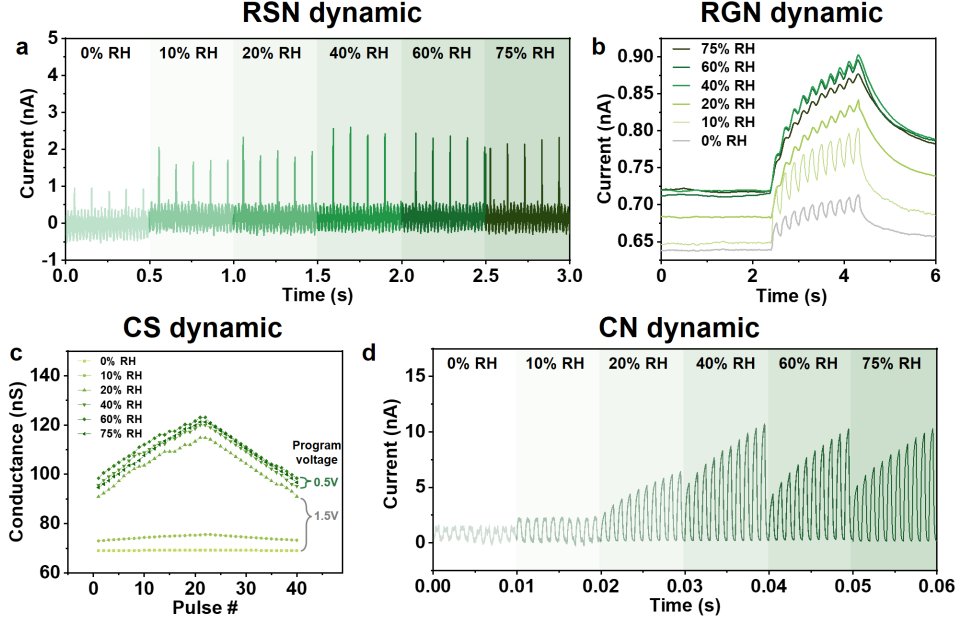
variance of 0.006 and 0.0005, respectively. (e) Cycle-to-cycle endurance of the UANV device in CS dynamic for 100 cycles, (f) Cyclic LRS and HRS, exhibiting low cycle-to-cycle variance of 0.01 and 0.02, respectively. (g) Cycle-to-cycle endurance of the UANV device in CN dynamic for 100 cycles, (h) Cyclic firing current, exhibiting low cycle-to-cycle variance of 0.0001.



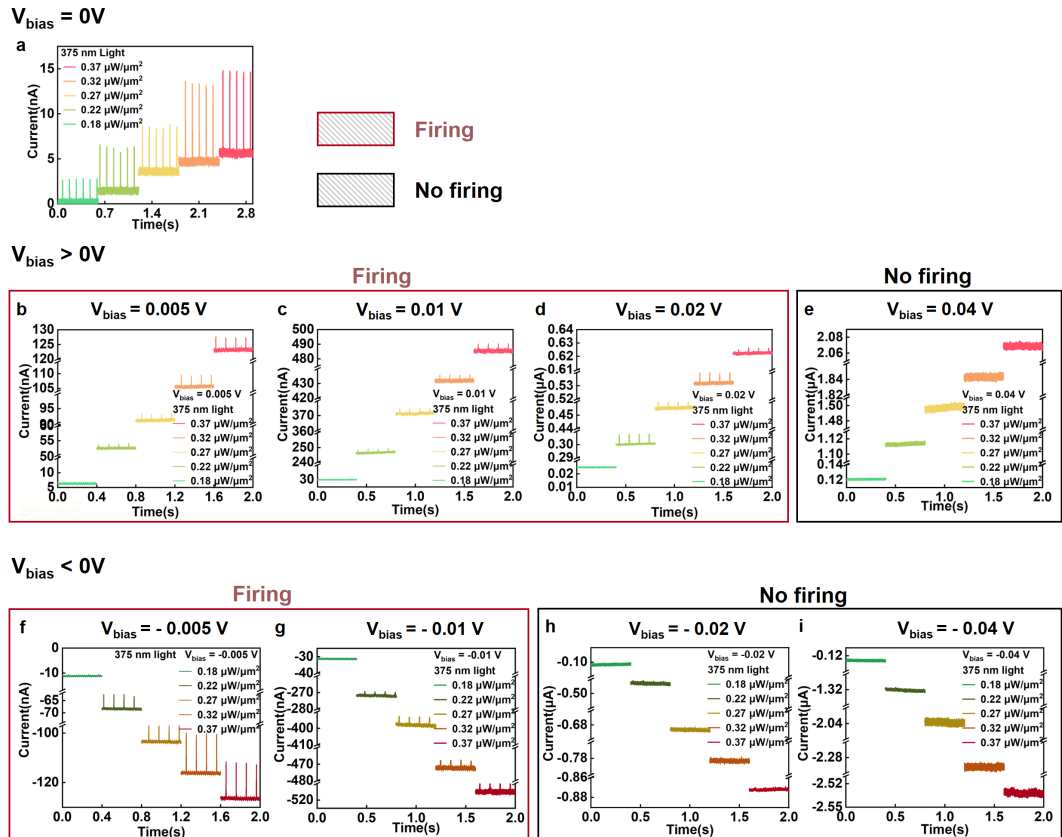
Supplementary Fig. 10 | Device-to-device variation of UANV device array in four dynamics. (a) Device-to-device variation operating in RSN dynamic under 375 nm light of $0.22 \mu\text{W}/\mu\text{m}^2$, and (b) cumulative distribution plots. (c) Distribution of photocurrent and dark current of devices in RGN dynamic, triggered by 450 nm light pulse ($0.22 \mu\text{W}/\mu\text{m}^2$, pulse width of 50 ms), with a read voltage of 40 mV, and (d) cumulative distribution plots. (e) Distribution of device currents at HRS and LRS when the device operates in CS dynamic, and (f) cumulative distribution plots. The HRS and LRS are programmed by $0 - \pm 0.5$ V voltage sweeping, respectively. (g) Distribution of firing currents and OFF current of the devices operating in CN dynamic, and (h) cumulative distribution plots. The firing currents are triggered by 10 voltage pulses of 1.5 V with a pulse width and interval of 0.5 ms. The device-to-device variations of the four dynamics are extracted as 0.098 in RSN dynamic, 0.034 in RGN dynamic, 0.013 in CS dynamic and 0.003 in CN dynamic.



Supplementary Fig. 11 | RSN dynamics under varying light intensities from low to high and back to low. The continuous optical spiking behaviours when the light intensity varies from low ($0.10 \mu\text{W}/\mu\text{m}^2$) to high ($0.37 \mu\text{W}/\mu\text{m}^2$) and back to low ($0.13 \mu\text{W}/\mu\text{m}^2$), with stable and repeatable spiking behaviours.

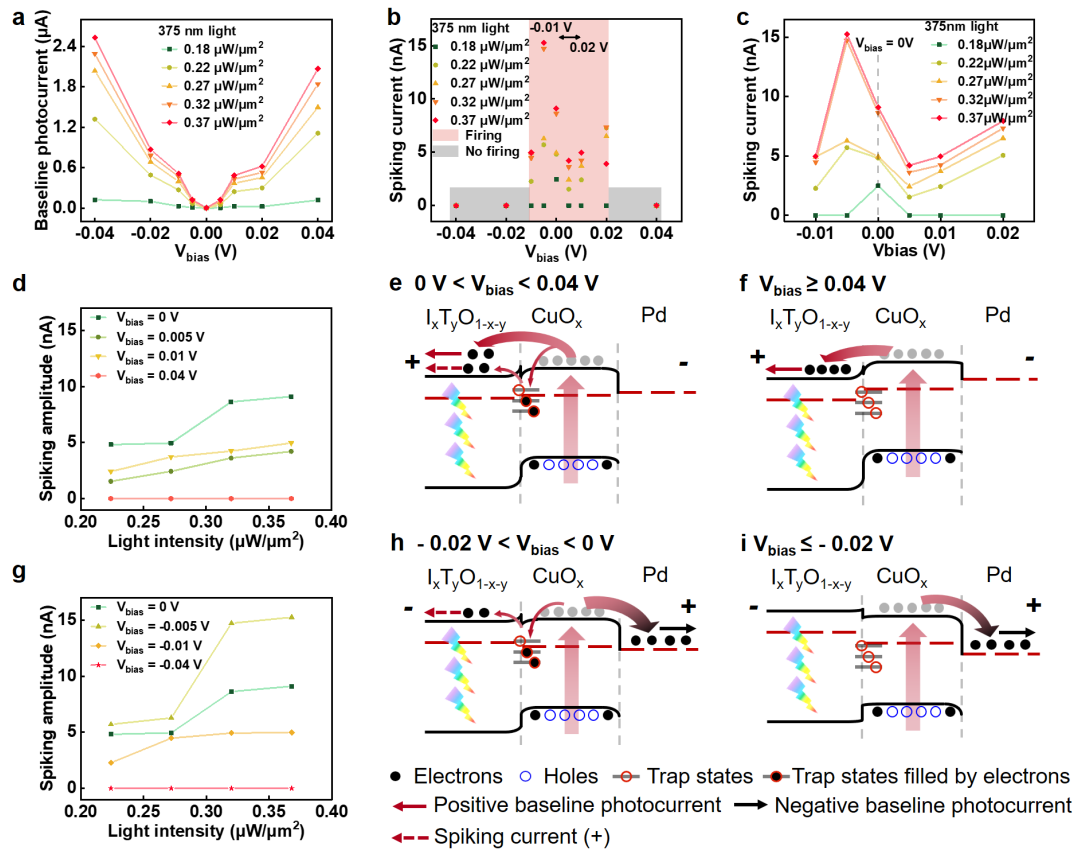


Supplementary Fig. 12 | Four dynamic behaviours under different humidity conditions: (a) RSN dynamic, (b) RGN dynamic, (c) CS dynamic and (d) CN dynamic.

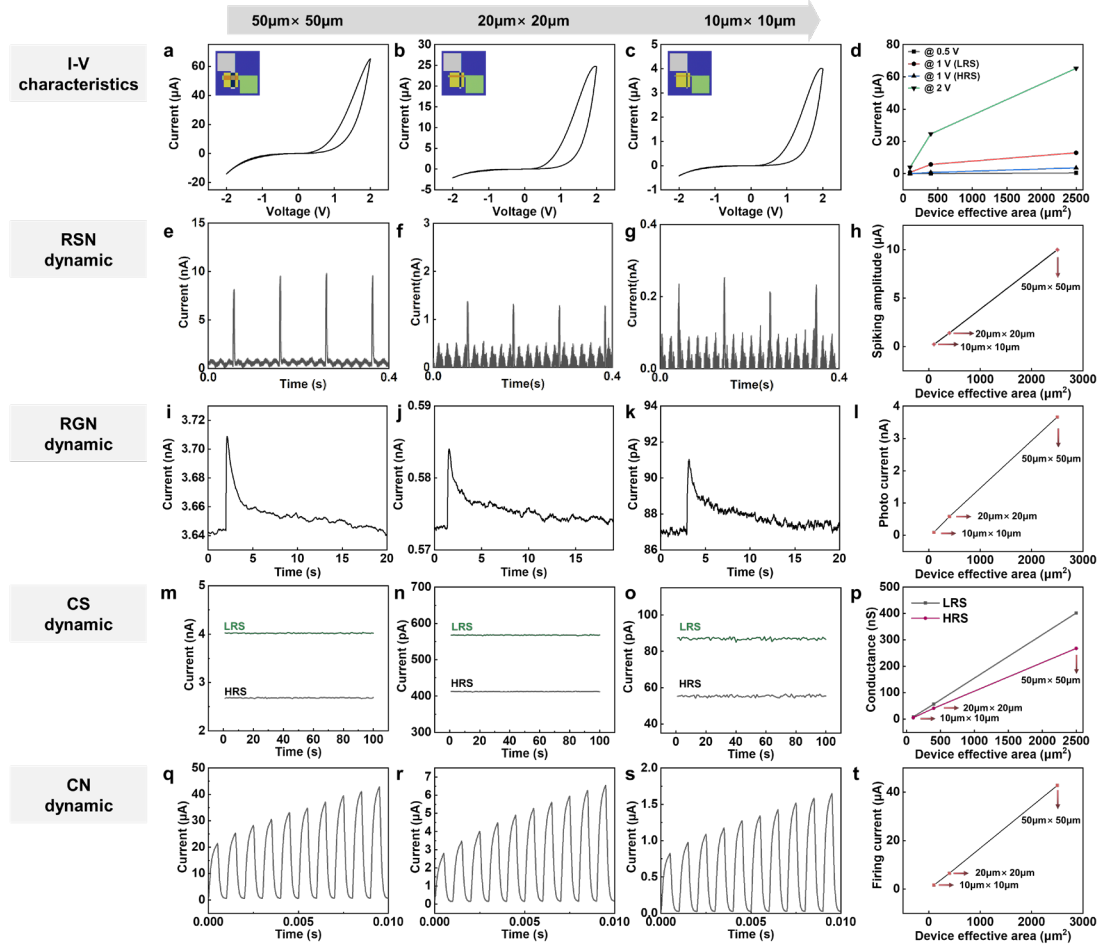


Supplementary Fig. 13 | Photoresponsive leaky-integrate-and-fire (LIF) spiking characteristics of the UANV device in RSN dynamic under different light intensities and different voltage biases. The voltage bias is applied to the $I_xT_yO_{1-x-y}$ electrode and the Pd electrode is grounded. (a) $V_{bias} = 0V$, (b) $V_{bias} = 0.005V$, (c) V_{bias}

