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Grain-Size-Controlled Resistive Switching Memories Enabling Domain-Specific Functionality for Real-Time Video Signal Processing

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ABSTRACT

Conventional neuromorphic platforms often rely on heterogeneous device integration to deliver multiple functionalities, a strategy that increases system complexity and hinders scalability. Here, we present a platform based on a grain-size-controlled resistive switching memory (RSM) array incorporating a Sn-halide perovskite thin film. A photo-thermochemical process produces laterally varying grain sizes and therefore spatially graded grain-boundary densities across the array. This intentionally introduced structural heterogeneity produces domain-dependent volatile threshold-switching behavior and short-term neural dynamics, since local grain-boundary density controls conductive-filament formation and ionic transport. As a result, time-dependent processing primitives—nonlinear conductance modulation, relaxation dynamics, integrate-and-fire responses, and signal separability—arise intrinsically and differentially across spatial domains, with their characteristics finely tunable via grain-boundary density. We validate the approach in a real-time spatiotemporal signal-processing system for autonomous-driving tasks, illustrating that grain-boundary engineering provides a scalable, fabrication-friendly route to embed diverse temporal functions within a single RSM array.

1 | Introduction

The rapid progress of artificial intelligence (AI) has driven growing interest in neuromorphic computing across diverse application domains, including autonomous driving [1], smart sensing [2], healthcare [3], and real-time video analytics [4]. Time-dependent signal-processing paradigms, such as reservoir computing, are especially appealing for these tasks because they enable low-power, real-time handling of continuous data streams. Short-term dynamical responses are central to these paradigms, since they provide the transient memory and nonlinear trans-

formations needed to encode temporal information effectively [5–11].

Resistive switching memories (RSMs) are emerging as strong candidates for implementing such temporal processors due to their rapid switching [12], low energy requirements [13], and inherent scalability [14]. Two-terminal RSM devices are particularly attractive because they deliver high integration density, architectural simplicity, and straightforward mapping to crossbar arrays [15–18]. Volatile RSMs, which naturally reproduce short-term neural dynamics, are therefore well suited to time-dependent signal

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processing applications [5–7]. Successful temporal computation, however, depends on heterogeneity in device response, including variations in threshold voltages, gain, decay times, and nonlinear transfer characteristics, so that network nodes operate across different temporal and amplitude regimes. Historically, this diversity has been introduced by integrating different device stacks or materials, or by performing device-by-device postfabrication tuning. Such strategies increase fabrication complexity, calibration overhead, and energy consumption, and they hinder scaling to large arrays [19–22]. Consequently, methods that enable selective control of volatile switching behavior and the spatial programming of domain-specific functions within a single device array are a crucial enabler for scalable, next-generation time-dependent neuromorphic systems.

The switching behavior of RSM is primarily governed by the structural and chemical properties of the switching medium [23, 24]. A variety of materials have been investigated for this purpose, including metal oxides [25–27], polymers [28–30], and perovskites [31–33]. