

Acoustic-optical information reservoir system based on triboelectric acoustic sensor tuned oxide photoelectronic neuromorphic transistor

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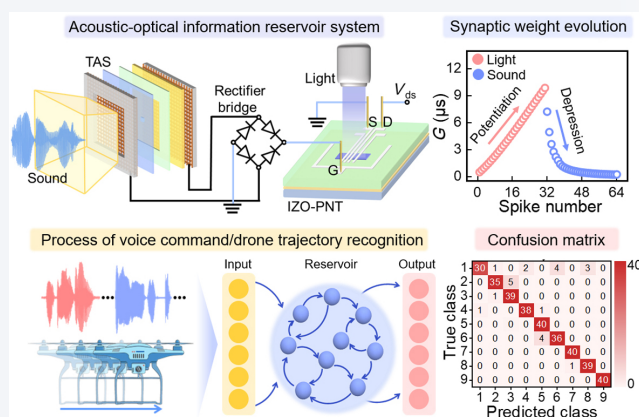
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ABSTRACT: The rapid developments of internet of things (IoT) technology have greatly promoted the evolution of human-machine interaction (HMI). Mimicking the auditory and visual mechanisms offers new possibilities for real time multimodal information processing. Here, an acoustic-optical information reservoir system (AOIRS) is proposed by integrating a triboelectric acoustic sensor (TAS) with an indium-zinc-oxide photoelectronic neuromorphic transistor. With an acoustic coupling cavity, the TAS exhibits excellent sound wave collection capacity and durability. A high sensitivity of ~ 1.1 V/dB is obtained. Thus, interesting neural activities are mimicked on the AOIRS under sound wave signals. The synaptic weight of AOIRS can be repeatedly updated by light and sound stimuli. In addition, AOIRS can act as a physical reservoir to map voice commands and drone trajectory images into high-dimensional conductance states, achieving efficient voice command and drone trajectory recognition via a multi-layer perceptron (MLP) classifier. The average testing accuracy after 200 epochs for voice command and drone trajectory is $\sim 89.8\%$ and 93.6% , respectively. The present AOIRS has great potentials in the fields of voice intelligent sensing and low-altitude industry.

KEYWORDS: triboelectric acoustic sensor, oxide photoelectronic neuromorphic transistor, acoustic-optical information reservoir system, voice command recognition, drone trajectory recognition

1 Introduction

With the rapid developments of internet of things (IoT) technology [1, 2], human-machine interaction (HMI) modes have undergone significant reformations [3, 4]. By mimicking the perceptual mechanisms of the brain, such as auditory and visual perceptions, HMI is continuously upgrading towards a more natural and intelligent mode [5, 6]. For brain nervous system, sound waves trigger vibrations in the eardrum, which are then converted into electrical signals by cochlear hair cells. Similarly, when light stimuli enter the eye, photoreceptor cells in the retina



convert light signals into electrical signals. These signals are transmitted to the brain for processing via auditory and visual nerves, respectively. Finally, auditory and visual perceptions are formed in the corresponding regions of the brain [7, 8]. Figure 1(a) schematically shows the formation of auditory and visual perceptions. Additionally, brain can synchronously integrate sound and light stimuli, enabling efficient perception and processing of environmental information [9, 10]. Inspired by the brain perceptual activities, bionic perceptual systems that can simulate brain auditory and visual perceptions can help achieve more realistic HMI experiences. Interestingly, triboelectric acoustic sensors (TASs) can be used in such perceptual systems to perceive sound information due to their unique self-powered characteristic and low cost [11–13]. Based on frictional electrification and electrostatic induction effects, it can effectively convert sound wave signals into electrical signals and exhibit a wide response range of sound frequency. However, TAS with a planar structure cannot effectively

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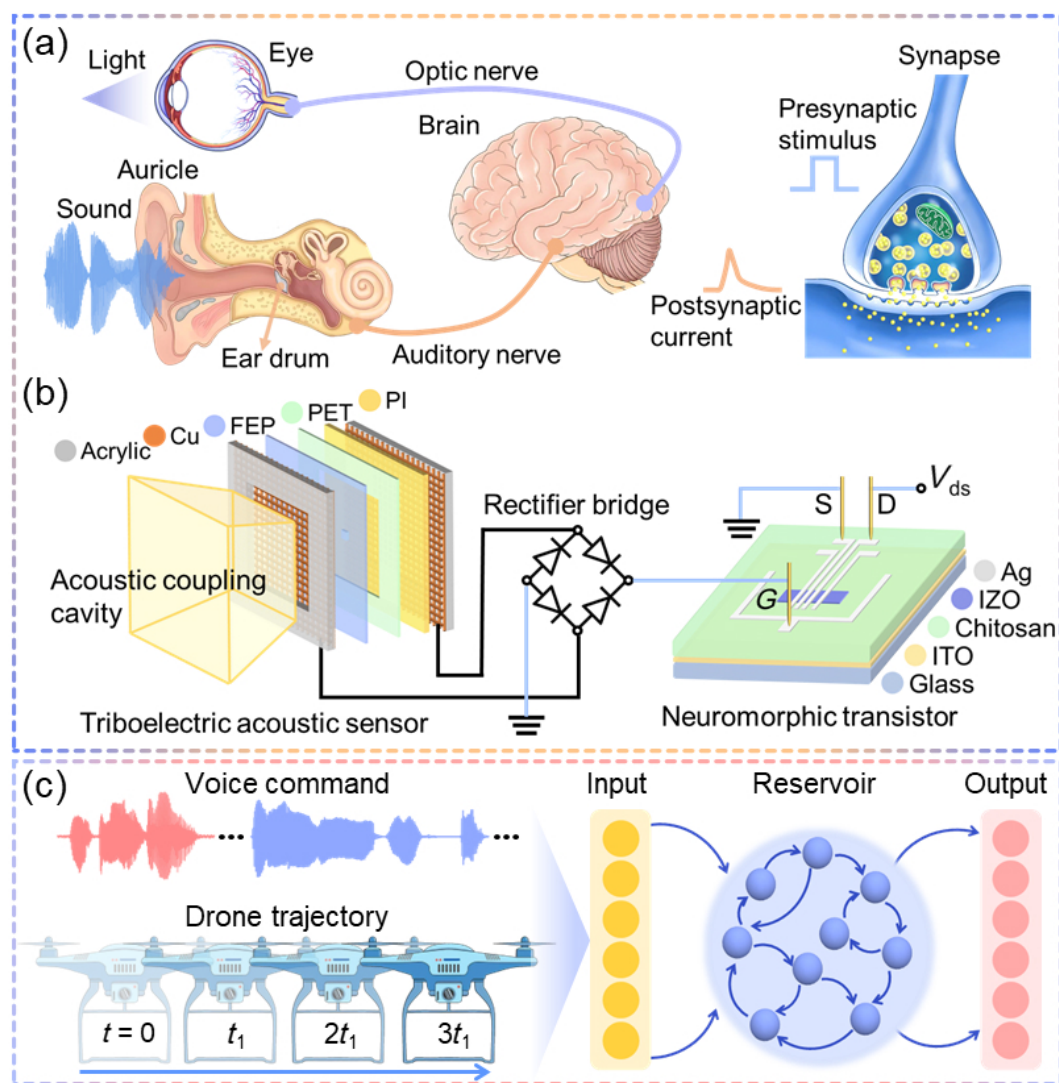


Figure 1 (a) Schematic diagram of the formation of auditory and visual perceptions. (b) Schematic diagram of AOIRS. (c) Schematic diagram of voice command/drone trajectory recognition.

capture sound wave signals when the sound source is far away from it. Fortunately, introducing an acoustic coupling cavity with a three-dimensional structure on TAS can greatly improve its ability to collect sound wave signals [14, 15]. This inspires our investigation into the highly sensitive acoustic perceptual computing system.

On the other hand, researchers have proposed neuromorphic devices, including two-terminal memristors [16–19], three-terminal transistors [20–23], optoelectronic devices [24, 25] and memtransistors [26, 27]. Under unique spiking, rich synaptic functions and advanced neuromorphic computing have been achieved. Interestingly, photoelectronic neuromorphic transistors (PNT) integrate optical perception and synaptic computing, achieving advanced neuromorphic applications, including motion trajectory perception [28], polymorphic optical information decoding [29], and simulation of polarized visual behavior [30]. It is reported that integrating triboelectric sensors with artificial neural networks enables the construction of multimodal perception system, which effectively expand perceptual dimensions and markedly enhance environmental adaptability [31, 32]. Similarly, bionic perceptual system integrating TAS with PNT is expected to simulate auditory and visual perception behaviors of the brain,

achieving real time perception and computing of auditory and optical information. As a simplified recursive neural network framework, reservoir computing (RC) has attracted great attention due to its advantages in processing complex temporal signals [33, 34]. The core of the reservoir computing is mapping the input signals into a high-dimensional feature space via nonlinear dynamic characteristics of the reservoir, optimizing the output layer weights to achieve effective processing of the input signals [35, 36]. In electrolyte gated oxide transistor, ionic/electronic interfacial coupling poses interesting interfacial dynamic process, demonstrating temporal coupling and short-term and long-term synaptic plasticity [37, 38]. With inherent nonlinear dynamic characteristic, such electrolyte gated oxide transistor is quite suitable as a physical reservoir [39, 40]. Under the assistance of a multi-layer perception (MLP) classifier [41, 42], it is expected to achieve effective classification of voice commands or images with low power consumption.

In the present work, an acoustic-optical information reservoir system (AOIRS) is proposed by integrating a TAS with an indium-zinc-oxide photoelectronic neuromorphic transistor (IZO-PNT), as shown in Fig. 1(b). With the acoustic coupling cavity structure, the

open-circuit voltage, short-circuit current, and output power density of the TAS under the sound wave signal (110 dB, 200 Hz) can reach ~ 20.4 V, ~ 3.8 μ A, and ~ 30.3 mW/m², respectively. It exhibits a high sensitivity of ~ 1.1 V/dB. It can also capture voice commands with rich features. The IZO-PNT could mimic typical synaptic behaviors under voltage and light stimuli. Thus, the AOIRS could achieve a series of neural activities. As shown in Fig. 1(c), the AOIRS can act as a physical reservoir to map voice commands and drone trajectory images into high-dimensional conductance states. Thus, efficient voice command and drone trajectory recognition can be achieved via a MLP classifier. The average testing accuracy after 200 epochs for voice command and drone trajectory reaches $\sim 89.8\%$ and 93.6% , respectively. The present AOIRS has great potentials in the fields of voice human-computer interaction and drone-related low-altitude industry.

2 Experimental

2.1 Fabrication of triboelectric acoustic sensor

Left inset of Fig. 1(b) schematically shows the structure of TAS. It is composed of hollow acrylic frames, copper meshes, fluorinated ethylene-propylene (FEP) membrane, polyimide (PI) membrane, and rectangular annular polyethylene terephthalate (PET) strip. To obtain the upper electrode, a copper mesh was attached to a hollow acrylic frame. Then, a FEP membrane with thickness of ~ 15 μ m was attached to the copper mesh to act as a friction layer. Another copper mesh was attached to another hollow acrylic frame to obtain the lower electrode. A PI membrane with thickness of ~ 40 μ m was attached to the copper mesh to act as another friction layer. Next, a rectangular annular PET strip with thickness of ~ 100 μ m was placed around and in the center of the PI membrane to act as a spacer. Then, the upper and lower parts were assembled to obtain the original device. Acoustic coupling cavity was composed of 4 identical trapezoidal PET membranes with thickness of 0.5 mm, as schematically shown in Fig. S1(a) in the Electronic Supplementary Material (ESM). It adopted a quadrangular frustum structure, featuring a square large port with a side length of 4 cm, a square small port with a side length of 2.5 cm, and a vertical height of 3 cm between the two base planes of the frustum. Finally, the acoustic coupling cavity was fixed on the original device with ultraviolet (UV) glue to obtain TAS. Figure S1(b) in the ESM shows the top-view photograph of the TAS, featuring an effective area and a total height of ~ 6.25 cm² and ~ 3.5 cm, respectively. Such acoustic coupling cavity can improve the sound wave collection capability.

2.2 Fabrication of indium-zinc-oxide photoelectronic neuromorphic transistor

Figure S2 in the ESM schematically shows the fabrication of the present IZO-PNT. First of all, chitosan solution was prepared by dissolving 2 wt.% chitosan powder and 2 wt.% acetic acid in 96 wt.% deionized water. Then, the solution was drop-coated on the conductive surface of ITO glass substrates. After drying at 45 °C for 5 h, a chitosan-based solid state electrolyte film was formed. Subsequently, IZO channels were deposited on the chitosan film by sputtering IZO target (In₂O₃:ZnO = 90 wt.%, 10 wt.%) using a metal shadow mask under pure Ar ambient. During sputtering, RF power, sputtering pressure, and Ar flow rate were set to 100 W, 0.8 Pa, and 40 sccm, respectively. Finally, Ag based source (S), drain (D), and gate (G) electrodes were deposited by thermal evaporation.

As shown in the inset of Fig. S2 in the ESM, the present IZO-PNT shares a common channel and a common coplanar gate. The channel width was fixed at 1300 μ m. While the channel length can be modulated, i.e., channel 1 with length of 200 μ m for S1/D1 and channel 2 with length of 950 μ m for S2/D2. This endows the IZO-PNT with rich functions. The chitosan solution was also drop-coated on a silicon substrate, and it can be peeled off for characterization after drying.

2.3 Characterization and electrical measurements

Thicknesses of chitosan film and size of copper mesh were characterized using scanning electron microscopy (SEM). Young's modulus (E) of the FEP membrane and PI membrane were obtained by using an INSTRON mechanical testing system (Model 5944). Surface morphologies of FEP, PI, and chitosan film were measured using atomic force microscopy (AFM). Specific capacitance of chitosan film was characterized by using an IM3533 impedance analyzer. A speaker is adopted to load sound on TAS, as shown in Fig. S1(c) in the ESM. Output performance of TAS was measured with an oscilloscope (MSO22) and a source meter (Keithley 2601B). Electrical performances of the IZO-PNT and the AOIRS were measured with a semiconductor parameter analyzer (Keithley 4200A SCS). All the electrical characterizations were performed under air relative humidity of $\sim 45\%$.

2.4 Model parameters and data preprocessing

For voice command recognition, a MLP with an input layer, a 100-neuron hidden layer (ReLU activation), and a 10-category output layer was utilized. During training, an Adam optimizer was used with an initial learning rate of 0.003, which was decayed to 50% of its current value every 10 epochs. L₂ regularization with α of 0.0001, a batch size of 32, and a maximum training epochs of 200 were adopted. Each conductance state was min-max normalized, followed by sliding window slicing with window of 45 and a stride of 1. The dataset was stratified split with a ratio of 8:2 for training and testing, respectively.

For drone trajectory recognition, another MLP was adopted with an input layer, a 200-neuron hidden layer (ReLU activation), and a 9-category output layer. During training, the Adam optimizer was used with an initial learning rate of 0.0004, which is decayed to 50% of its current value every 5 epochs. The decay strategy was only applied within the first 80% of the total training epochs. L₂ regularization with α of 0.0005, a batch size of 128, and a maximum training epochs of 200 were adopted. The conductance states were min-max normalized separately for each category. The dataset was stratified split with a ratio of 8:2 for training and testing, respectively.

3 Results and discussion

3.1 Working principle and performance of TAS

Triboelectric nanogenerator (TENG) is a novel energy conversion device based on frictional electrification and electrostatic induction effects. It can efficiently convert environmental mechanical energy into electrical energy, including pressure and sound waves [43–45]. Due to the advantages of simple structure, diverse materials, low cost and high sensitivity, TENG has shown great potential in fields of self-powered sensing and intelligent sensing. In addition, researchers introduced TENG into the field of auditory perception

and developed TAS. It can sensitively capture sound wave signals without the need of external power supply, achieving efficient acoustic detection and recognition. Figure 2(a) schematically shows the working principle of the present TAS. At the initial state, the FEP membrane and the PI membrane come into contact when the sound wave signal is loaded on the TAS. Due to frictional electrification and electrostatic induction effects, the FEP membrane with higher electronegativity will carry negative charges, while the PI membrane will carry positive charges. When the sound wave causes friction layers to separate, a potential difference will be formed between the two electrodes, driving electrons from the top electrode to the bottom electrode. When the sound wave causes friction layers to separate to the maximum extent, electrostatic equilibrium is reached between the two electrodes. At this time, there is no current in external circuit. When the sound wave causes friction layers to contact again, the potential difference between the two electrodes decreases, driving electrons to flow back from the bottom electrode to the top electrode. When friction layers come into full contact again, there is no current in external circuit, i.e., the triboelectric charge distribution returns to the initial state. Thus, sound wave signals will trigger an alternating voltage.

Figures 2(b) and 2(c) show AFM surface morphologies of the FEP membrane and the PI membrane, respectively. The surface RMS values are ~ 72.84 and ~ 0.66 nm, respectively. Figure 2(d) shows SEM image of the copper mesh. The length of square aperture and the diameter of the wire are ~ 90 and ~ 50 μm , respectively. Figure 2(e) shows tensile stress (σ) vs. strain (ϵ) curves of FEP and PI membranes. In the elastic deformation range of the membrane, the Young's modulus (E) can be calculated with the following equation [46]

$$E = \sigma / \epsilon \quad (1)$$

Thus, E values of FEP membrane and PI membrane are estimated to be ~ 0.45 and ~ 1.84 GPa, respectively. In addition, the maximum deformation displacement (W_{max}) of the membrane under sound wave signals can be calculated by the following equation [47]

$$W_{\text{max}} = \beta \cdot A \cdot P(1 - \nu^2) / Et^3 \quad (2)$$

where β , P , ν , A , and t are coefficient, sound pressure, poisson ratio, constant related to the size of the vibration membrane, and thickness of the vibration membrane. The FEP membrane with a smaller E value (~ 0.45 GPa) and t value (~ 15 μm) will obtain larger W_{max} under the same sound wave signal. Figure S3 in the ESM shows open-circuit-voltage (V_{oc}) of the original TAS without the installation of acoustic coupling cavity triggered by the same sound wave signals (110 dB, 200 Hz). The V_{oc} value reaches ~ 3.64 V when the sound enters from FEP. While it is only ~ 3.05 V when the sound enters from PI. Therefore, allowing sound wave signal to enter from the FEP membrane will enable TAS to achieve better performance.

Figure 2(f) shows the frequency dependent positive V_{oc} values of the TAS triggered by sound wave signals at a fixed SPL of 110 dB. The distance between the friction layer of TAS and the speaker is fixed at ~ 4 cm. The V_{oc} value decreases when the sound frequency moves away from 200 Hz. Thus, the present TAS has a resonance frequency of ~ 200 Hz. Figure 2(g) shows SPL dependent V_{oc} responses of the TAS triggered by sound wave signals at a fixed sound frequency of 200 Hz. The V_{oc} value increases from ~ 0.8 to ~ 20.4 V with the increased SPL from 78 to 110 dB. Correspondingly, short-circuit current (I_{sc}) of the TAS under the same sound wave signals increases from ~ 0.1 to ~ 3.8 μA with the increased SPL from 78 to 110 dB, as shown in Fig. S4 in the ESM.

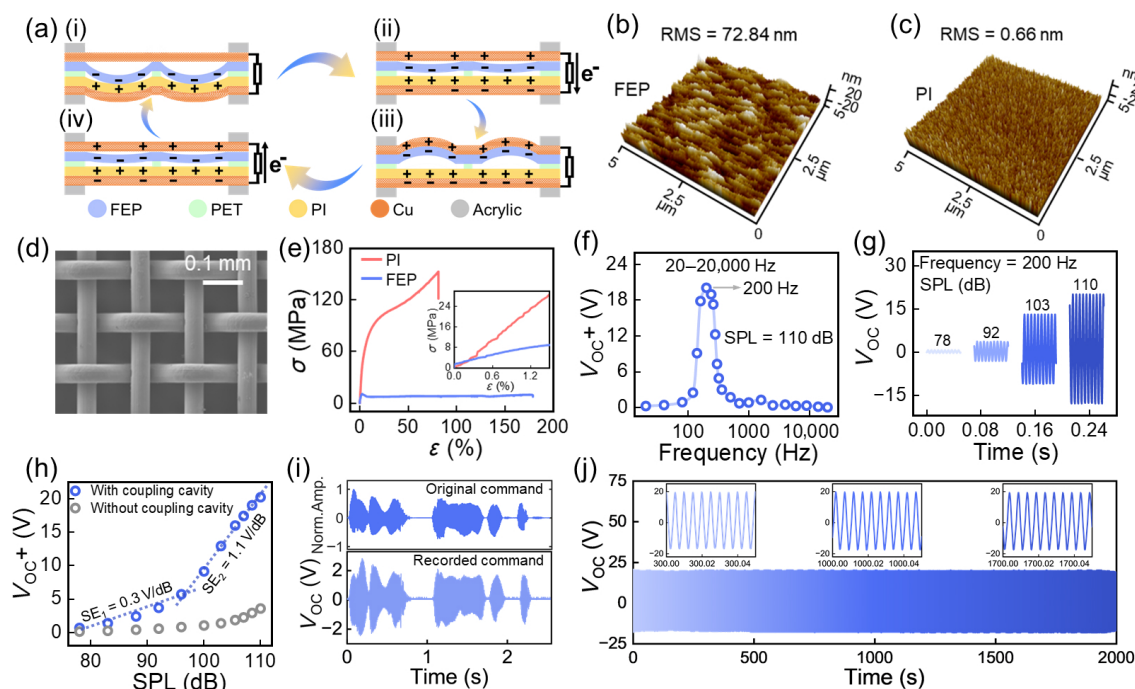


Figure 2 (a) Schematic diagram of the operation mechanism of the TAS. (b) AFM surface morphology of the FEP membrane. (c) AFM surface morphology of the PI membrane. (d) SEM image of copper mesh. (e) Tensile stress (σ) vs. strain (ϵ) curves of FEP and PI membranes. (f) Frequency dependent positive V_{oc} values of the TAS triggered by sound wave signals at a fixed SPL of 110 dB. (g) SPL dependent V_{oc} responses of the TAS triggered by sound wave signals at a fixed sound frequency of 200 Hz. (h) Positive V_{oc} values as a function of SPL values at the fixed sound frequency of 200 Hz. (i) Comparison of original waveform of voice command and the recorded V_{oc} . (j) V_{oc} of the TAS triggered by a sound wave signal (110 dB, 200 Hz) with a duration of ~ 2000 s.

The blue circles in Fig. 2(h) show positive V_{oc} values as a function of SPL values at the fixed sound frequency of 200 Hz. Here, the sensitivity is defined by the following equation

$$SE = \Delta V_{oc} / \Delta SPL \quad (3)$$

when SPL is below 96 dB, the SE value is ~ 0.3 V/dB. When the SPL exceeds 96 dB, it reaches ~ 1.1 V/dB. As comparison, the TAS without acoustic coupling cavity exhibits lower sensitivity, as shown by the grey circles in Fig. 2(h). Furthermore, the sound source distance affects the sound wave collecting capacity for TAS, as shown in Fig. S5(a) in the ESM. The positive V_{oc} value of TAS with acoustic coupling cavity decreases from ~ 20.1 to ~ 7.8 V with the increased distance from ~ 4 to ~ 8 cm. While for TAS without acoustic coupling cavity, it decreases from ~ 3.6 to ~ 1.1 V with the increased distance from ~ 4 to ~ 8 cm. The results indicate the positive effects for the acoustic coupling cavity. V_{oc} can also be full wave rectified, as shown in Fig. S5(b) in the ESM. V_{oc} of the TAS is ~ 16.1 V after full-wave rectification, slightly lower than that without rectification of ~ 20.4 V. Figure S5(c) in the ESM shows the rectified output voltage and output current of the TAS at different loaded resistances under the same sound wave signal (110 dB, 200 Hz). As the loaded resistance increases gradually, the output voltage and output current increases and decreases, respectively. Under the load resistance of 5 M Ω , the output power density of the TAS can reach ~ 30.3 mW/m 2 , as shown in Fig. S5(d) in the ESM. Figures S6(a) and S6(b) in the ESM also show temperature dependent and air relative humidity dependent V_{oc} of the TAS, respectively. The V_{oc} decreases from ~ 1.96 to ~ 0.93 V with the increased temperature from ~ 21.8 to ~ 70.1 °C. While the humidity has almost no influences. Figure S6(c) in the ESM shows V_{oc} triggered by a sound wave signal (110 dB, 200 Hz) with a duration of 2000 s. Under UV illumination, there is only a slight decrease in V_{oc} from ~ 19.6 to ~ 18.1 V. When there is no UV illumination, the V_{oc} remains constant. In terms of long-term stability, the V_{oc} slightly decreases from ~ 20.4 to ~ 19.2 V in ~ 170 days, indicating good stability, as shown in Fig. S6(d) in the ESM. TAS can efficiently capture speech information with rich features. As shown in Fig. 2(i), the top panel and the bottom panel show the original waveform of voice command and the recorded V_{oc} . It is observed that similar waveforms are obtained. Figures S7(a) and S7(b) in the ESM show the frequency domain diagrams of the original waveform and the recorded V_{oc} of the command, respectively. Interestingly, highly similar frequency distribution characteristics is exhibited at the lower frequency range (< 2000 Hz). TAS also exhibits good durability, as shown in Fig. 2(j). There are no observable changes in V_{oc} responses under the sound wave signal with the duration of ~ 2000 s. All the results indicate good performances for the present acoustic coupling cavity assistant TAS.

3.2 Electrical performance and synaptic responses of IZO-PNT

Owing to electric-double-layer (EDL) effect of the chitosan based electrolyte, IZO-PNT can simulate synaptic behaviors at low voltages. Figure 3(a) shows cross-sectional SEM image of the chitosan film. The thickness is ~ 15.1 μm . Figure 3(b) shows AFM surface morphology of the chitosan film. The surface RMS value is only ~ 0.98 nm. Figure 3(c) shows frequency dependent specific capacitance of the chitosan-based electrolyte film. A big EDL capacitance of ~ 5.1 $\mu\text{F}/\text{cm}^2$ is obtained at 1 Hz. Figure S8(a) in the

ESM shows output curves of the IZO-PNT for channel 1. The results indicate good ohmic contact at the S/D electrode. Figure S8(b) in the ESM shows five repeated transfer curves. Owing to the migration of protons within the electrolyte, an anti-clockwise hysteresis window is observed [48, 49]. These curves approach with each other very well, indicating good stabilities. The ON/OFF ratio, subthreshold swing, threshold voltage, and mobility are $\sim 1.0 \times 10^5$, ~ 104 mV/dec, ~ 0.3 V, and ~ 1.5 $\text{cm}^2/(\text{V}\cdot\text{s})$, respectively. Figure 3(d) shows the transfer curves under illumination with different optical power intensities at a fixed light wavelength of 365 nm. These curves drift upwards with the increased optical power intensity. The I_{ds} value increases from 1.12×10^{-6} to 3.52×10^{-5} A at V_{gs} of 0 V with the increased optical power intensity from 0 to 57.2 mW/cm 2 . In addition, IZO-PNT with different channel lengths will also exhibit different performance. As shown in Fig. S8(c) in the ESM, the ON/OFF ratio decreases from 1.0×10^5 to 1.1×10^4 with the increased channel length from 200 to 950 μm . IZO-PNT with a higher ON/OFF ratio could achieve more reliable signal processing. Therefore, subsequent tests were conducted on channel 1.

Excitatory postsynaptic current (EPSC) plays a crucial role in nervous system, serving as a fundamental mechanism for information transmission between neurons. When excitatory neurotransmitters bind to receptors on postsynaptic membrane, EPSC response will be triggered [50, 51]. Owing to the EDL effect at the chitosan/IZO interface, EPSC response could be mimicked on the IZO-PNT. Figure 3(e) shows spike amplitude dependent EPSC responses with fixed V_{ds} at 0.1 V. The EPSC peak value increases from ~ 0.2 to ~ 3.2 μA with the increased spike amplitude from 1 to 4 V. In all subsequent tests, the V_{ds} value is fixed at 0.1 V. Figure 3(f) shows spike duration dependent EPSC responses. The EPSC peak value increases from ~ 0.9 to ~ 15.1 μA with the increased spike duration from 10 to 500 ms. Inset in Fig. 3(g) shows typical EPSC response triggered by paired spikes (2 V, 20 ms) with an interval time (ΔT) of 10 ms. The second absolute EPSC value (A_2) is higher than the first one (A_1), mimicking typical paired-pulse facilitation (PPF) effects. Here, PPF index, defined as $A_2/A_1 \times 100\%$, is $\sim 153\%$. Figure 3(g) shows PPF index as a function of ΔT . It drops sharply with the increased ΔT value. Then, it gradually decreases to $\sim 100\%$ at higher ΔT values. Figure S8(d) in the ESM shows spike number dependent EPSC responses. The EPSC peak value increases from ~ 0.8 to ~ 4.3 μA with the increased spike number from 1 to 50. In addition, persistent photoconductance effects are always observed in metal oxide semiconductors [52, 53]. This helps mimic typical synaptic responses [54]. Under light illumination, oxygen vacancy (V_o) within the IZO will ionize into shallow donor states (V_o^+ and V_o^{2+}). Thus, electron density in IZO will increase. This could trigger an EPSC response. Figure 3(h) shows optical power intensity dependent EPSC responses. The light wavelength and duration are fixed at 365 nm and 50 ms, respectively. The EPSC peak value increases from ~ 14.9 to ~ 39.2 nA with the increased optical power intensity from 6.8 to 57.2 mW/cm 2 . EPSC responses also exhibit spike duration and spike number dependent characteristics under optical stimulus, as shown in Figs. S8(e) and S8(f) in the ESM. In addition, a higher EPSC response will be triggered when simultaneously loading voltage and optical stimuli on the IZO-PNT. Figure 3(i) shows EPSC responses triggered by 20 consecutive spikes (2 V, 10 ms) with the frequency of 50 Hz under different optical power intensities. The EPSC peak value increases from ~ 3.7 to ~ 4.5 μA with the increased optical power intensity from 0 to 57.2 mW/cm 2 .

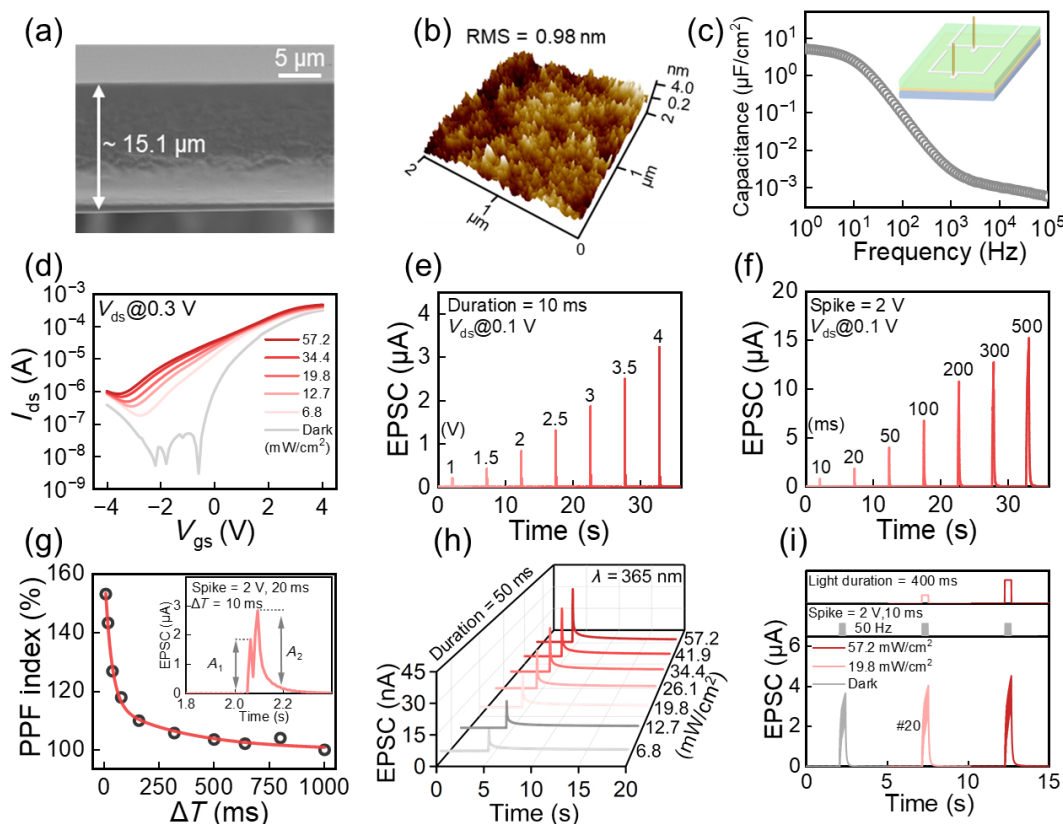


Figure 3 (a) Cross-sectional SEM image and (b) AFM surface morphology of the chitosan-based electrolyte film. (c) Frequency dependent specific capacitance of the chitosan film. (d) Transfer curves of the IZO-PNT under different optical power intensities at a fixed light wavelength of 365 nm. (e) Spike amplitude dependent EPSC responses. (f) Spike duration dependent EPSC responses. (g) PPF index as a function of ΔT value. Inset: Typical EPSC response triggered by paired spikes (2 V, 20 ms) with an interval time (ΔT) of 10 ms. (h) Optical power intensity dependent EPSC responses. (i) EPSC response triggered by 20 consecutive spikes (2 V, 10 ms) with frequency of 50 Hz under different optical power intensities.

3.3 Neuromorphic functions of AOIRS

In order to achieve the perception and computation with sound information, an AOIRS is proposed by connecting TAS with IZO-PNT, as schematically shown in Fig. 1(b). TAS could perceive sound wave signals and convert them into alternating voltages. They can be converted into positive voltages after full-wave rectification and loaded to the gate of IZO-PNT [55]. Thus, protons within chitosan migrate towards the electrolyte/channel interface, inducing electrons in the channel and triggering synaptic potentiation. Under UV illumination, oxygen vacancies within the IZO channel ionize into shallow donor states (V_{O}^+ and V_{O}^{2+}), leading to persistent photoconductivity (PPC) effect due to the increase in electron density. In another word, synaptic potentiation can be triggered under UV illumination. Therefore, the channel current of IZO-PNT can be directly modulated by sound wave signals or UV light. Figure S9 in the ESM shows EPSC responses triggered by a sound wave signal (94 dB, 1 s) with different frequencies. The EPSC peak value increases from ~ 1.7 to ~ 5.9 μA with the increased sound frequency from 160 to 200 Hz. While it decreases from ~ 5.9 to ~ 3.8 μA with the increased sound frequency from 200 to 240 Hz. Figure 4(a) shows the sound frequency dependent EPSC peak values triggered by sound wave signals (94 dB, 1 s). Obviously, the present AOIRS is most sensitive to sound wave signals with frequency of 200 Hz. Figure 4(b) shows EPSC response triggered by a sound wave signal (200 Hz, 1 s) under different SPLs. The EPSC peak value increases from ~ 0.9 to

~ 15.4 μA with the increased SPL value from 83 to 99 dB. Figure 4(c) shows EPSC responses at different sound wave duration time. The EPSC peak value increases from ~ 1.0 to ~ 21.8 μA with the increased duration from 0.3 to 3.0 s. Figure 4(d) shows sound number dependent EPSC responses triggered by sound wave signals (89 dB, 200 Hz, 0.5 s) with a fixed interval time (0.5 s). The EPSC peak value increases from ~ 1.1 to ~ 30.3 μA with sound number from 1 to 30. Additionally, the imitation of “Learning–Forgetting–Relearning” activities could also be achieved by sound stimuli, as shown in Fig. 4(e). A learning threshold is set at 30.8 μA . At the first learning stage, 30 consecutive sound wave signals (89 dB, 200 Hz, 0.5 s) with spike interval of 0.5 s will induce EPSC peak value to a learning threshold. In 60 s, the EPSC value decreases to ~ 13.0 μA . At the second learning stage, only 10 sound wave signals are enough to let EPSC value reach the learning threshold. In 60 s, the EPSC value decreases to ~ 16.1 μA . At the third learning stage, only 7 sound wave signals are enough to let EPSC value reach the threshold. These results indicate that previous learning activities are helpful for the following learning activities, as is quite similar to the “Learning–Forgetting–Relearning” activities in our brain [56].

The AOIRS can also perceive synchronized sound and light stimuli. Figure 4(f) shows EPSC responses triggered by 20 consecutive sound wave signals (90 dB, 200 Hz, 0.5 s) with ΔT of 0.5 s under different optical power intensities. The EPSC peak value increases from ~ 27.5 to ~ 51.9 μA with the increased optical power intensity from 0 to 57.2 mW/cm². When sound stimuli stop, the

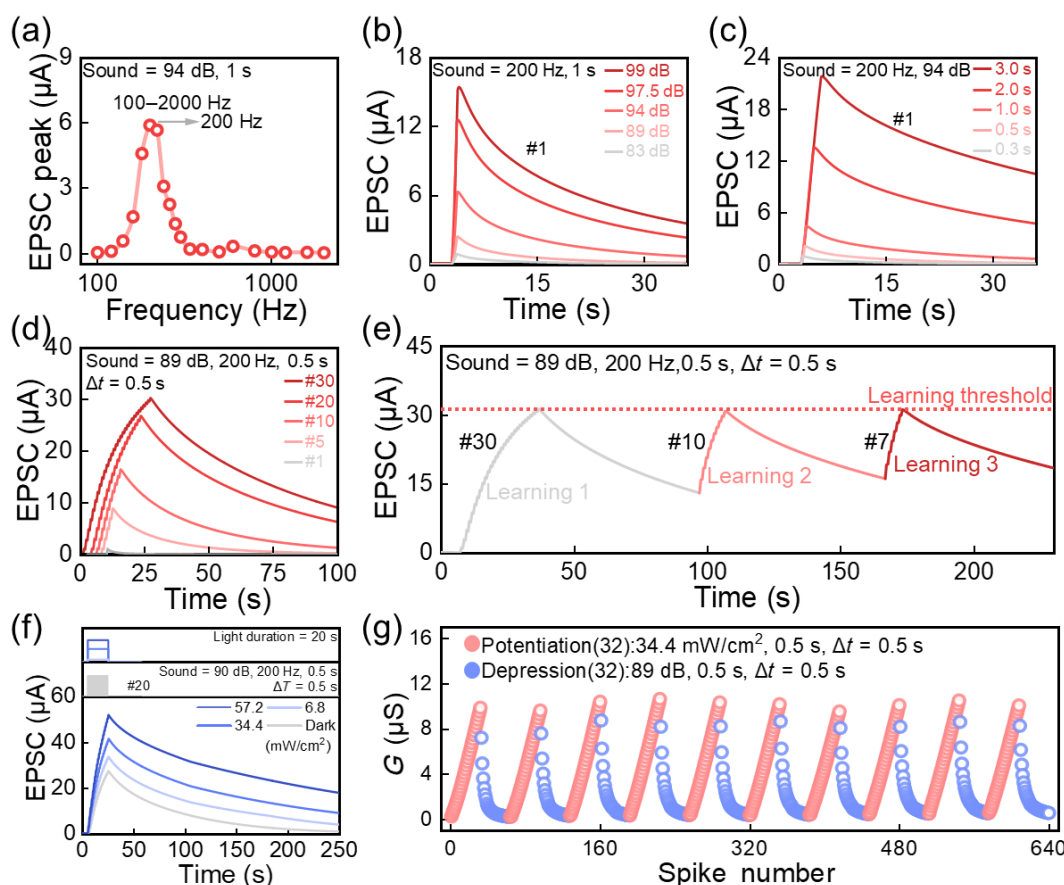


Figure 4 (a) Sound frequency dependent EPSC peak values triggered by sound wave signals (94 dB, 1 s). (b) EPSC response triggered by a sound wave signal (200 Hz, 1 s) under different SPLs. (c) EPSC response triggered by a sound wave signal (94 dB, 200 Hz) with different durations. (d) Sound number dependent EPSC responses triggered sound wave signals (89 dB, 200 Hz, 0.5 s) with a fixed interval time of 0.5 s. (e) Imitation of “Learning–Forgetting–Relearning” activities under sound wave signals. (f) EPSC responses triggered by 20 consecutive sound wave signals (90 dB, 200 Hz, 0.5 s) with ΔT of 0.5 s under different optical power intensities. (g) Synaptic weight evolution for 10 repeated optical spikes (potentiation)/sound stimuli (depression).

EPSC value decays slowly. Alternating voltages generated on the TAS can also be rectified into negative voltages by connecting the negative terminal of the rectifier bridge to the gate of IZO-PNT. Thus, a reverse electric field drives protons to migrate back from the interface into the electrolyte, decreasing the channel carrier concentration and achieving synaptic depression. As shown in Fig. S10 in the ESM, EPSC value increases from ~ 0.04 to ~ 1.01 μA under 32 consecutive optical stimuli (34.4 mW/cm^2 , 0.5 s). While it decreases to ~ 0.05 μA under 32 sound stimuli (89 dB, 200 Hz, 0.5 s). The ΔT value of sound/optical stimuli is fixed at 0.5 s. Figure 4(g) shows synaptic weight evolution for 10 repeated sound/optical cycles. These results indicate that synaptic weights exhibit good stability. The extracted heat maps of conductance change (ΔG) and switching characteristics are shown in Figs. S11(a) and S11(b) in the ESM, respectively. The color corresponds to the cumulative distribution function (CDF) at each conductance state. The repeatable synaptic weight modulation characteristic enables the device to achieve stable learning and rapid forgetting during neural network training.

3.4 Voice command and drone trajectory recognition based on AOIRS

RC is an efficient neuromorphic computing framework that maps input signals into a high-dimensional space through a “reservoir” with nonlinear dynamic characteristics, followed by training and

classification using a readout layer [57, 58]. In IZO-PNT, migration/relaxation of protons and release/capture of photo generated carriers generate nonlinear conductivity responses, thereby forming a variety of internal conductance states and short-term memory effects. Therefore, AOIRS based on IZO-PNT can map temporal inputs to high-dimensional conductance states and directly implement reservoir computation on hardware. Firstly, a framework based on AOIRS for voice command recognition is proposed, as schematically shown in Fig. 5(a). In order to confirm the performance of reservoir states, different 4-bit sound spikes are input to the AOIRS. The interval time (ΔT) between “0” signal (0 Hz, 0 dB, 0.5 s) and “1” signal (200 Hz, 83 dB, 0.5 s) is 2 s. Interestingly, distinct final conductance levels are observed under different 4-bit sound spikes, indicating good separability of the AOIRS, as shown in Fig. 5(b). In addition, the AOIRS exhibits short-term memory dynamics in response to sound trains with varied ΔT , SPLs, and frequencies, as shown in Fig. 5(c) and Figs. S12(a) and S12(b) in the ESM, respectively. The sound duration is fixed at 0.5 s. These results indicate that the AOIRS has the potential to map sound wave signals with rich features into high-dimensional conductance states. Table S1 in the ESM shows texts of 9 voice commands. The waveforms and STFT spectrograms of 9 voice commands are shown in Figs. S13 and S14 in the ESM, respectively. Figures 5(d) and 5(e) show conductance response triggered by voice command 1 and voice command 9, respectively. Distinct

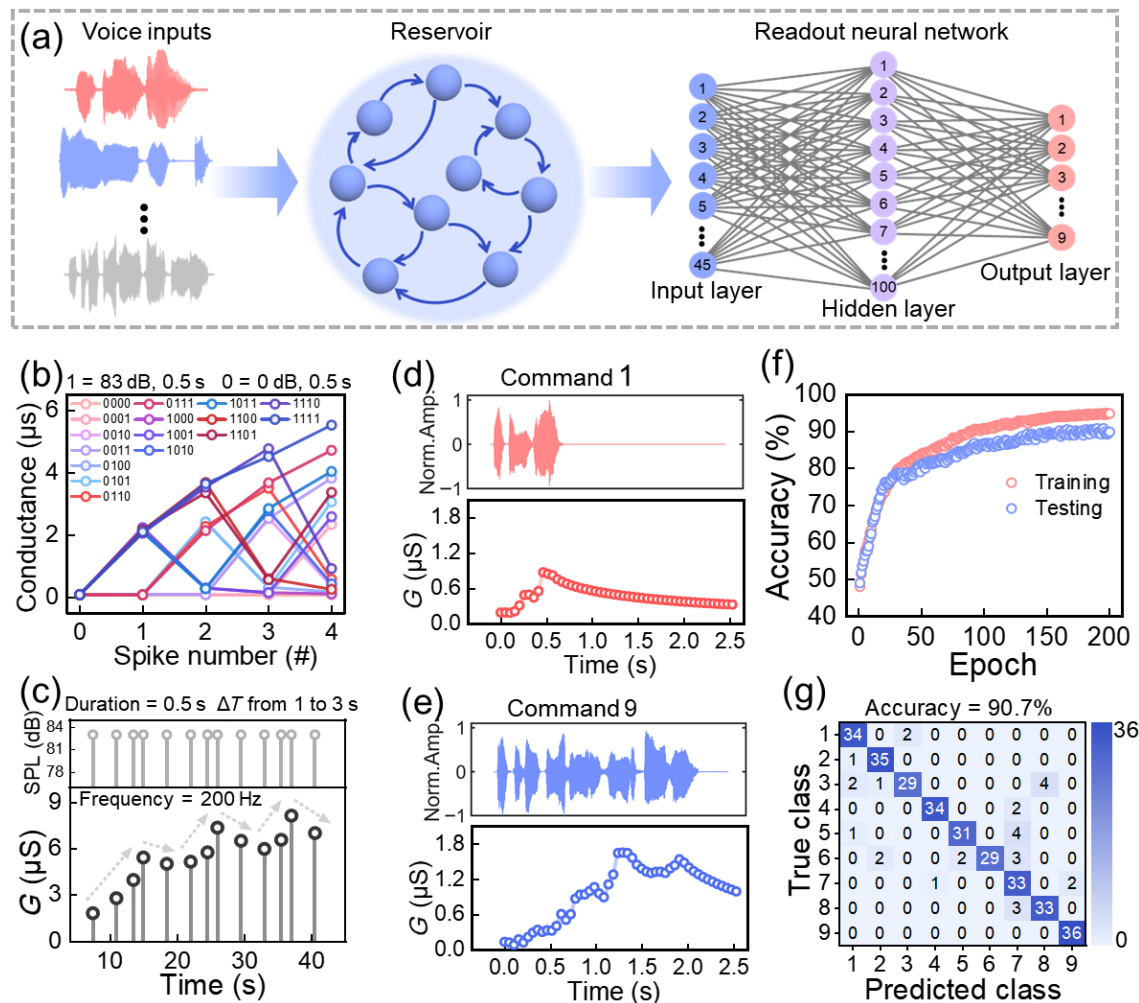


Figure 5 (a) Schematic diagram of voice command recognition. (b) Conductance response triggered by different 4-bit sound spikes. (c) Conductance responses triggered by sound trains with varied ΔT . (d) Conductance response triggered by voice command 1. (e) Conductance response triggered by voice command 9. (f) Accuracy of voice command recognition as a function of epoch. (g) Confusion matrix for 9 voice commands.

conductance profiles are obtained under different voice commands, demonstrating the capability of the AOIRS to encode and differentiate complex voice information. In order to explore the performance of voice command recognition on AOIRS, 270 voice command samples are collected from 30 different individuals, i.e., 9 command categories with 30 samples per category. The TAS convert these voice commands into electrical signals, which are then full-wave rectified and input to the gate of the IZO-PNT. After being processed, these voice commands are mapped into high-dimensional conductance states under a sampling rate of 50 ms. The number of conductance states corresponding to each voice command is fixed at 50. The conductance states of all voice commands is sliced with a sliding window of 45 and a step size of 1, respectively. Therefore, a total of 1620 conductance state samples corresponding to 9 categories were obtained. Finally, a MLP classifier is employed as the readout layer to classify these conductance state data, thereby achieving efficient voice command recognition. In order to eliminate the absolute difference, all the conductance state samples are normalized during the classification stage. These conductance state data are divided into training and testing sets in a ratio of 8:2. As shown in Fig. 5(f), the training accuracy and testing accuracy reach $\sim 94.8\%$ and $\sim 89.8\%$ after 200 epochs, respectively. Figure 5(g) shows the best confusion

matrix of test set for the 9 voice commands, with average recognition accuracy of $\sim 90.7\%$. These results indicate that efficient recognition of voice commands can be achieved based on AOIRS, demonstrating its prospects in voice human-computer interaction.

As a combination of modern flight and intelligent technology, drones have been widely used in various fields such as aerial photography and scientific research, playing an important role in promoting the development of low-altitude economy. During the operation of drone swarms, accurate recognition of individual drone trajectory is essential for collision avoidance and collaborative management. Interestingly, the present AOIRS also shows potential in drone trajectory recognition. As shown in Fig. 6(a), the drone may move towards eight directions (up, up-right, right, down-right, down, down-left, left, up-left) or remain still. Based on the dynamic movement characteristics of the drone, the positions of drone at different time points ($t = 0, t_1, t_2, t_3$) are recorded and collected into a dataset. As shown in Fig. S15 in the ESM, the dataset contains 9 labels (label 0–8) and 1800 samples corresponding to 9 trajectories of the drone. Each sample contains four frames of images (40×40 pixels), corresponding to the position of the drone at four time points ($t = 0, t_1, t_2, t_3$). As shown in Fig. 6(b), black pixel and white pixel are mapped into “0” and “1” signals, i.e., spike (0 mW/cm², 100 ms) and spike (6.8 mW/cm², 100 ms), respectively. By

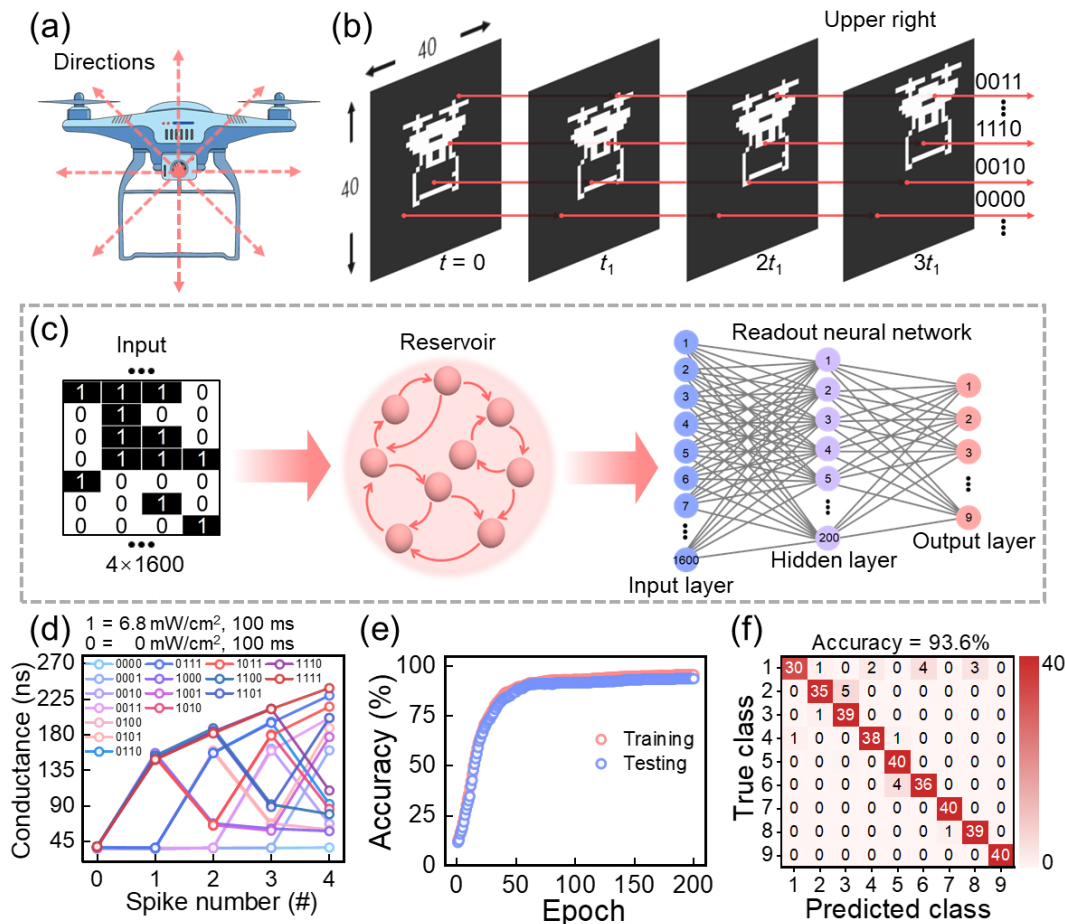


Figure 6 (a) Schematic diagram of drone movement direction. (b) Schematic diagram of converting the dynamic trajectory of drone movement into spike trains. (c) Schematic diagram of drone trajectory recognition. (d) Conductance response triggered by different 4-bit optical spike. (e) Accuracy of drone trajectory recognition as a function of epoch. (f) Confusion matrix for 9 drone trajectories.

sequentially mapping the pixels at the same position in four frames of drone images, the drone trajectory can be converted into 4-bit spike trains of the same size (4×1600). Figure 6(d) shows conductance response triggered by different 4-bit optical spikes, where the interval time (ΔT) between adjacent spikes is fixed at 50 ms. Distinct final conductance levels are also observed under different 4-bit optical spikes. As shown in Fig. 6(c), all the 4-bit optical spikes corresponding to each drone trajectory are mapped into high-dimensional conductance states through AOIRS. The number of conductance states corresponding to each drone trajectory is 1600. Finally, a MLP classifier is employed as the readout layer to classify these conductance state data. All the conductance state data are also normalized and divided into training and testing sets in a ratio of 8:2. As shown in Fig. 6(e), the training accuracy and testing accuracy reach $\sim 95.4\%$ and $\sim 93.6\%$ after 200 epochs, respectively. Figure 6(f) shows the best confusion matrix of testing set for the 9 drone trajectories. These results indicate that efficient drone trajectory recognition can be achieved based on AOIRS, which helps drone swarms maintain accurate formation, avoid collisions in complex dynamic environments, and provide key data support for autonomous decision-making in large-scale collaborative tasks. Table S2 in the ESM also compares typical parameters of multimodal neuromorphic systems based on triboelectric nanogenerators and synaptic transistors. The present IZO-PNT has relatively low power consumption. In addition, the

present AOIRS can recognize complex temporal signals such as voice commands and drone trajectories, demonstrating the great potentials.

4 Conclusion

In summary, an AOIRS based on TAS and IZO-PNT is proposed. With the unique acoustic coupling cavity, the V_{OC} and I_{SC} of TAS under sound wave signal (110 dB, 200 Hz) can reach ~ 20.4 V and ~ 3.8 μ A, respectively. It exhibits a high sensitivity (~ 1.1 V/dB) and good durability. Its output power density reaches ~ 30.3 mW/m². In addition, TAS can also capture voice commands with rich features. Thus, the AOIRS can simulate interesting neural activities under sound wave signals. It exhibits enhanced memory characteristic under synchronized sound and light stimuli. In addition, the synaptic weights can be repeatedly updated by light and sound stimuli. As a physical reservoir, the AOIRS can map voice commands and drone trajectory images into high-dimensional conductance states. Thus, efficient voice command and drone trajectory recognition can be achieved via a MLP classifier. The average testing accuracy after 200 epochs for voice command and drone trajectory is $\sim 89.8\%$ and 93.6% , respectively. The present AOIRS has great potentials in the fields of voice intelligent sensing and low-altitude industry.

Electronic Supplementary Material: Supplementary material

(schematic diagram of the acoustic coupling cavity, photograph of the testing configuration of the TAS, flow chart of the fabrication processing of IZO-PNT, VOC of TAS under different conditions, electrical performance optical synaptic responses of IZO-PNT, EPSC responses triggered by sound wave signals, heat map representation of ΔG vs. G switching characteristics, waveforms, STFT spectrograms and text of 9 voice commands, schematic diagram of 9 drone trajectories, and typical parameters of multimodal neuromorphic systems) is available in the online version of this article at <https://doi.org/10.26599/NR.2026.94908978>.

Data availability

All data needed to support the conclusions in the paper are presented in the manuscript and the Electronic Supplementary Material.

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Declaration of competing interest

All the contributing authors report no conflict of interests in this work.

Author contribution statement

S. Y. Z.: Data curation, methodology, validation, software, writing – original draft, writing – review & editing. W. S. W.: Data curation, methodology, validation. W. X. T.: Methodology, validation. L. F. W.: Data curation. B. B. L.: Methodology. W. L. Z.: Validation. C. S. L.: Validation. L. Q. Z.: Methodology, project administration, funding acquisition, writing – original draft, writing – review & editing. All the authors have approved the final manuscript.

Use of AI statement

None.

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