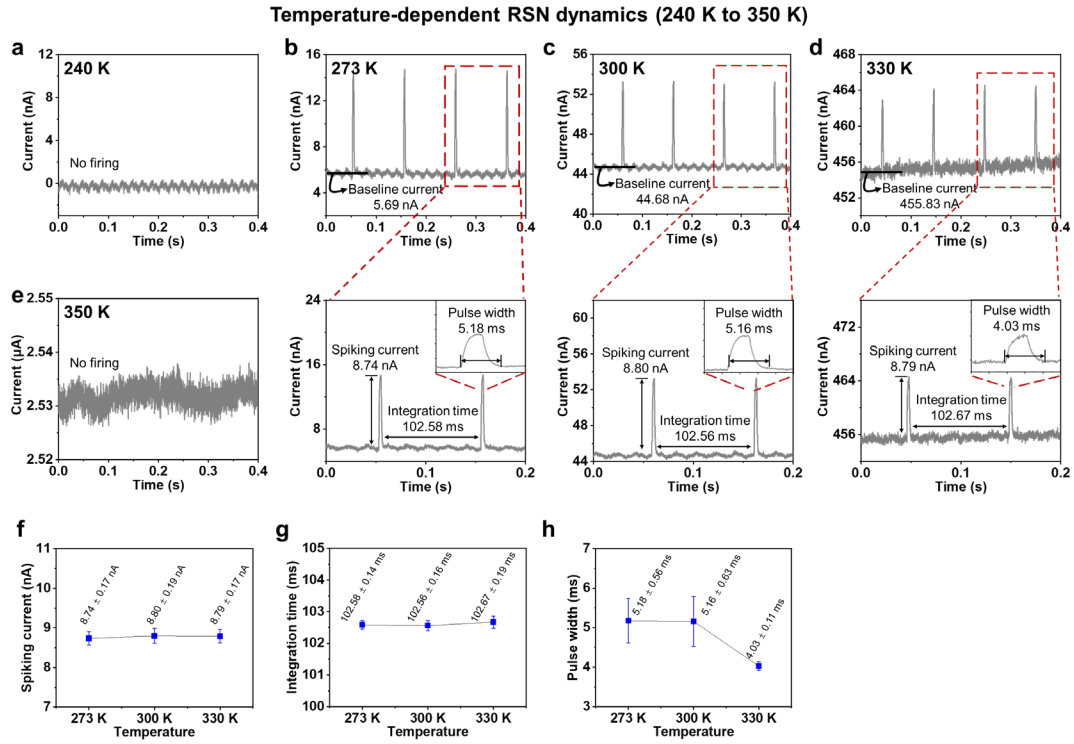
= 0.01 V, (d) $V_{\text{bias}} = 0.02$ V, (e) $V_{\text{bias}} = 0.04$ V, (f) $V_{\text{bias}} = -0.005$ V, (g) $V_{\text{bias}} = -0.01$ V, (h) $V_{\text{bias}} = -0.02$ V, (i) $V_{\text{bias}} = -0.04$ V.



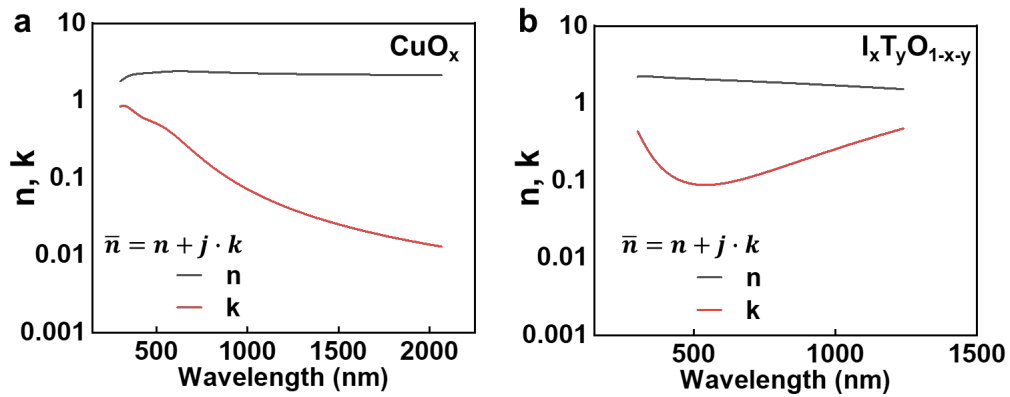
Supplementary Fig. 14 | The systematic studies of the photoresponsive LIF spiking under different voltage biases. (a) Plots of the baseline photoresponsive current as a function of the voltage bias under different light intensities. (b) Plots of the spiking current as a function of the voltage bias under different light intensities. (c) Plots of the spiking current as a function of light intensity after different positive voltages. (d) Plots of the spiking current as a function of positive voltage bias under different light intensities. (e) RSN dynamic working principle under voltage bias of 0 V to 0.04 V. (f) RSN dynamic working principle under voltage bias exceeding 0.04 V (inclusive). (g) Plots of the spiking current as a function of light intensity under different negative voltage biases. (h) RSN dynamic working principle under the voltage bias of -0.02 V to 0 V. (i) RSN dynamic working principle of UANV device with voltage bias lower than -0.02 V.



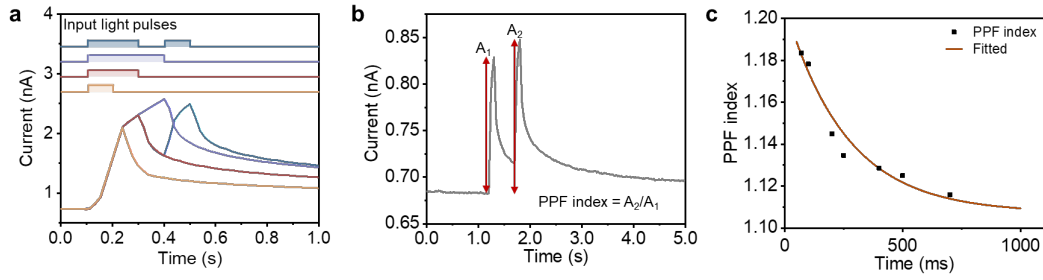
Supplementary Fig. 15 | Area-dependent device characteristics. Current-voltage sweeping curves ($0\text{ V} - 2\text{ V} - 0\text{ V} - -2\text{ V} - 0\text{ V}$) of the as-fabricated UANV device with effective area of (a) $50\text{ }\mu\text{m} \times 50\text{ }\mu\text{m}$, (b) $20\text{ }\mu\text{m} \times 20\text{ }\mu\text{m}$, (c) $10\text{ }\mu\text{m} \times 10\text{ }\mu\text{m}$. (d) Plots of the current extracted at different voltages as a function of the effective device areas. Output current of the RSN dynamic in the devices with different areas of (e) $50\text{ }\mu\text{m} \times 50\text{ }\mu\text{m}$, (f) $20\text{ }\mu\text{m} \times 20\text{ }\mu\text{m}$, (g) $10\text{ }\mu\text{m} \times 10\text{ }\mu\text{m}$. (h) Plots of the spiking amplitude as a function of the device area in the RSN dynamic. Output current of the RGN dynamic in the devices with different effective areas of (i) $50\text{ }\mu\text{m} \times 50\text{ }\mu\text{m}$, (j) $20\text{ }\mu\text{m} \times 20\text{ }\mu\text{m}$, (k) $10\text{ }\mu\text{m} \times 10\text{ }\mu\text{m}$. (l) Plots of the photocurrent as a function of the device area in RGN dynamic. HRS and LRS current of the CS dynamic in the devices with different effective areas of (m) $50\text{ }\mu\text{m} \times 50\text{ }\mu\text{m}$, (n) $20\text{ }\mu\text{m} \times 20\text{ }\mu\text{m}$, (o) $10\text{ }\mu\text{m} \times 10\text{ }\mu\text{m}$. (p) Plots of the conductance at LRS and HRS as a function of the device area in CS dynamic. Output current of the CN dynamic in the devices with different effective areas of (q) $50\text{ }\mu\text{m} \times 50\text{ }\mu\text{m}$, (r) $20\text{ }\mu\text{m} \times 20\text{ }\mu\text{m}$, (s) $10\text{ }\mu\text{m} \times 10\text{ }\mu\text{m}$. (t) Plots of the firing current as a function of the device area in CN dynamic. The results show a clear linear scaling relationship of the measured current with device area, proving the area-dependent switching in all four dynamics.



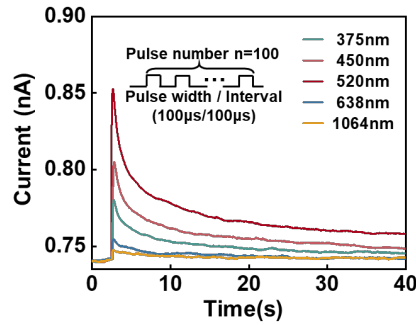
Supplementary Fig. 16 | RSN dynamics under different temperatures. (a) 240 K, (b) 273 K, (c) 300 K, (d) 330 K and (e) 350K. (f) Plot of spiking amplitude, (g) integration time, and (h) spiking width as a function of temperature with mean value and error bars indicated. Error bars in f–h represent the standard deviation of 30 cycles measured from the same device.



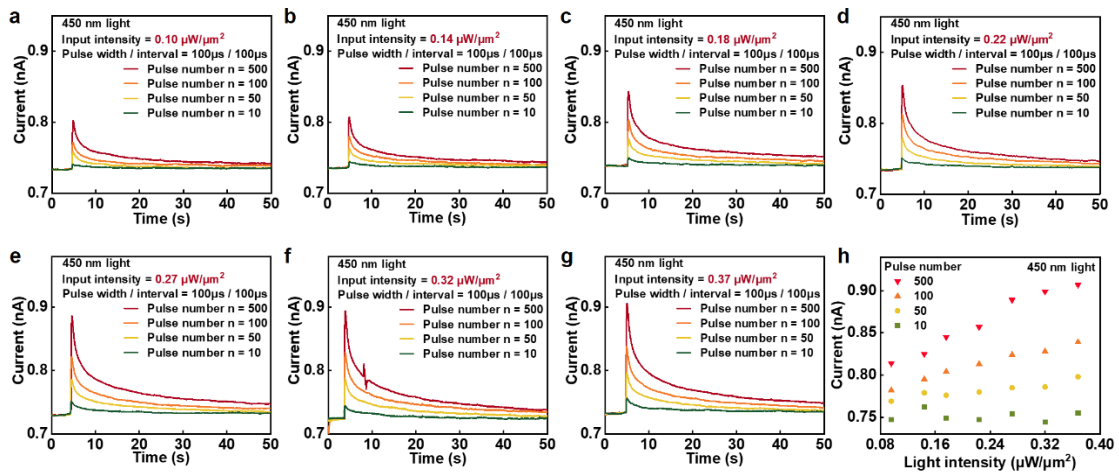
Supplementary Fig. 17 | The complex refractive index of the as-fabricated $\text{I}_x\text{T}_y\text{O}_{1-x-y}$ and CuO_x films.



Supplementary Fig. 18 | Pulse-number and interval-dependent RGN dynamics. (a) Current response ($V_{\text{read}} = 40$ mV) under 450 nm light pulse sequence with varying light pulse number and time interval. The light intensity used is $0.37 \mu\text{W}/\mu\text{m}^2$. (b) Paired-pulse facilitation (PPF) effect, where a pair of light pulses was applied (the light intensity, pulse width and interval are $0.10 \mu\text{W}/\mu\text{m}^2$, 100 ms, and 500 ms) with $V_{\text{read}} = 40$ mV. (c) Optical PPF ratio as a function of the time interval Δt (100-700 ms) between the two pulses, defined as A_2/A_1 . Decaying exponential relation with Δt , and can be modelled by a biexponential decay equation: $\text{PPF ratio} = C_0 + C_1 e^{-\Delta t/\tau_1} + C_2 e^{-\Delta t/\tau_2}$, where τ_1 and τ_2 represent the fast and slow decay time constants, respectively. τ_1 and τ_2 are extracted as 1.87 ms and 260.48 ms.

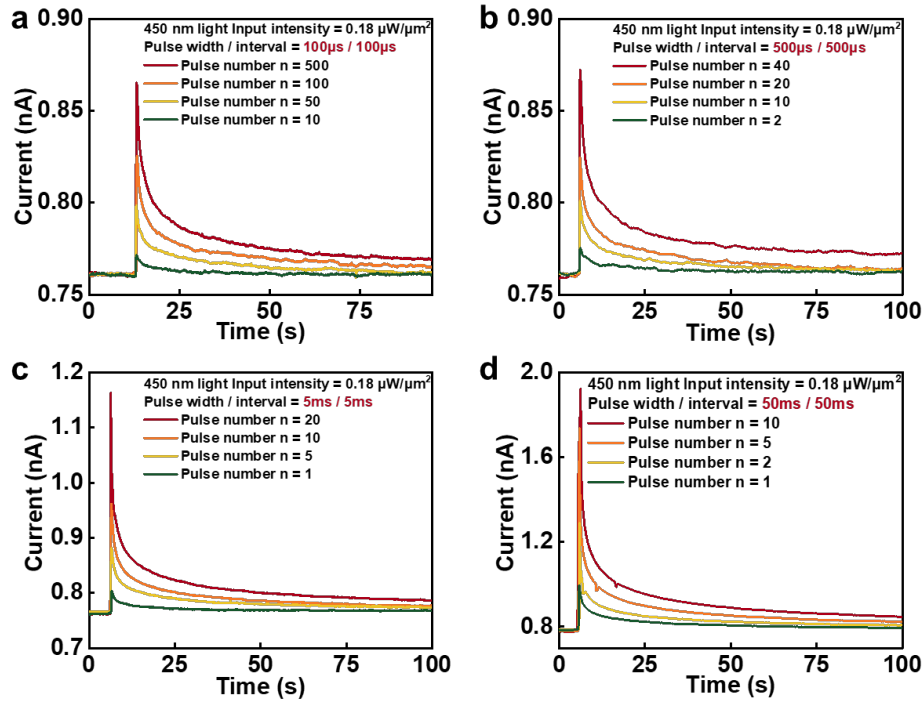


Supplementary Fig. 19 | Wavelength-dependent RGN dynamics at the wavelengths of 375 nm, 450 nm, 520 nm, 638 nm, 1064 nm.

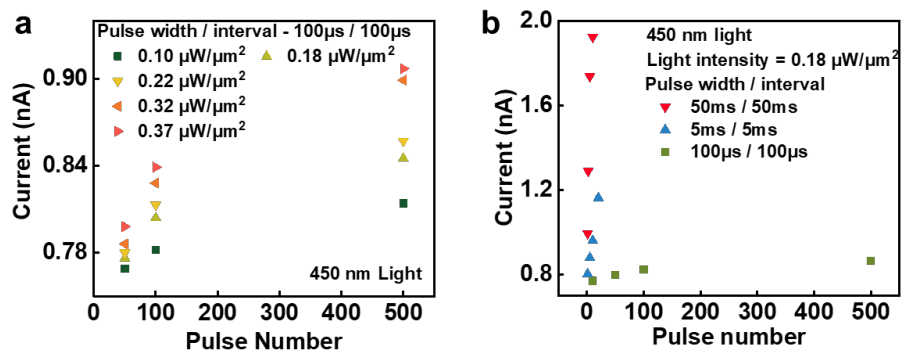


Supplementary Fig. 20 | Light pulse number- and intensity-dependent RGN dynamic characteristics with 450 nm light stimuli (pulse width = 100 μs ; pulse

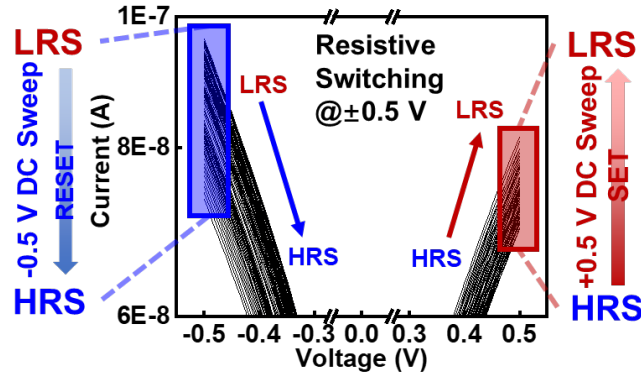
interval = 100 μ s). (a)-(g) Current-time characteristics of the UANV device under continuous light pulse stimuli with different pulse numbers of 10, 50, 100 and 500 at different light intensities ranging from 0.10 μ W/ μ m² to 0.37 μ W/ μ m². (h) Plots of the output current as a function of light intensities with different pulse numbers.



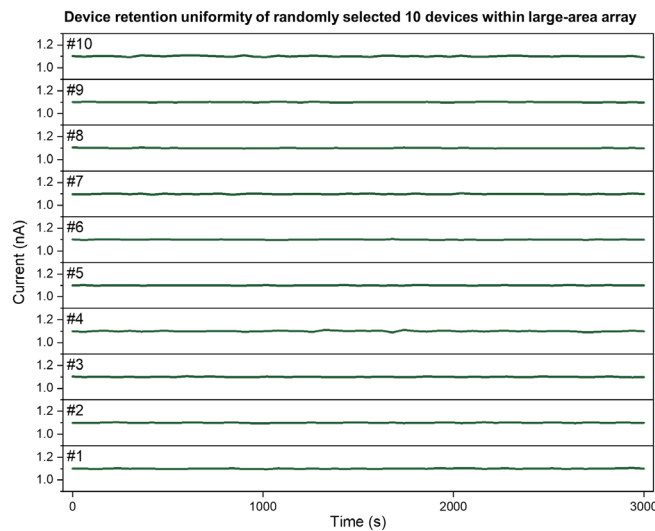
Supplementary Fig. 21 | Light pulse width, interval and number-dependent RGN dynamic characteristics. Different variations of pulse width/interval are characterized, including a) 100 μ s/ 100 μ s, b) 500 μ s/ 500 μ s, c) 5 ms/ 5 ms, and d) 50 ms/ 50 ms.



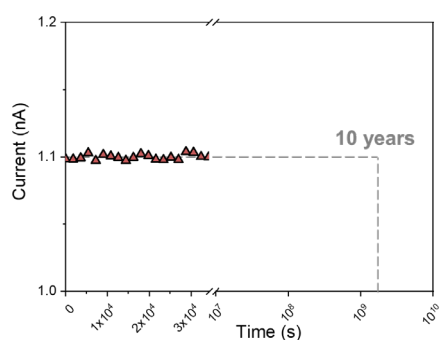
Supplementary Fig. 22 | Plots of the output current of the device in RGN dynamic as a function of pulse number at (a) different light intensities and (b) different pulse widths and pulse intervals.



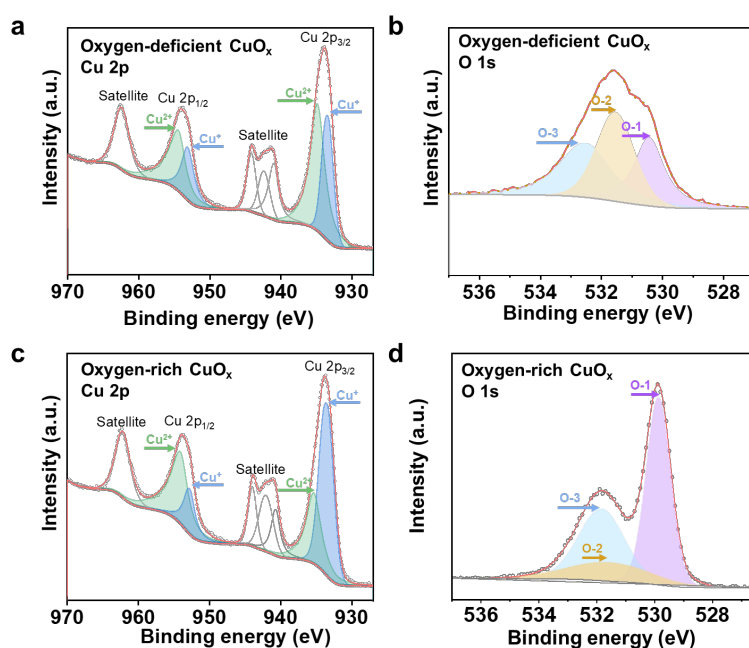
Supplementary Fig. 23 | Consecutive I-V switching characteristics in UANV device in CS dynamic under 80 positive sweeps and 80 negative sweeps. The sweeping voltage was first applied from 0 V to 0.5 V for the 1st to 80th positive sweeps and from 0 V to -0.5 V for the last 81st to 160th negative sweeps, corresponding to continuous high resistance state (HRS) to low resistance state (LRS) transition and LRS to HRS transition.



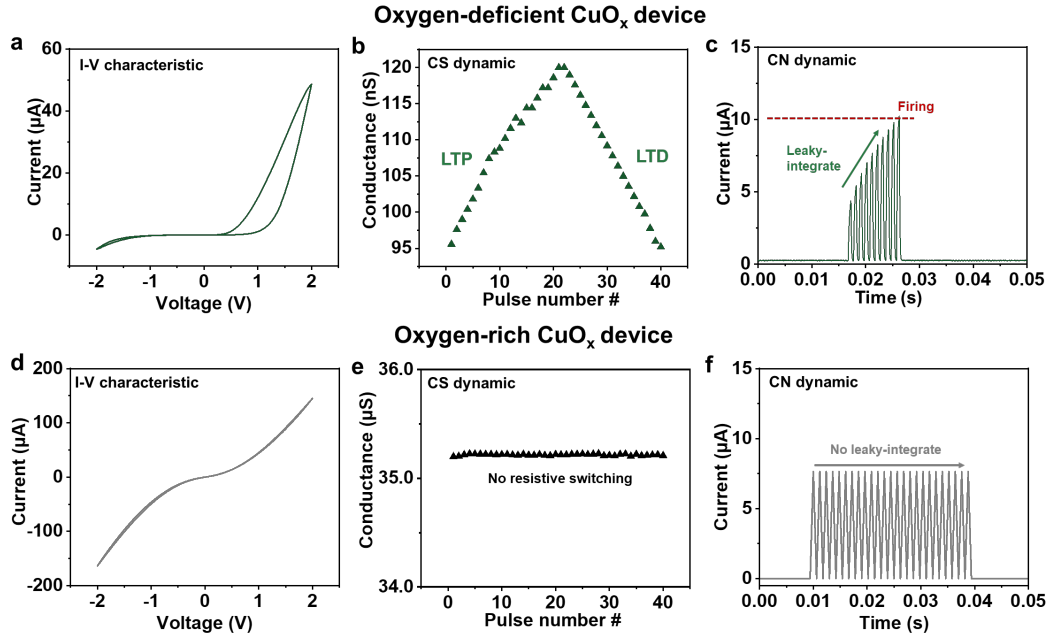
Supplementary Fig. 24 | Retention of 10 randomly selected UANV devices in CS dynamic with read voltage of 10 mV. To assess the uniformity of the retention in CS dynamic across the device array, we randomly selected 10 devices from the wafer and retention tests were performed. The devices all exhibit consistent high resistance state retention over 3000 s, with small variation across the large-area array.



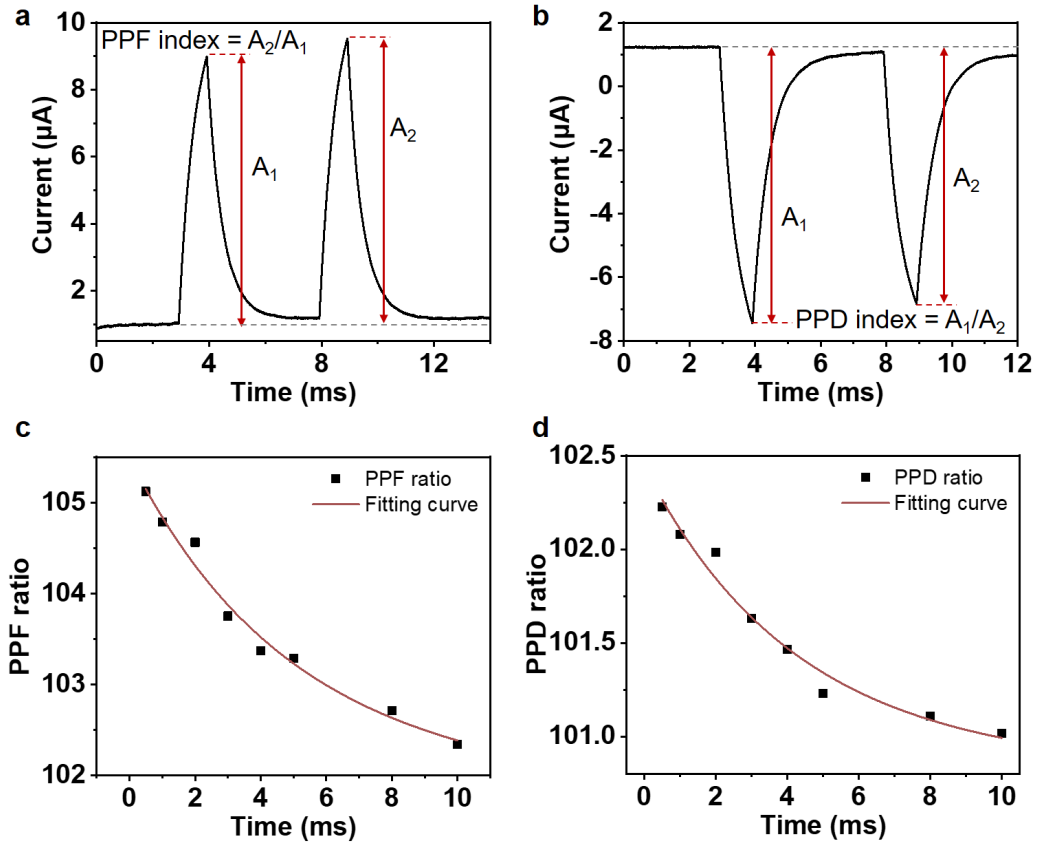
Supplementary Fig. 25 | Retention of UANV device in CS dynamic over 10 hours and extrapolation to 10 years.



Supplementary Fig. 26 | Narrow scans of (a) Cu 2p and (b) O 1s spectrum of the oxygen-deficient CuO_x thin films. Narrow scans of (c) Cu 2p and (d) O 1s spectrum of the oxygen-rich CuO_x thin films.



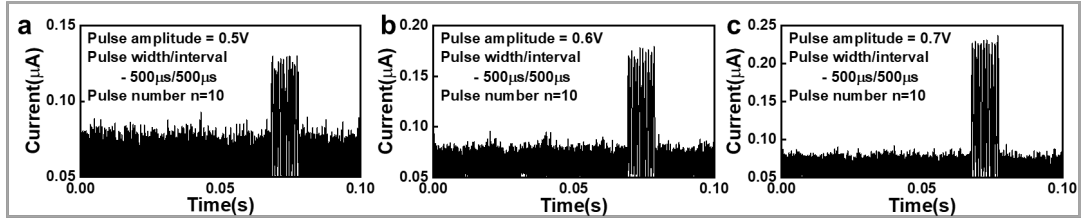
Supplementary Fig. 27 | (a) I-V characteristics, (b) CS and (c) CN dynamics in oxygen-deficient devices. (d) I-V characteristics, (e) CS and (f) CN dynamics in oxygen-rich devices.



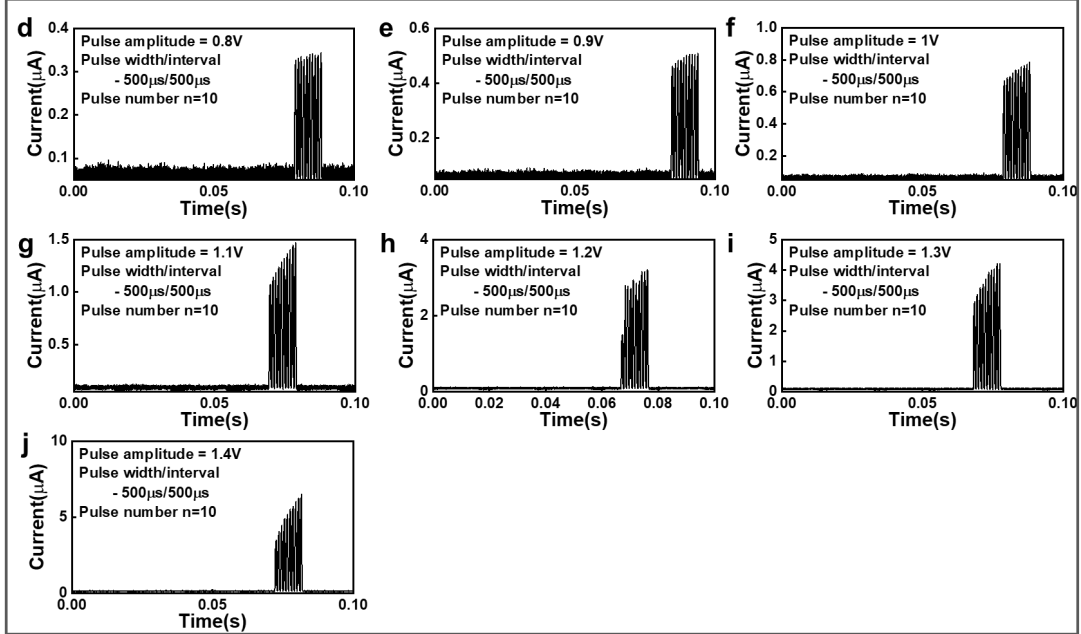
Supplementary Fig. 28 | Paired-pulse facilitation (PPF) and Paired-pulse depression (PPD) in CN dynamics. (a) PPF, where a pair of light pulses was applied

(the input voltage, pulse width and time interval between pulses (Δt) are 1.5 V, 1 ms, and 0.5-10 ms, respectively) with $V_{read} = 0.5$ V. (b) PPD, where a pair of voltage pulses was applied (the input voltage, pulse width and Δt are -1.5 V, 1 ms, and 0.5-8 ms, respectively) with $V_{read} = 0.5$ V. (c) Electrical PPF ratio as a function of Δt , defined as A_2/A_1 , where the red line represents fitting results using the double exponential decay function. (d) Electrical PPD ratio as a function of Δt , defined as A_1/A_2 , where the red line represents fitting results using the double exponential decay function. The PPF and PPD ratios exhibit a decaying exponential relation with increasing Δt , and can both be modelled by a biexponential decay equation. τ_1 and τ_2 for PPF are extracted as 4.65 ms and 87.93 ms, respectively. τ_1 and τ_2 for PPD are extracted as 4.16 ms and 167.08 ms, respectively.

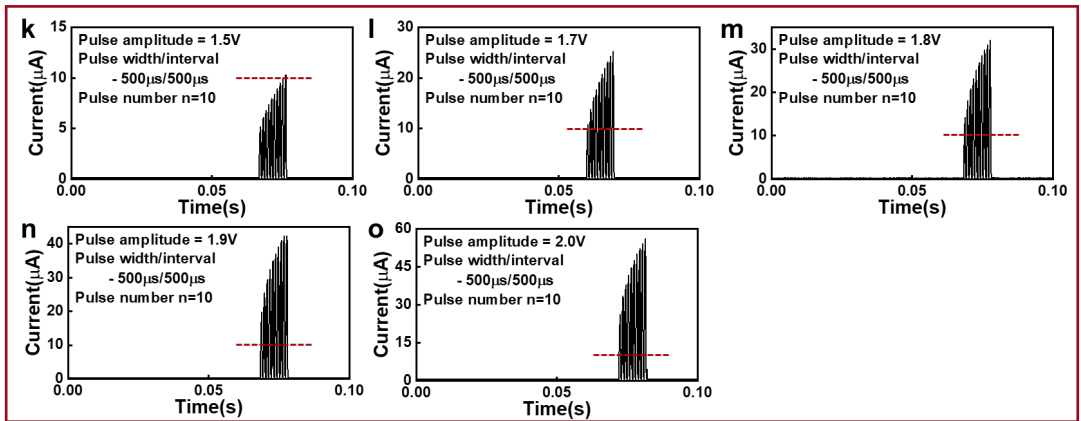
No integration and fire



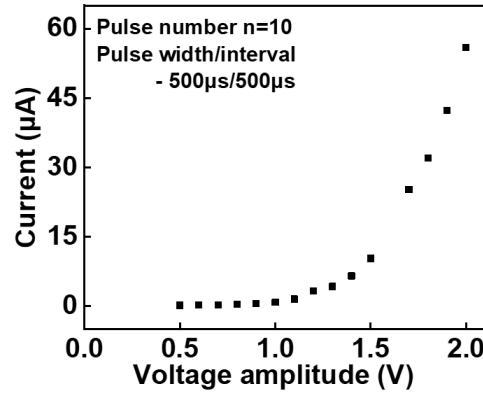
Integration without fire



Integration and fire

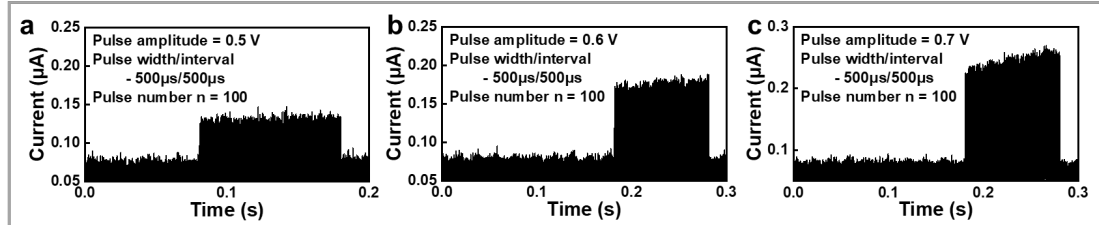


Supplementary Fig. 29 | CN dynamic characteristics with different pulse amplitudes (0.5-2 V) and identical pulse number. Pulse width, interval and number are fixed at 500 μs , 500 μs and 10, respectively. (a)-(c) No integration and firing occur when the pulse amplitude is 0.5 V-0.7 V. (d)-(j) Integration and no firing occur when the pulse amplitude is 0.8 V-1.4 V. (k)-(o) Integration and firing occur when the pulse amplitude is from 1.5 V-2 V.

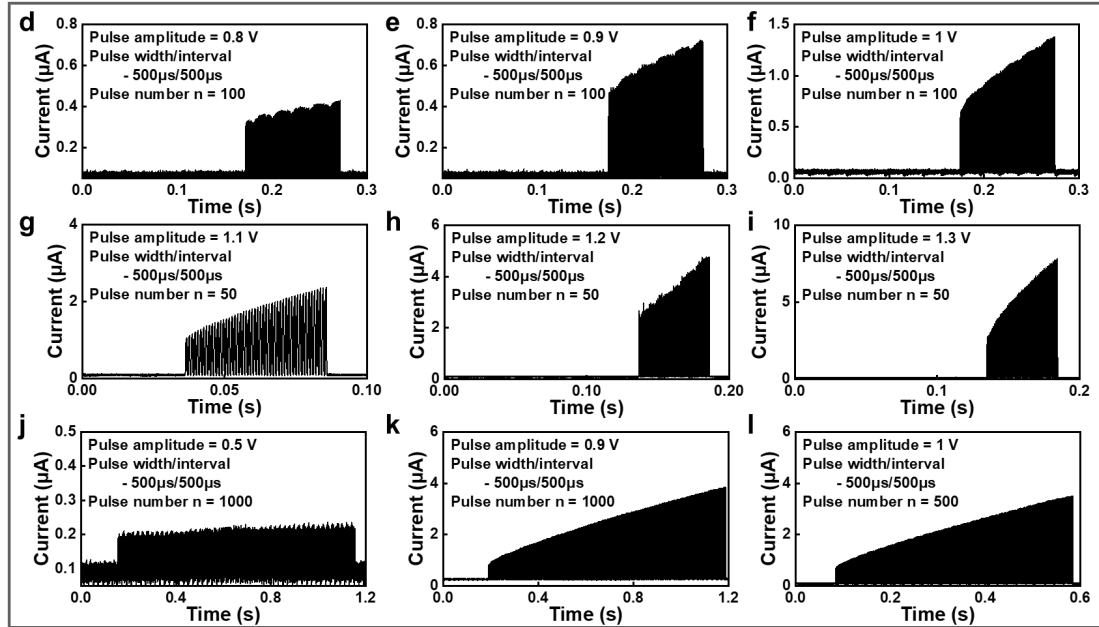


Supplementary Fig. 30 | Output current of the UANV device in CN dynamic as a function of pulse amplitude. The pulse width, interval and number are fixed at $500\mu\text{s}$, $500\mu\text{s}$ and 10, respectively. Current is extracted after the 10th pulse.

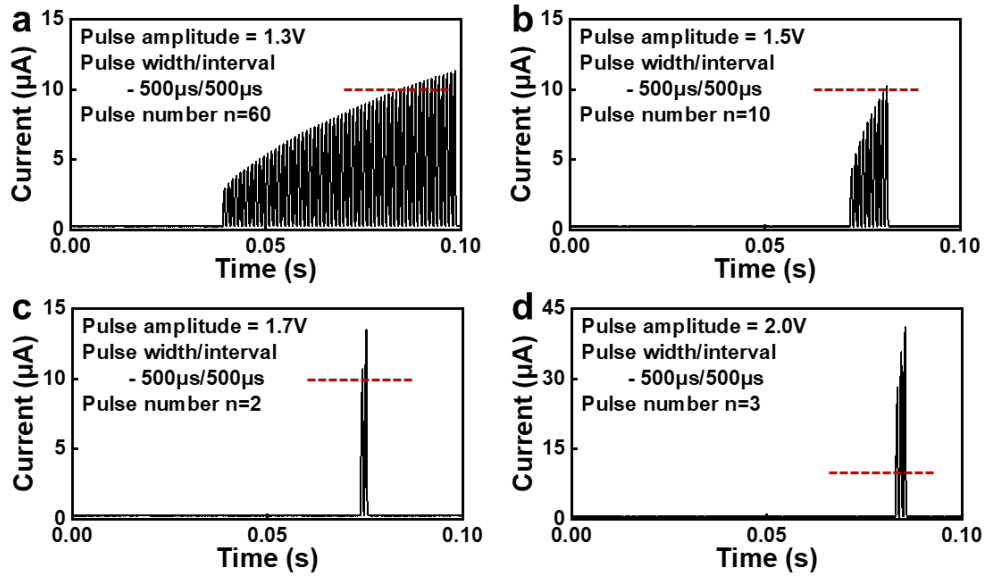
No integration and fire



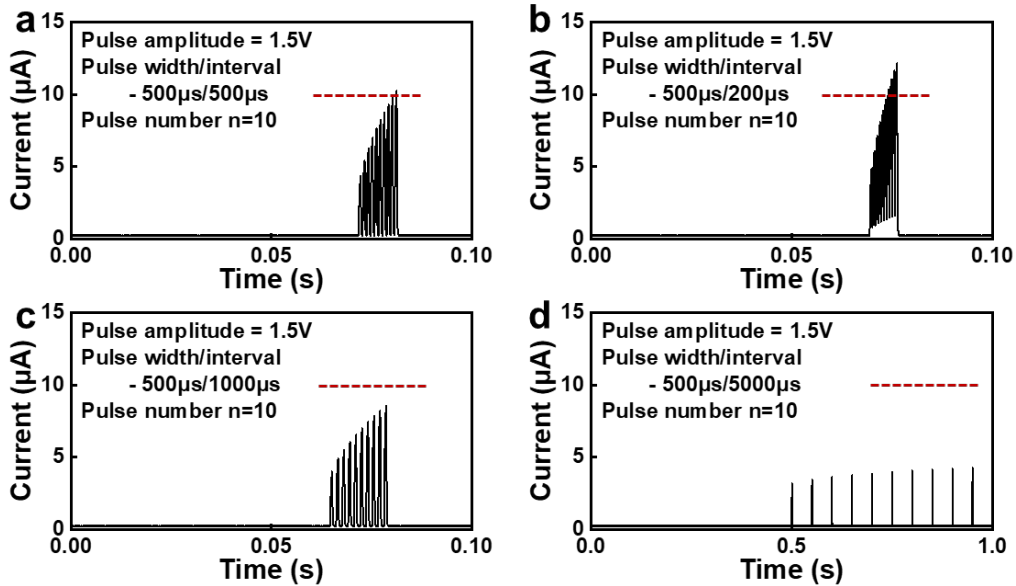
Integration without fire



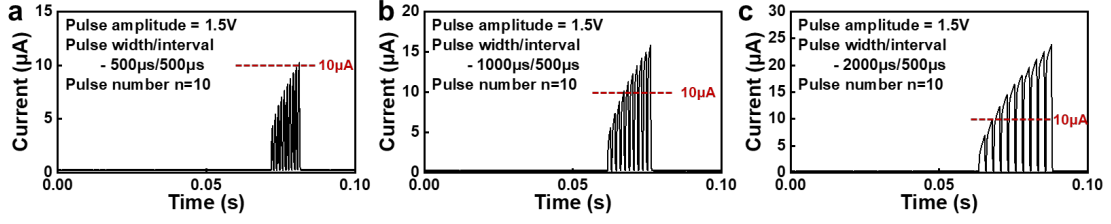
Supplementary Fig. 31 | CN dynamic characteristics with different pulse numbers ($n = 50/100/500/1000$) and pulse amplitudes (0.5 V-1.3 V): no firing. (a)-(c) no integration and fire, (d)-(l) while there is integration observed, no firing occurs when the pulse amplitude and number are smaller than a threshold value.



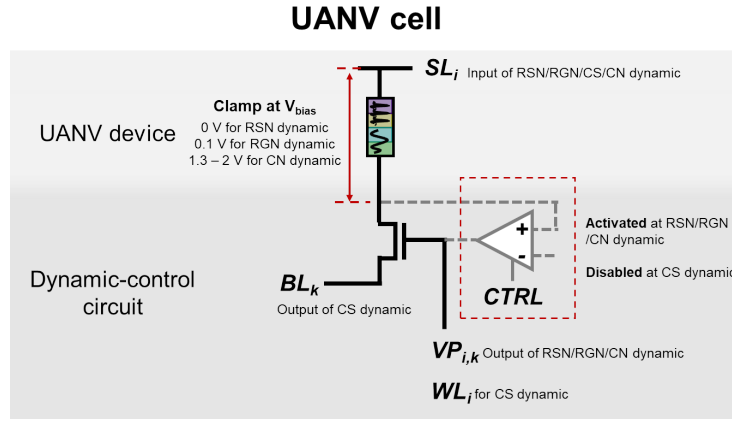
Supplementary Fig. 32 | CN dynamic characteristics with different pulse numbers ($n = 2/3/10/60$) and pulse amplitudes (1.3 V-2 V): firing. Examples of conditions that cause firing with different pulse amplitudes and numbers. Pulse width/interval is fixed at 500 μs/500 μs. (a) pulse amplitude = 1.3 V; pulse number $n = 60$. (b) pulse amplitude = 1.5 V; pulse number $n = 10$. (c) pulse amplitude = 1.7 V; pulse number = 2. (d) pulse amplitude = 2.0 V; pulse number $n = 3$.



