AI sensors

Editorial

Recent Advances in Two-Dimensional Materials for In-Sensor Computing

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Edge sensing systems seamlessly integrate multimodal signals for capturing visual, spectral, pressure, acoustic, and chemical data through robots, wearables, and distributed nodes at the sensing front end [1,2]. In conventional pipelines, these heterogeneous signals are digitized and transferred to memory and processors before task-relevant features are extracted. The resulting data movement becomes costly as pixel counts, spectral channels, and sensor arrays scale, with direct consequences for bandwidth, latency and power consumption. In-sensor computing (ISC) mitigates data-transfer overhead by embedding signal processing directly within the detection stage, such as filtering, weighting, integration, and storage, thereby enabling downstream circuits to process compressed physical representations rather than raw stimuli.

Two-dimensional (2D) materials are well suited to ISC because much of their active volume is directly exposed to external fields and adsorbates. Light, strain, pressure, temperature, ions, and gas molecules can modulate carrier transport in atomically thin channels without the long diffusion paths typical of bulk semiconductors. Graphene offers high mobility, broadband absorption and mechanical compliance, while transition-metal dichalcogenides (TMDs) combine sizable bandgaps, strong excitonic effects and trap-mediated photoconductivity. In addition, 2D perovskites, 2D ferroelectrics and phase-change materials add ion migration, polarization memory, and switchable optical constants [1,2]. In the device stack structure, the responses of these materials set the transfer function between a stimulus and an electrical/optical output, which in turn serves as the computational primitive.

Photodetectors and phototransistors provide the most direct route to realize 2D-material ISC. A 2D semiconductor image sensor has shown that the photoresponsivity matrix of a pixel array can store neural-network weights, so image acquisition and recognition occur in the same hardware platform [3]. Programmable MoS_2 photodetectors carry this principle into spectroscopy: by shaping the spectral responsivity, the detector implements a linear operator for regression or classification before a full spectrum is recorded [4]. Black phosphorus image sensors use related programming for broadband infrared inputs through tunable conductance and responsivity [5]. Graphene adds functions at mechanical and mid-infrared interfaces: its compliance supports pressure sensing, and graphene photodetectors can operate at zero bias for mid-infrared and polarization-resolved detection [6,7]. These examples recast the detector as a front-end operator rather than a passive transducer followed by software.

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Other ISC devices place memory and temporal dynamics closer to the sensing event. Optoelectronic synapses translate optical inputs into conductance states that decay, accumulate or persist, giving the sensor a history-dependent response. In α-In_2Se_3, ferroelectric polarization couples to optoelectronic processes and supports controllable temporal dynamics for reservoir computing [8]. Monolithic 2D perovskites exploit ion–exciton coupling to generate persistent photocurrent and photonic synaptic behavior for visual preprocessing and low-power memory [9]. 2D phase-change materials provide non-volatile optical states for reconfigurable photonic memory [10]. Similar logic appears in ferroelectric field-effect transistors (FETs), memtransistors and memristor arrays, where a sensing event writes or updates a local conductance state. Trap-state dynamics in MoS_2 phototransistor arrays have been used to emulate graded neurons for motion perception [11], while nonlinear optical responses in bare MoS_2 point to programmable free-space neuromorphic computation [12]. Human-visual-pathway hardware further links local detection, memory and decision functions in 2D-material devices [13].

The device layer in Figure 1 links material response to application-level function. Material class alone does not determine whether a stimulus is weighted, stored, temporally filtered or optically processed, because the relevant operation is defined by device architecture. Photodetectors and phototransistors convert optical inputs into programmable photoresponse weights [3,4], optoelectronic synapses and graded-neuron devices introduce temporal filtering and short-term plasticity [8,9,11–13], and ferroelectric FETs provide non-volatile polarization control [2,8], whereas memristors and memtransistors store local weights and support analog multiply–accumulate operations [1,2]. Waveguide-integrated photonic devices combine detection, filtering, and optical weighting on chip [14,15]; the mapping is therefore functional rather than one-to-one. Programmable photodetectors and phototransistors naturally address optical pixels and spectra [3–5], compliant or resonant 2D structures process pressure and mechanical cues [6], and mid-infrared photonic platforms process gas-mixture information by treating spectra as weighted inputs [14]. These device routes define a shared ISC sequence, from input to material response, device state and task-level output, that connects machine vision, electronic skin, spectral analysis, robotic perception, and neuromorphic computing.

Photonic integration extends ISC to chip scale. When 2D materials are coupled to silicon waveguides, micro-ring resonators or Mach–Zehnder interferometers, optical propagation, resonance, and interference can participate in computation rather than merely deliver the signal. A mid-infrared silicon waveguide platform with graphene photodetectors has shown photonic ISC in which detector responsivity provides dynamic weighting for image preprocessing, gesture recognition and gas-mixture classification [14]. Complementary metal-oxide semiconductor (CMOS)-compatible AlN/Si waveguide systems further show that feature extraction and neural operations can be arranged near the sensing interface through integrated resonators and interferometers [15]. This route is well matched to spectral and chemical sensing because the input is already optical. Detection, filtering, and inference can then be distributed along the optical path instead of assigned to separate hardware blocks.

The transition from devices to deployable 2D-material ISC systems remains constrained by the limitation of materials and integration issues. Large-area growth, transfer and packaging will introduce defects, residues, and interface disorder, leading to spatial nonuniformity and temporal drift across the array. The same processes that provide memory, such as traps, ions, ferroelectric domains, and phase transitions, can also introduce hysteresis, fatigue, temperature sensitivity and device-to-device variation [1,2,8–10]. Evaluation therefore needs to pair sensing metrics and recognition accuracy with energy per operation, latency, retention, endurance, calibration cost, trainability, and readout-circuit compatibility. These criteria should be reported at both single-device and array levels, since a device that performs well as an isolated sensor may change after transfer, encapsulation, or circuit integration. For ISC, the stability of calibration is inseparable from computation, because drift in responsivity, threshold voltage or memory window directly changes the physical weight assigned to an input. Therefore, benchmarking should include repeated sensing–computing cycles under relevant optical, mechanical, thermal, or chemical backgrounds, rather than only static sensitivity or offline classification accuracy. It is also important to distinguish weights trained in software from states that are programmed and retained in the sensing device. Further progress will require co-design across materials synthesis, device architecture, interconnects, photonic or electronic pre-processing and learning algorithms [1,2,14,15]. At the system level, future 2D-material ISC should be positioned within edge sensing systems, where transduction, compression, local adaptation, and decision support are partitioned across the material stack, readout circuit, and edge processor. In such a framework, the 2D-material sensing front end can perform early-stage filtering, weighting, temporal integration, or feature extraction, while the edge processor undertakes higher-level fusion, model updating, and task-level inference. This direction calls for multimodal front ends that fuse optical, mechanical, acoustic, and chemical channels near the source, while reporting system-level figures of merit such as energy per decision, latency, calibration overhead, privacy, and on-node learning capability [16–18]. A central objective is to turn 2D materials from high-performance sensing layers into physical computing elements that support local perception at the sensory edge.

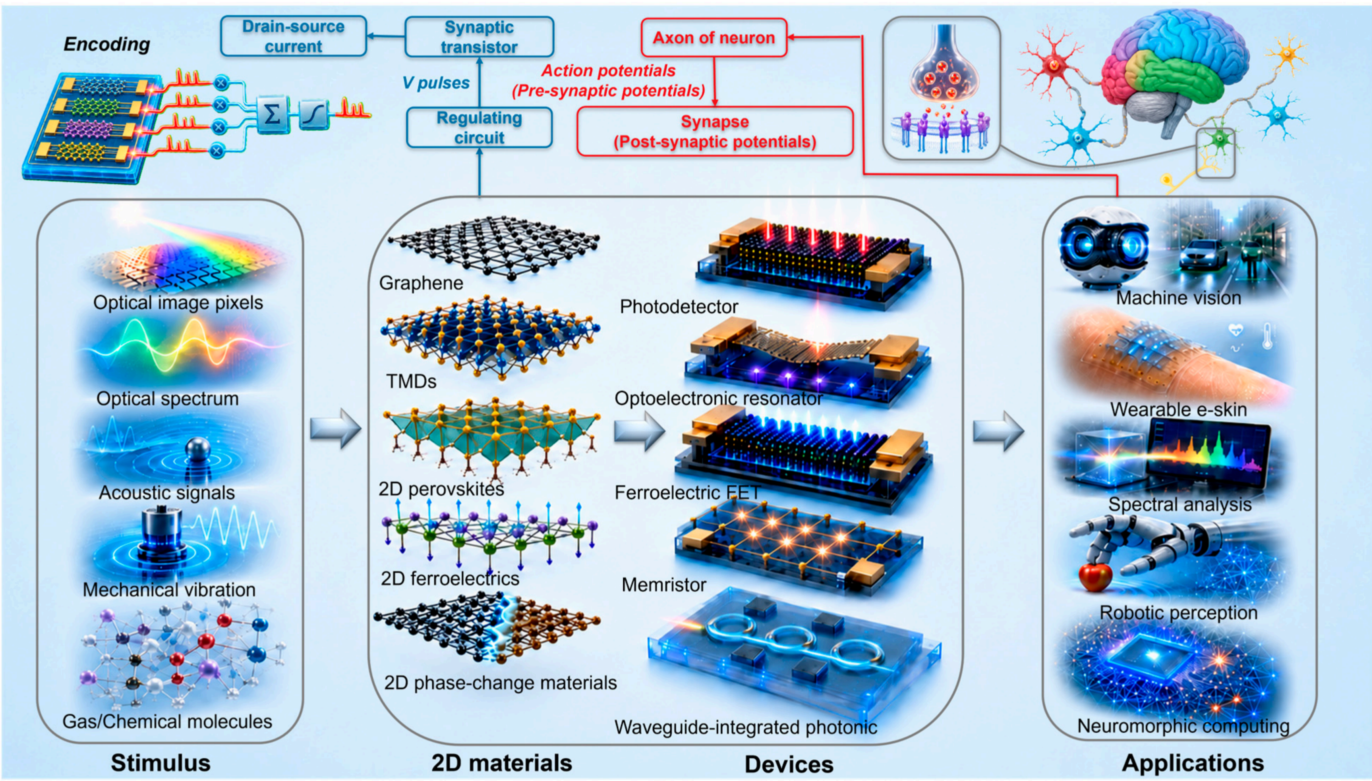

Figure 1. Schematic of 2D-material ISC for multimodal intelligent perception. Optical image pixels, optical spectra, pressure/mechanical signals and gas-mixture chemical signatures are transduced by graphene, transition-metal dichalcogenides, 2D perovskites, 2D ferroelectrics and 2D phase-change materials. The device layer includes photodetectors/phototransistors, optoelectronic synapses, ferroelectric field-effect transistors, memristor arrays and waveguide-integrated photonic devices, which support machine vision, wearable electronic skin, spectral analysis, robotic perception, and neuromorphic computing.

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