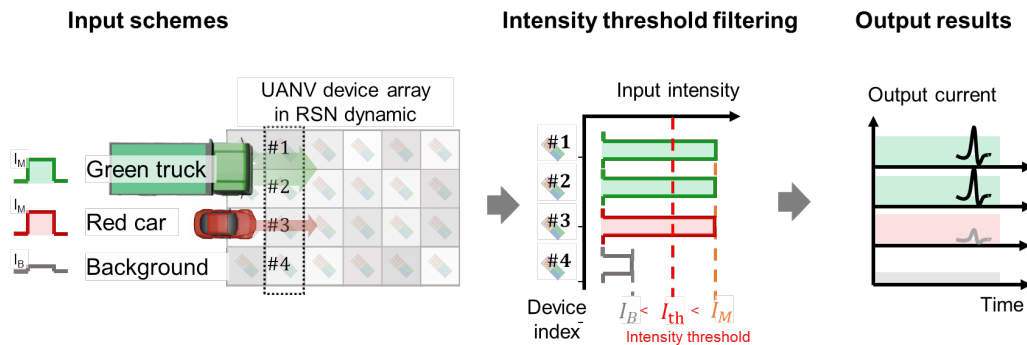
Supplementary Fig. 33 | Pulse frequency-dependent CN dynamics. The pulse width, pulse number, and pulse amplitude are 500 μs, 10, and 1.5 V, respectively, with intervals of 500/200/1000/5000 μs shown in (a)-(d), respectively.



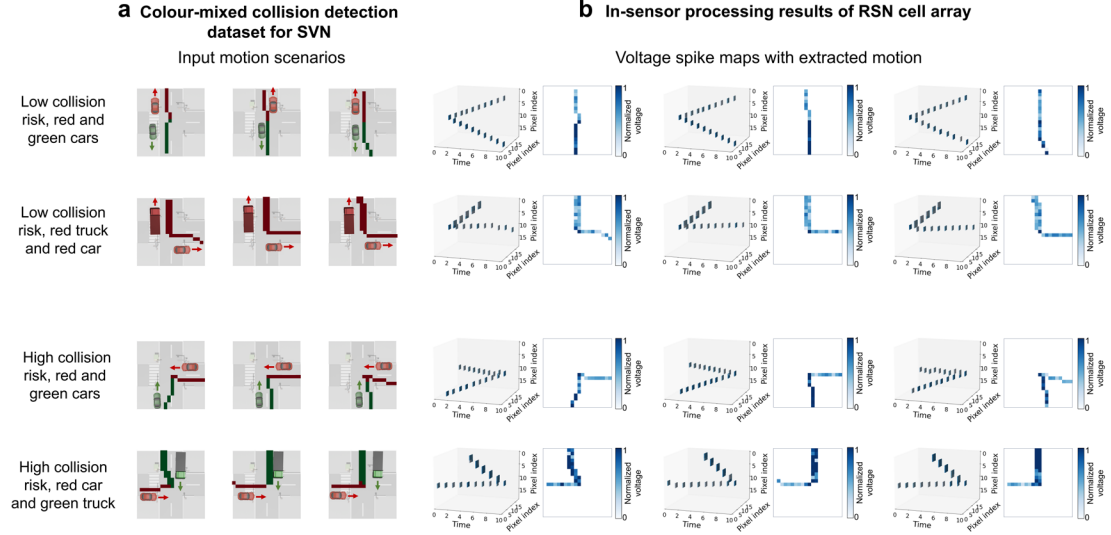
Supplementary Fig. 34 | Pulse width-dependent CN characteristics. Pulse amplitude, interval and number are fixed at 1.5 V, 500 μs and 10, respectively. Device responses using pulse widths of 500/1000/2000 μs are shown in (a)-(c), respectively.



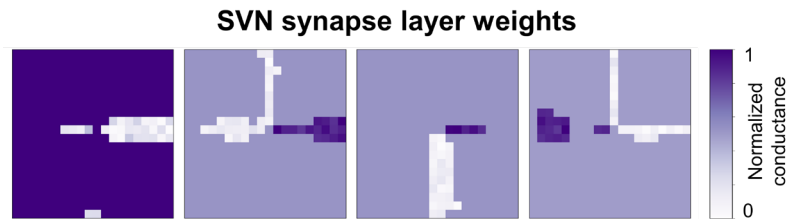
Supplementary Fig. 35 | Configuration and operation of four dynamics (RSN, RGN, CS and CN dynamics) in the ultra-adaptive cell. In RSN, RGN, and CN dynamics, the dynamic-control circuit is reconfigured to a voltage clamp for desired device biasing conditions through a negative feedback loop, while simultaneously performing current-to-voltage conversions for UANV device readout. In CS dynamic, the dynamic-control circuit is reconfigured as an access transistor with the amplifier disabled to form a 1T1R crossbar-like connection.



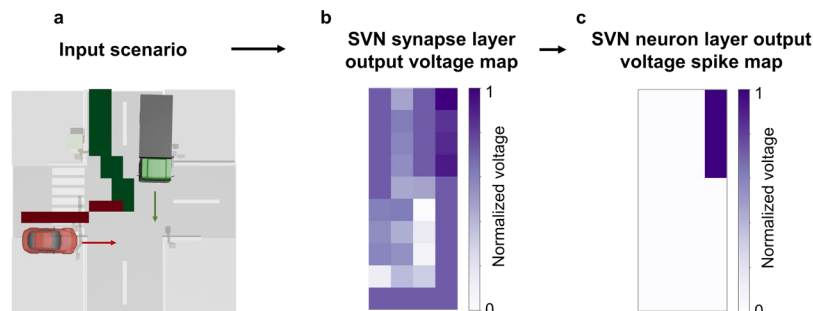
Supplementary Fig. 36 | Spiking in-sensor processing scheme in an RSN dynamic array. Illustration of the event-based colour-mixed motion extraction and filtering, and the filtering scheme based on device wavelength-dependent LIF spiking characteristics with intensity-based threshold.



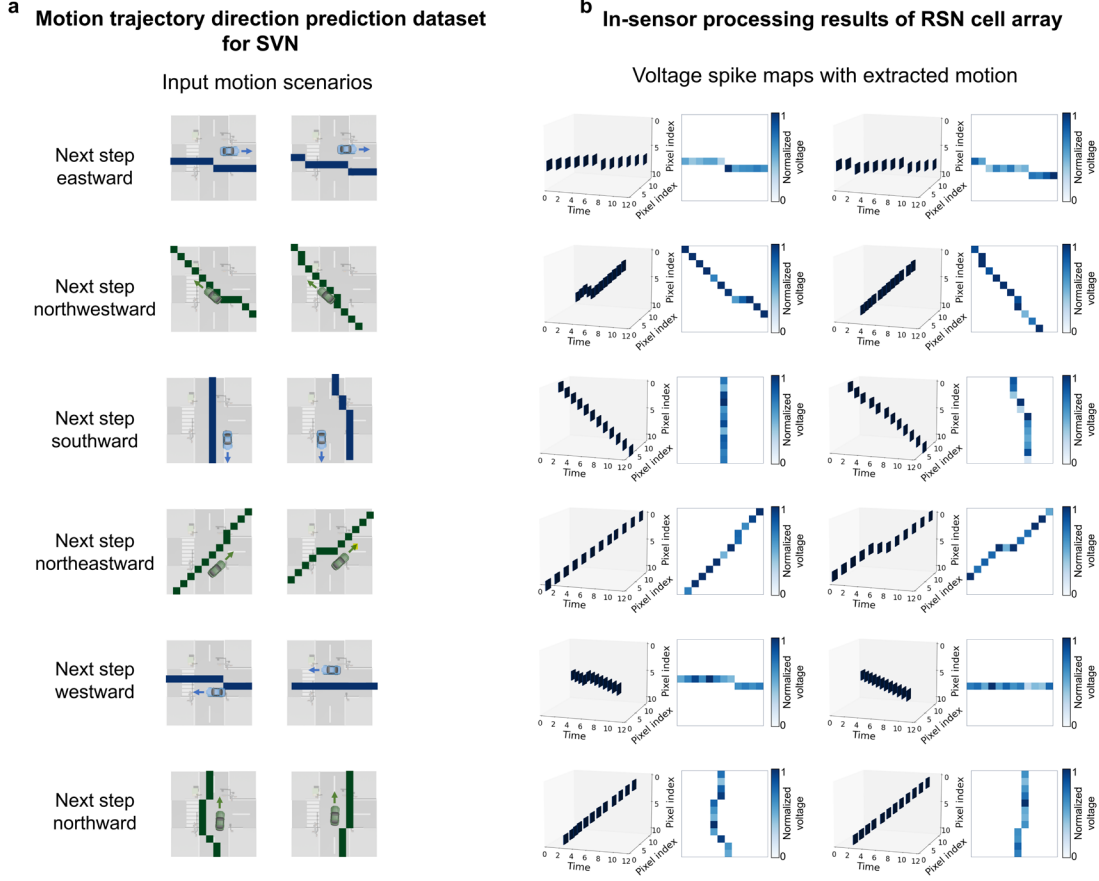
Supplementary Fig. 37 | Colour-mixed collision detection dataset and in-sensor processing results in scenario 1. (a) The colour-mixed collision detection datasets are in the form of colour-mixed motion trajectory images. They are categorized into four types of collision risk scenarios, representing two low-risk and two high-risk situations (situation 1: low risk, red and green cars; situation 2: low risk, red truck and red car; situation 3: high risk, red and green cars; situation 4: high risk, red car and green truck). Each scenario is represented by a sequence of 10 consecutive motion steps. A total of 649 motion scenarios were used to train the spiking visual network (SVN), while 151 motion scenarios were reserved for testing. (b) The corresponding in-sensor processing results generated by the RSN cell array consist of four types of spike map patterns. Each spike map pattern comprises sequences of 10 spike maps, with each spike map having a resolution of 20×20 pixels.



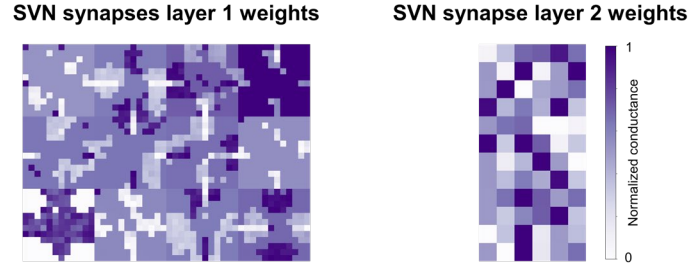
Supplementary Fig. 38 | Weights of SVN synapse layer represented by CS cell array conductance for scenario 1.



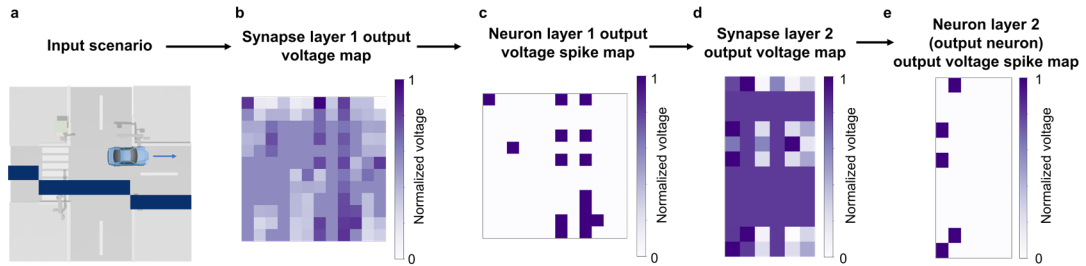
Supplementary Fig. 39 | Example of SVN processing in scenario 1. (a) An input sample from the test dataset. (b) Output voltage map of the CS cell array (synapse layer of the SVN). (c) Output voltage spike map of the CN cell array (neuron layer of the SVN).



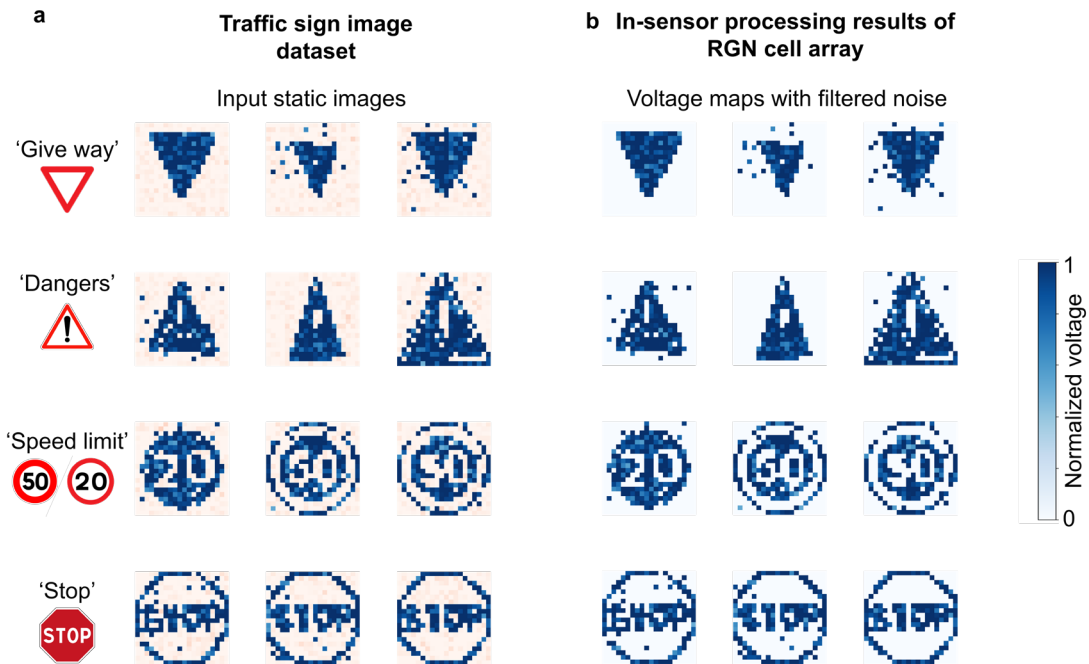
Supplementary Fig. 40 | Motion trajectory direction prediction dataset and in-sensor processing result in scenario 2. (a) The motion trajectory direction prediction dataset comprises motion trajectory images of a target vehicle, classified into six scenario types corresponding to subsequent motion directions, including north, south, east, west, northwest, and northeast. Each scenario is represented by a sequence of 12 consecutive motion steps. The dataset includes 960 motion scenarios for training the SVN, with the remaining 240 motion scenarios for testing the model. (b) In-sensor processing results of RSN cell array, corresponding to six categories of voltage spike map patterns. Each voltage spike map pattern consists of a sequence of 12 voltage spike maps, each with a resolution of 12×12 pixels.



Supplementary Fig. 41 | Weights of SVN synapse layers represented by CS cell array conductance for scenario 2.

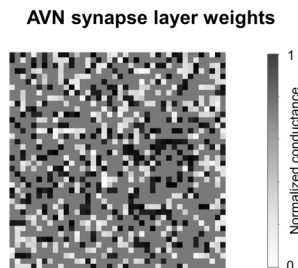


Supplementary Fig. 42 | Example of SVN processing in scenario 2. (a) A sample input taken from the test dataset. (b) The output voltage map of the CS cell array (synapse layer 1 of the SVN). (c) The output voltage spike map of the CN cell array (neuron layer 1 of the SVN). (d) The output voltage map of the CS cell array (synapse layer 2 of the SVN). (e) The output voltage spike map of the CN cell array (neuron layer 2 (output neurons) of the SVN).

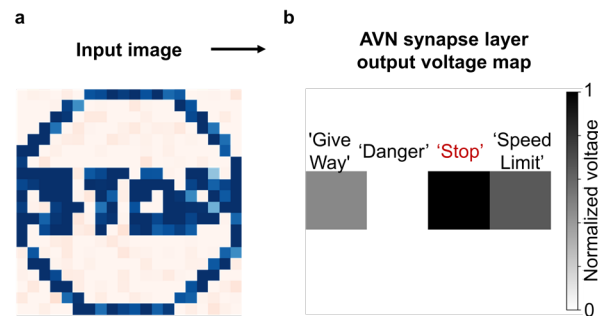


Supplementary Fig. 43 | Traffic sign image dataset and in-sensor processing result in scenario 3. (a) The traffic sign image dataset consists of static images of traffic signs,

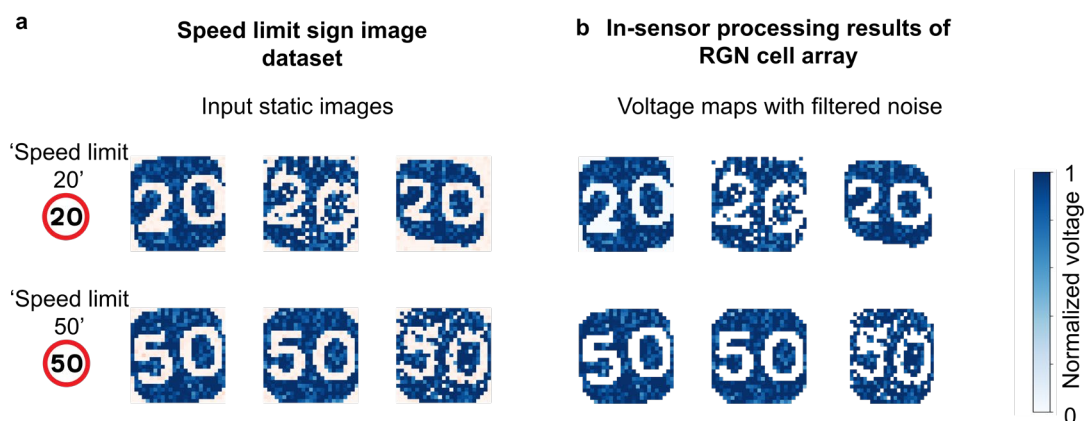
categorized into four types: 'Give Way', 'Danger', 'Speed Limit', and 'Stop'. Each image has a resolution of 20×20 pixels. A total of 288 images were utilized for training the non-spiking artificial network (AVN), with 72 additional images reserved for testing. (b) The corresponding in-sensor noise filtering processing results from the RGN cell array, consisting of four types of voltage map patterns.



Supplementary Fig. 44 | Weights of AVN synapse layer represented by CS cell array conductance for scenario 3.

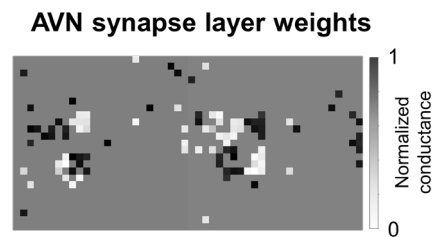


Supplementary Fig. 45 | Example of AVN processing in scenario 3. (a) An input sample from the test dataset. (b) Output voltage map of the CS cell array (synapse layer of the AVN).

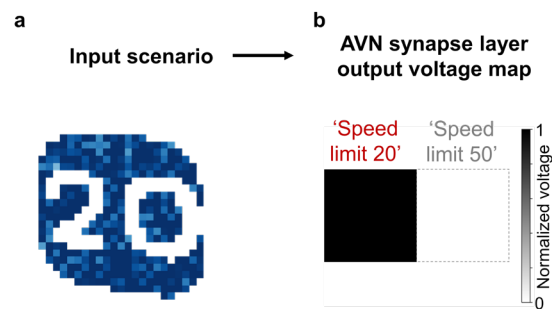


Supplementary Fig. 46 | Speed limit sign image dataset and in-sensor processing result in scenario 4. (a) The image dataset consists of static speed limit signs, categorized into two types: 'Speed Limit 20' and 'Speed Limit 50'. Each image has a resolution of 25×25 pixels. A total of 320 images were utilized for training the AVN,

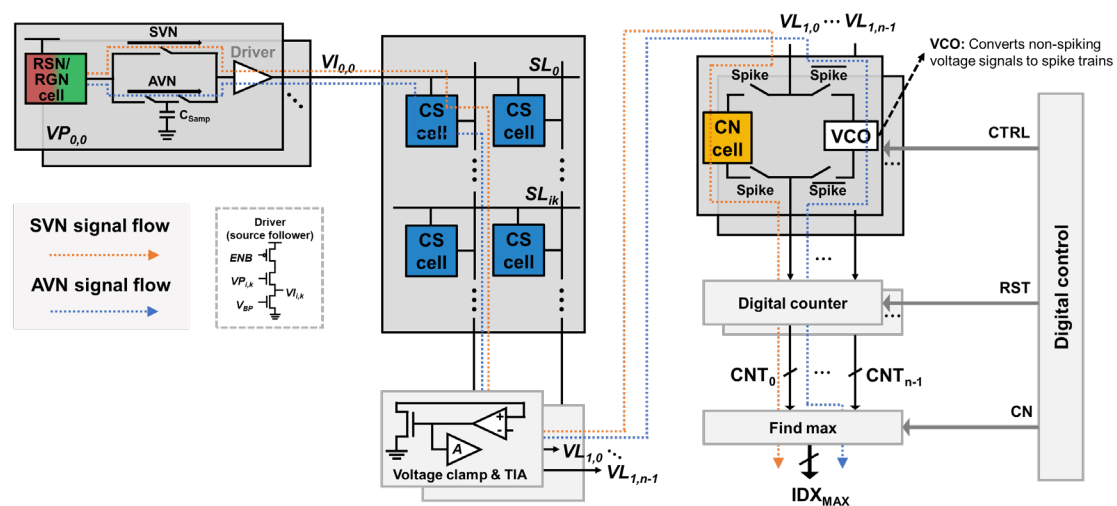
with 80 additional images reserved for testing. (b) The corresponding in-sensor noise filtering processing results, generated from the RGN cell array.



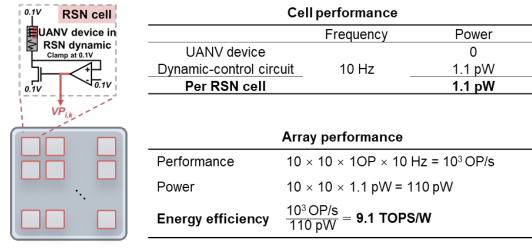
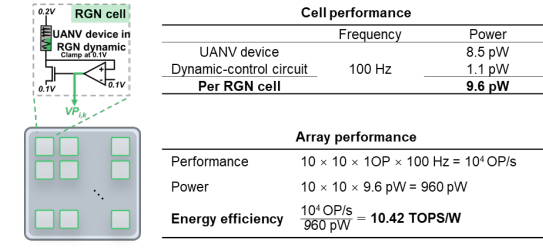
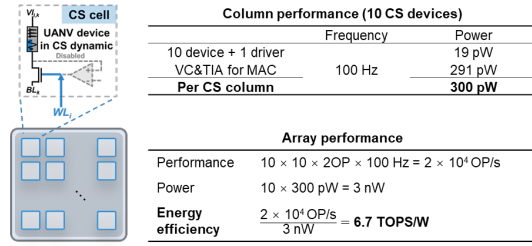
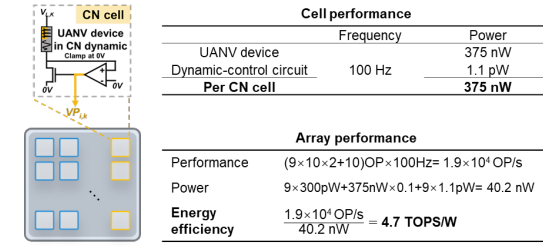
Supplementary Fig. 47 | Weights of AVN synapse layer represented by CS cell array conductance for scenario 4.



Supplementary Fig. 48 | Example of AVN processing in scenario 4. (a) An input scenario sample from the test dataset. (b) Output voltage map from the CS cell array (synapse layer of the AVN).



Supplementary Fig. 49 | System architecture and signal flow of the proposed AGVI system, including RSN/RGN cell-based sensory neurons, CS cell-based synapses, and CN cell-based neurons. The system's signal flow is reconfigurable to fully support spiking/non-spiking in-sensor/in-memory processing.

a RSN array for spiking in-sensor computing**b RGN array for non-spiking in-sensor computing****c CS array for non-spiking in-memory computing****d CS and CN array for spiking in-memory computing**

Supplementary Fig. 50 | Performance and power consumption metrics for various computing schemes in a 10×10 array, including (a) spiking in-sensor computing, (b) non-spiking in-sensor computing, (c) non-spiking in-memory computing and (d) spiking in-memory computing.

Supplementary Table 2 | Performance metrics of the SVN in Scenario 1.

Spiking visual network : Scenario 1				
Performance	Spiking in-sensor computing	RSN dynamic cell	$70 \times 70 \times 10P \times 10 \text{ Hz} = 4.9 \times 10^4 \text{ OP/s}$	$4.9 \times 10^4 \text{ OP/s}$
	Spiking in-memory computing	CS dynamic cell	$(4900 \times 4 \times 2 \times 2 + 4) \text{ OP} \times 10 \text{ Hz} = 7.84 \times 10^5 \text{ OP/s}$	$7.84 \times 10^5 \text{ OP/s}$
		CN dynamic cell	$4 \text{ OP} \times 10 \text{ Hz} = 40 \text{ OP/s}$	
		Digital circuits	$8 \text{ OP} \times 10 \text{ Hz} = 80 \text{ OP/s}$	
	Total			$8.33 \times 10^5 \text{ OP/s}$
Power	Spiking in-sensor computing	RSN dynamic cell	$70 \times 70 \times 1.1 \text{ pW} = 5.39 \text{ nW}$	5.39 nW
	Spiking in-memory computing	CS dynamic cell	$4900/10 \times 4 \times 2 \times 19 \text{ pW} + 4 \times 291 \text{ pW} = 75.64 \text{ nW}$	150.65 nW
		CN dynamic cell	$375 \text{ nW} \times 0.2 + 4 \times 1.1 \text{ pW} = 75 \text{ nW}$	
		Digital circuits	7.92 pW	
	Total			156.04 nW
Power efficiency	Spiking in-sensor computing		$4.9 \times 10^4 \text{ OP/s} / 5.39 \text{ nW}$	9.09 TOPS/W
	Spiking in-memory computing		$7.84 \times 10^5 \text{ OP/s} / 150.65 \text{ nW}$	5.21 TOPS/W
	Combined in-sensor and in-memory computing		$8.33 \times 10^5 \text{ OP/s} / 156.04 \text{ nW}$	5.34 TOPS/W

Supplementary Table 3 | Performance metrics of the SVN in Scenario 2.

Spiking visual network : Scenario 2				
Performance	Spiking in-sensor computing	RSN dynamic cell	$70 \times 70 \times 10P \times 10 \text{ Hz} = 4.9 \times 10^4 \text{ OP/s}$	$4.9 \times 10^4 \text{ OP/s}$
	Spiking in-memory computing	CS dynamic cell	$(4900 \times 12 \times 2 \times 2 + 12 \times 6 \times 2 \times 2 + 6) \text{ OP} \times 10 \text{ Hz} = 2.35 \times 10^6 \text{ OP/s}$	$2.36 \times 10^6 \text{ OP/s}$
		CN dynamic cell	$(12 + 6) \text{ OP} \times 10 \text{ Hz} = 180 \text{ OP/s}$	
		Digital circuits	$2 \text{ OP} \times 10 \text{ Hz} = 120 \text{ OP/s}$	
	Total			$2.4 \times 10^6 \text{ OP/s}$
Power	Spiking in-sensor computing	RSN dynamic cell	$70 \times 70 \times 1.1 \text{ pW} = 5.39 \text{ nW}$	5.39 nW
	Spiking in-memory computing	CS dynamic cell	$4900/10 \times 12 \times 2 \times 19 \text{ pW} + 6 \times 2 \times 19 \text{ pW} + (12+6) \times 291 \text{ pW} = 228.91 \text{ nW}$	378.93 nW
		CN dynamic cell	$2 \times 375000 \text{ pW} \times 0.2 + (12 + 6) \times 1.1 \text{ pW} = 150.02 \text{ nW}$	
		Digital circuits	11.88 pW	
	Total			384.33 nW
Power efficiency	Spiking in-sensor computing		$4.9 \times 10^4 \text{ OP/s} / 5.39 \text{ nW}$	9.09 TOPS/W
	Spiking in-memory computing		$2.36 \times 10^6 \text{ OP/s} / 378.93 \text{ nW}$	6.22 TOPS/W
	Combined in-sensor and in-memory computing		$2.4 \times 10^6 \text{ OP/s} / 384.33 \text{ nW}$	6.26 TOPS/W

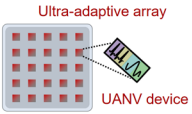
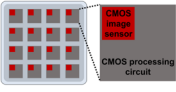
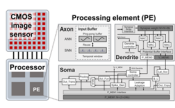
Supplementary Table 4 | Performance metrics of the non-spiking AVN in Scenario 3.

Non-spiking artificial visual network : Scenario 3				
Performance	Non-spiking in-sensor computing	RGN dynamic cell	$70 \times 70 \times 10P \times 100 \text{ Hz} = 4.9 \times 10^5 \text{ OP/s}$	$4.9 \times 10^5 \text{ OP/s}$
	Non-spiking in-memory computing	CS dynamic cell	$(4900 \times 4 \times 2 \times 2 + 4) \text{ OP} \times 100 \text{ Hz} = 7.84 \times 10^6 \text{ OP/s}$	$7.84 \times 10^6 \text{ OP/s}$
		Digital circuits	$12 \text{ OP} \times 100 \text{ Hz} = 1200 \text{ OP/s}$	
	Total			$8.33 \times 10^6 \text{ OP/s}$
Power	Non-spiking in-sensor computing	RGN dynamic cell	$70 \times 70 \times 9.6 \text{ pW} = 47.04 \text{ nW}$	47.04 nW
	Non-spiking in-memory computing	CS dynamic cell	$4900/10 \times 4 \times 2 \times 19 \text{ pW} + 4 \times 291 \text{ pW} = 75.64 \text{ nW}$	75.69 nW
		Digital circuits	$4 \times 9.3 \text{ pW} + 7.92 \text{ pW} = 45.12 \text{ pW}$	
	Total			122.73 nW
Power efficiency	Non-spiking in-sensor computing		$4.9 \times 10^5 \text{ OP/s} / 47.04 \text{ nW}$	10.42 TOPS/W
	Non-spiking in-memory computing		$7.84 \times 10^6 \text{ OP/s} / 75.69 \text{ nW}$	103.6 TOPS/W
	Combined in-sensor and in-memory computing		$8.33 \times 10^6 \text{ OP/s} / 122.73 \text{ nW}$	67.89 TOPS/W

Supplementary Table 5 | Performance metrics of the non-spiking AVN in Scenario 4.

Non-spiking artificial visual network : Scenario 4				
Performance	Non-spiking in-sensor computing	RGN dynamic cell	$70 \times 70 \times 10P \times 100 \text{ Hz} = 4.9 \times 10^5 \text{ OP/s}$	$4.9 \times 10^5 \text{ OP/s}$
	Non-spiking in-memory computing	CS dynamic cell	$(4900 \times 2 \times 2 \times 2 + 2) \text{ OP} \times 100 \text{ Hz} = 3.92 \times 10^6 \text{ OP/s}$	$3.92 \times 10^6 \text{ OP/s}$
		Digital circuits	$6 \text{ OP} \times 100 \text{ Hz} = 600 \text{ OP/s}$	
	Total			$4.41 \times 10^6 \text{ OP/s}$
Power	Non-spiking in-sensor computing	RGN dynamic cell	$70 \times 70 \times 9.6 \text{ pW} = 47.04 \text{ nW}$	47.04 nW
	Non-spiking in-memory computing	CS dynamic cell	$4900/10 \times 2 \times 2 \times 19 \text{ pW} + 2 \times 291 \text{ pW} = 37.82 \text{ nW}$	37.84 nW
		Digital circuits	$2 \times 9.3 \text{ pW} + 3.96 \text{ pW} = 22.56 \text{ pW}$	
	Total			84.88 nW
Power efficiency	Non-spiking in-sensor computing		$4.9 \times 10^5 \text{ OP/s} / 47.04 \text{ nW}$	10.42 TOPS/W
	Non-spiking in-memory computing		$3.92 \times 10^6 \text{ OP/s} / 37.84 \text{ nW}$	103.6 TOPS/W
	Combined in-sensor and in-memory computing		$4.41 \times 10^6 \text{ OP/s} / 84.88 \text{ nW}$	52.96 TOPS/W

Supplementary Table 6 | Comparisons of the representative neuromorphic vision systems with our work⁴⁻⁶.

		This work	Pixel processor array [4]	Multi-mode DVS [5]	Tianjic chip [6]
Architecture		Reconfigurable in-sensor and in-memory computing	Near-sensor computing architecture		Near-memory computing architecture
					
Reconfigurable level		Reconfigurable at device, array and system level, Neuromorphic sensing and cognitive processing reconfigurable	Only neuromorphic sensing-reconfigurable at circuit level		Only cognitive processing-reconfigurable at circuit level
Processing modes		Spiking and non-spiking neuromorphic sensing; Spiking and non-spiking cognitive processing	Only non-spiking neuromorphic sensing	Only spiking neuromorphic sensing	Spiking and non-spiking cognitive processing
Neuromorphic sensing	Power consumption per pixel	Spiking: 1.1 pW Non-spiking: 9.6 pW	Non-spiking 18.77 μW	Spiking 148.7 pW	Not supported
	Energy efficiency	Spiking: 9.1 TOPS/W Non-spiking: 8.3 TOPS/W	Non-spiking 535 GOPS/W	Spiking 87 GOPS/W	
Cognitive processing	Power consumption	Spiking: 0.15 – 0.32 μW Non-spiking: 0.08 μW *	Not supported		SNN 0.4 W ANN 0.7 W
	Energy efficiency	Spiking: 52.0 – 73.0 TOPS/W Non-spiking: 103.6 TOPS/W **			SNN 0.649 TOPS/W ANN 1.278 TOPS/W
Area efficiency		$3.96 \times 10^6 \text{ OPS/F}^2$	N/A	59.2 OPS/F ²	69.4 OPS/F ²

* The power consumption presented is based on $10\ \mu\text{m} \times 10\ \mu\text{m}$ UANV devices. The power consumption for cognitive processing is $0.15\ \mu\text{W}$ for SVN in scenario 1, $0.32\ \mu\text{W}$ for SVN in scenario 2 and $0.08\ \mu\text{W}$ for AVNs in scenarios 3 and 4, all considering the power consumption brought by the peripheral circuits. All the circuits in this vision system are designed using a commercial 180 nm CMOS Process Design Kit (PDK).

** The image size is unified as 70×70 . The energy efficiency for cognitive processing is $5.2\ \text{TOPS W}^{-1}$ @ 10 Hz to $52\ \text{TOPS W}^{-1}$ @ 100 Hz for SVN in scenario 1 (vehicle attribute-aware collision detection), $7.3\ \text{TOPS W}^{-1}$ @ 10 Hz to $73\ \text{TOPS W}^{-1}$ @ 100 Hz for SVN in scenario 2 (motion direction prediction) and $10.4\ \text{TOPS W}^{-1}$ @ 10 Hz to $103.6\ \text{TOPS W}^{-1}$ @ 100 Hz for AVN (traffic sign recognition and speed limit digit recognition).

Supplementary Note 1

The electronic properties of the CuO_x and $\text{I}_x\text{TyO}_{1-x-y}$ layers in the UANV device were uniquely tuned in order to obtain the desired multi-dynamics. X-ray Photoelectron Spectroscopy (XPS) spectra, ultra-violet photoelectron spectroscopy (UPS) and ultra-violet visible spectroscopy (UV-vis) absorbance and transmission spectra characterizations were conducted to examine the material properties and energy band structure of the stack. Supplementary Fig. 2a shows the XPS spectra of Cu 2p and O 1s of the CuO_x layer, and Sn 3d and In 3d of the $\text{I}_x\text{TyO}_{1-x-y}$ layer. The deconvoluted O 1s spectra suggest the presence of defects in the oxygen-deficient CuO_x layer. Supplementary Fig. 2b further shows the XPS spectra of Sn 3d and In 3d of the $\text{I}_x\text{TyO}_{1-x-y}$ layer. Supplementary Fig. 3 further validates the defect uniformity in the CuO_x thin film by XPS at multiple spots across the wafer, confirming the uniform distribution of defects within the large-area thin film. Thereafter, the work functions (Φ), and energy differences between E_C and E_F of the $\text{I}_x\text{TyO}_{1-x-y}$, CuO_x and Pd layers characterized via UPS are shown in Supplementary Fig. 4. Supplementary Fig. 5a – 5c shows the UV-vis absorbance and transmission spectra of the $\text{I}_x\text{TyO}_{1-x-y}$ and CuO_x layers, respectively. Supplementary Fig. 6a and 6b present the Tauc plots for bandgap extraction. The CuO_x and $\text{I}_x\text{TyO}_{1-x-y}$ layers have extracted bandgap energies of 2.3 eV and 2.4 eV, respectively. According to the UPS and UV-vis spectra, the energy band diagram of the device is deduced and shown in Supplementary Fig. 7. This energy band structure is instrumental for realizing the concurrent presence of the four dynamics associated with the device.

Supplementary Note 2

The UANV device exhibits a photovoltaic effect, as shown in Supplementary Fig. 8a and b. The device exhibits an open-circuit voltage V_{oc} of 32 mV and a short-circuit current I_{sc} of 5 nA under the $0.37\ \mu\text{W}/\mu\text{m}^2$ 450 nm light illumination. Under light illumination, the photogenerated electrons in the CuO_x layer tend more to move toward

and be collected by the $\text{I}_x\text{T}_y\text{O}_{1-x-y}$ electrode, while the photogenerated holes are collected by the Pd electrode, therefore producing I_{sc} , contributing to the baseline current in the RSN dynamic under zero bias.

Supplementary Note 3

Supplementary Fig. 12 illustrates the four dynamics under these humidity conditions. In Supplementary Fig. 12a and b, the RSN and RGN dynamics are shown under varying humidity. These results demonstrate that the devices maintain highly stable photoresponsive LIF spiking characteristics (Supplementary Fig. 12a) and light-tuneable nonlinear short-term temporal dynamics (Supplementary Fig. 12b) across the measured humidity range, confirming their functional robustness under humidity variations. The slightly reduced photoresponse current for both RSN and RGN dynamics in the 0%-20% RH range can be attributed to reduced trap sites caused by water molecules. Both RSN and RGN dynamics are closely related to the interfacial trap sites and bulk trap sites in CuO_x . Water molecules can indirectly introduce trap sites in oxides by reacting with oxide ions to form hydroxyl and protons, which creates additional trap sites⁷⁻¹⁰. Therefore, when humidity levels decrease below 10 %, the reduced trap sites lead to a degradation of the performance in the RSN and RGN dynamics.

Supplementary Fig. 12c illustrates the CS dynamics under varying humidity conditions. The long-term potential (LTP)/ long-term depression (LTD) switching characteristics remain stable within the 40-75% RH range. When humidity decreases below 20% RH, the required programming voltage increases significantly from 0.5 V to 1.5 V. Further reduction to 10% and 0% RH leads to a notable degradation of the on/off ratio under the programming voltage of 1.5 V. This phenomenon correlates with the switching mechanism dominated by O^{2-} ions migration-controlled $\text{I}_x\text{T}_y\text{O}_{1-x-y}/\text{CuO}_x$ interfacial barrier. The observed humidity dependence likely stems from reduced O^{2-} ions mobility under dehydrated conditions, as water molecules normally enhance ion diffusion through proton/oxygen provision in the oxide matrix^{8,9,11,12}. The presence of adsorbed water molecules, therefore, effectively lowers operational voltages in CS mode.

The CN dynamic presents a similar phenomenon to that in the CS dynamic, as illustrated in Supplementary Fig. 12d. The operational mechanism in CN mode primarily involves barrier height modulation through mobile O^{2-} ions redistribution and electron trapping/ de-trapping processes at the CuO_x trap sites. When the humidity drops below 20% RH, the leaky-integrate process is weakened, mainly attributed to the reduced mobility of O^{2-} ions and reduced density of available trap sites.

In summary, water molecules positively influence both dynamics through two synergistic effects: (1) enhancing ionic conductivity by facilitating O^{2-} ion migration, and (2) maintaining functional trap site density. Notably, the device maintains robust performance across a broad humidity spectrum (20-75% RH), demonstrating practical environmental useability.

Supplementary Note 4

When the incident light interacts with the CuO_x layer, electron-hole pairs are generated throughout the layer, of which only the portion of electron-hole pairs near both interfaces (in the space charge region) is dynamically swept by the built-in electric field. Part of the generated electrons gets swept across to the $I_xT_yO_{1-x-y}$ electrodes, forming the baseline current. Meanwhile, the rest of the generated electrons first start to fill the inverted triangular well trap, which are subsequently funnelled down to the interface trap states below E_c . The accumulation of electrons at the interface trap states causes the energy band of the CuO_x to start bending in response to a net doping effect of the filled traps. This results in the gradual reduction of the effective barrier height. The time during which the effective barrier height reduces before any current spikes is defined as the integration period. The interfacial barrier height reduction process is a competition between the leaked current across the interface and the filling of the trap states. The large number of unfilled trap states at the beginning results in a faster rate of energy band bending, and then starts to slow down when the empty trap states start to reduce. When the number of trapped electrons reaches a threshold, the E_f of $I_xT_yO_{1-x-y}$ layer gets pulled down far enough below the E_f of CuO_x , and together with an effective reduction of the interfacial barrier height for the onset of electron tunnelling to occur. The start of the electron tunnelling results in the current spike of the device. At that instance, the continuously photoexcited electrons elevate above E_c in the triangular well trap and with a small enough barrier seen, they undergo a Fowler-Nordheim tunnelling process into the $I_xT_yO_{1-x-y}$ electrode, causing a sudden rush of current in the form of current spikes.

Supplementary Note 5

Supplementary Fig. 13-14 further shows the systematic studies of photoresponsive LIF spiking characteristics under different voltage biases. Overall, under the positive bias, the spiking current is smaller compared with that under the 0 V bias and increases with the increased voltage bias from 0.005 V to 0.02 V. When the voltage bias increases to 0.04 V, no firing spike is observed. At the negative bias, the spiking current under -0.005 V is larger than that under 0V bias and decreases with the voltage bias varying from -0.005 V to -0.01 V. Till a more negative bias of -0.02 V, the firing is then

terminated.

The output current under the voltage bias is constituted by the spiking current and the baseline photocurrent, which originates from the charging/discharging of the electrons at the $\text{CuO}_x/\text{I}_x\text{TyO}_{1-x-y}$ interfacial trapping states and the photocarrier transport (Supplementary Fig. 14). Under the positive bias, the electron barrier seen from CuO_x to $\text{I}_x\text{TyO}_{1-x-y}$ will be reduced, thereby enhancing the migration of photogenerated electrons towards the $\text{I}_x\text{TyO}_{1-x-y}$ electrode under the electric field and weakening the photogenerated electron injection into the trapping sites at the $\text{CuO}_x/\text{I}_x\text{TyO}_{1-x-y}$ interface. Thus, these result in smaller spiking current and larger baseline photocurrent at a small positive voltage bias (0.005 V to 0.02 V) compared to the case under 0 V voltage bias. Moreover, as a larger voltage bias of 0.04 V is applied, the conduction band of CuO_x is slightly above that of $\text{I}_x\text{TyO}_{1-x-y}$, resulting in that the vast majority of photogenerated electrons generated in the CuO_x tend to move towards the $\text{I}_x\text{TyO}_{1-x-y}$ instead of injecting into the trapping sites. Thus, the firing is terminated with no firing spike observed.

As a small negative voltage is applied to the $\text{I}_x\text{TyO}_{1-x-y}$ electrode, the electron barrier at the $\text{CuO}_x/\text{I}_x\text{TyO}_{1-x-y}$ interface (seen from CuO_x to $\text{I}_x\text{TyO}_{1-x-y}$) increases, thereby enhancing photogenerated electron injection into the trapping sites at the $\text{CuO}_x/\text{I}_x\text{TyO}_{1-x-y}$ interface, as well as enhancing the migration of photogenerated electrons toward Pd electrode under the electric field. These resulted in a larger spiking current and more negative baseline photocurrent (higher absolute value of the output current) at a voltage bias of -0.005 V compared to that under 0 V voltage bias. With a more negative voltage bias ($V_{\text{bias}} < -0.005$ V), more photoexcited electrons are collected by the Pd electrode, while fewer photogenerated electrons are injected into the trapping sites, resulting in a smaller spiking current compared to that under -0.005 V and more negative baseline photocurrent. Finally, when a higher voltage bias of -0.02 V was applied, most of the photogenerated electrons were collected by the Pd electrode, resulting in the termination of firing.

Supplementary Note 6

The temperature-dependent RSN dynamic measurements at temperatures of 240 K, 270 K, 300 K, 330 K and 350 K are shown in Supplementary Fig. 16a-e. When the temperature is lower than 273 K (Supplementary Fig. 16a), no photo-spiking behaviour is observed, attributed to the lower free carrier concentration and thermal energy of the carrier under the low temperature. At high temperatures (> 350 K, Supplementary Fig. 16e), the scattering process begins to dominate, which could contribute to noise, masking out the possible dynamics. Therefore, no photo-spiking was observed in these two cases.

At 273 K to 330 K (Supplementary Fig. 16b-d), the device functions normally with photoresponsive spiking behaviours. While the spiking amplitudes and integration time nearly remain unchanged within the temperature range (Supplementary Fig. 16g and h), we see a more obvious reduction of pulse width for the device from 5.18 ± 0.5 ms to 4.03 ± 0.12 ms as the temperature goes up from 273 K to 330 K (Supplementary Fig. 16i). This observation is also well consistent with our proposed photo-spiking mechanism as described in Supplementary Note 4. As the electron trapping at the interface undergoes no significant change within the small temperature range, the spiking current amplitude and integration time exhibit minimal variation. On the other hand, the spiking width is defined by the temporal interval spanning from the initiation of FN tunnelling to the complete discharge of all trapped electrons. At a higher temperature, the discharging and tunnelling process is further aided by the thermionic emission of high-energy carriers, resulting in a quicker discharge time and shortened spiking period, which agrees well with observations.

Supplementary Note 7

Radio frequency (RF) sputtering depositions with different oxygen partial pressures are employed to deposit CuO_x thin films with different oxygen stoichiometries. Specifically, oxygen-rich CuO_x films were deposited using an Ar/O_2 gas mixture with a 5:1 ratio, while oxygen-deficient CuO_x films were deposited in a pure Ar environment. Supplementary Fig. 26a-d show the XPS scans of Cu 2p and O 1s in oxygen-rich and oxygen-deficient CuO_x thin films. Supplementary Fig. 26a shows the narrow scan of Cu 2p of the oxygen-deficient CuO_x thin films. Cu 2p spectrum is deconvoluted into four peaks: $\text{Cu}^+ 2p_{1/2}$ (953.1 eV), $\text{Cu}^{2+} 2p_{1/2}$ (954.4 eV), $\text{Cu}^+ 2p_{3/2}$ (933.4 eV), $\text{Cu}^{2+} 2p_{3/2}$ (934.9 eV). Supplementary Fig. 26b shows the narrow scan of the O 1s spectrum of oxygen-deficient CuO_x thin films. O 1s spectrum is deconvoluted into three peaks: O-1 (Lattice Oxygen, 530.5 eV), O-2 (Chemisorbed Oxygen, 531.6 eV) and O-3 (Physically Adsorbed Oxygen, 532.6 eV). Generally, in oxygen-deficient CuO_x thin films, a significant increase in O-2, relative to the O-1 peak, indicates the presence of oxygen vacancies. This is because oxygen vacancies can lead to changes in the surface chemistry and electronic structure, resulting in an altered distribution of oxygen species¹³. Supplementary Fig. 26c and d show the narrow scans of Cu 2p and O 1s spectra of oxygen-rich CuO_x thin films, the ratio of O-2 to O-1 is significantly lower compared to that in the oxygen-deficient CuO_x thin films, suggesting a significant decrease in oxygen vacancies in the oxygen-rich CuO_x thin film.

Supplementary Fig. 27a-f demonstrate the I-V characteristics, CS and CN dynamics in both oxygen-rich and oxygen-deficient devices. In the oxygen-rich CuO_x device, the current-voltage (I-V) characteristic curve exhibits no hysteresis, and a lower Schottky

barrier as compared to the oxygen-deficient device due to a lower Fermi level. Also, the device shows no non-volatile switching behaviour for CS dynamic, and no leaky-integrate process for CN dynamic. In contrast, our reported oxygen-deficient CuO_x device exhibits an obvious hysteresis in the I-V curve, non-volatile resistive switching behaviour in the CS dynamic, and electrical LIF spiking characteristics in the CN dynamic. Hence, these results suggest that the CS and CN dynamics are all closely related to the oxygen-deficient characteristics in our device.

Supplementary Note 8

The dynamic-control circuit comprises an NMOS transistor and a leakage-based amplifier, which is reconfigurable to enable the UANV device's four visual dynamics (RSN, RGN, CS, and CN). For the RSN, RGN and CN dynamics, the dynamic-control circuit is reconfigured to a voltage clamp for desired device biasing conditions through a negative feedback loop (0 V for RSN dynamic, 0.04-0.1 V for RGN dynamic, 1.3-2 V for CN dynamic). During voltage clamping, the UANV device readout is simultaneously performed since the dynamic-control circuit can also be considered a transimpedance amplifier (TIA) for current-to-voltage conversions. For the CS dynamic, the dynamic-control circuit is reconfigured as an access transistor with the amplifier disabled to form a 1T1R crossbar-like connection for efficient MAC operations. Therefore, the ultra-adaptive cell ensures the array's homogeneity across RSN, RGN, CS, and CN dynamics, maintaining a homogeneous array structure for the ultrafine-grained reconfigurability and significantly reducing the complexity and area footprint for large-scale array integration.

Supplementary Note 9

In scenario 1, the UANV device array is reconfigured into an RSN dynamic array as the input sensory spiking neurons for the spiking in-sensor processing, and a CS dynamic array and a CN dynamic array as the synapses and output neurons for the SVN-based in-memory computing for event-based colour-mixed motion trajectory extraction and collision detection. The RSN dynamic array first extracts and encodes the continuous colour-mixed motion information (0-t) of two target vehicles (cars), including the trajectories and attributes (colour: red/green, type: truck/car) of two target vehicles, while filtering out the noisy static background based on the schemes depicted in Supplementary Fig. 36, resulting in the output spike maps (0-t) with extracted and encoded motion trajectories. Specifically, the RSN dynamic array can extract the vehicle movement trajectory and filter the static dark background information and simultaneously encode the motion trajectory information into motion event-based spiking signals according to light-intensity threshold spiking characteristics in the RSN

dynamic device. The moving vehicle with a larger-than-threshold input intensity ($I_M > I_{\text{threshold}}$) can be extracted by the RSN dynamic array, resulting in output current spikes, whereas the static dark background with a lower-than-threshold input intensity ($I_B < I_{\text{threshold}}$) can be filtered, resulting in no output current spikes. Additionally, colour information is encoded in the spike amplitude (Fig. 2e). The vehicle type is determined by the width of the trajectories encoded in the spike map. Broader trajectories correspond to trucks, while narrower ones correspond to cars (Supplementary Fig. 37a). The spike maps from the RSN dynamic array are sent to the CS dynamic array for MAC operation and the CN dynamic array for selecting the above-threshold signals and final decision-making.

Supplementary Note 10

In scenario 2, the UANV device array is reconfigured into an RSN dynamic array for the spiking in-sensor computing, a CS dynamic array and a CN dynamic array for SVN-based in-memory computing for event-based target vehicle motion trajectory extraction and accurate motion direction prediction. Each motion image includes 12 continuous motion steps (0-t). This configuration can predict the future motion direction at the 13th step out of six possibilities. As shown in Supplementary Fig. 40, the RSN dynamic array encodes the 12 continuous motion steps (0-t) in input motion into current spike signals and real-time filters the static background according to the light-intensity-threshold firing, outputting spike maps (0-t) with extracted motion trajectory. The spike maps from the RSN dynamic array are then sent to the CS dynamic array for MAC and the CN dynamic array for selecting above-threshold signals and decision-making.

Supplementary Note 11

In scenarios 3 and 4, the UANV device array is reconfigured into an RGN dynamic array, serving as the sensory non-spiking neurons for non-spiking in-sensor computing, and a CS dynamic array, which acts as the synapses for AVN-based in-memory computing, facilitating the recognition of traffic sign images and speed limit digits. The RGN dynamic array filters out background red noise since the photocurrents for noisy red pixels decay fast to the original state while the photocurrents corresponding to the target blue pixels are retained within the sampling time (See Supplementary Fig. 19). Therefore, the noise can be easily filtered, effectively enhancing the quality of the obtained image. The preprocessed traffic sign signals (voltage maps) from the RGN dynamic array are sent into the CS dynamic array for MAC. The category associated with the highest output amplitude is the final recognition result.

Supplementary Note 12

At the system level, Supplementary Fig. 49 depicts the design and implementation of the AGVI system. All the circuits in this vision system are designed using a commercial 180 nm CMOS Process Design Kit (PDK). The device power consumption was derived from experimental measurements of $10\text{ }\mu\text{m} \times 10\text{ }\mu\text{m}$ UANV devices, while the power consumption of the dynamic control circuit and peripheral circuits was obtained using Cadence Virtuoso using 180 nm technology node.

For the dynamic-control circuit, the leakage-based amplifier consumes 1.1 pW for the targeted 200 Hz bandwidth. Therefore, for a RSN dynamic cell, the total power consumption is 1.1 pW (Supplementary Fig. 50a), including a UANV device in RSN dynamic consuming 0 W and the associated control circuit consuming 1.1 pW (Supplementary Fig. 50a). For the RGN dynamic cell, the device in RGN dynamic consumes 8.5 pW and the dynamic-control circuit consumes 1.1 pW, leading to a total of 9.6 pW (Supplementary Fig. 50b). In the case of CS dynamic cells, each column (10 cells + driver) consumes 19 pW, with dynamic-control circuit consuming zero pW as it is disabled. Additionally, the voltage clamper and transimpedance amplifier (VC & TIA), shared across the 10 CS devices, consume 291 pW, resulting in a total power consumption of 300 pW (Supplementary Fig. 50c). In a CN dynamic cell, the device consumes 375 nW, and the dynamic-control circuit contributes 1.1 pW, yielding a total of 375 nW (Supplementary Fig. 50d).

For the full AGVI system, additional digital components are required. Specifically, the voltage-controlled oscillator (VCO) is responsible for converting non-spiking voltage signals into spike trains and consumes 9.3 pW. The digital counter and the find-max circuit are used for spike counting and decision-making. Their total power consumption scales with the number of decision categories: 3.96 pW for two categories, 7.92 pW for four categories and 11.88 pW for six categories.

To evaluate the overall power efficiency of the AGVI system, we first calculate the performance and power consumption metrics in the 10×10 device array for various computing schemes, including spiking in-sensor computing (Supplementary Fig. 50a), non-spiking in-sensor computing (Supplementary Fig. 50b), non-spiking in-memory computing (Supplementary Fig. 50c) and non-spiking in-memory computing (Supplementary Fig. 50d). Using these power consumption values, we further estimated the energy efficiency of the AGVI system when processing 70×70 pixel images, consistent with the reported image processing dimensions for comparison with other neuromorphic vision systems. The detailed results are summarized in Supplementary Tables 2-5, which provide comprehensive power efficiency calculations across different scenarios.

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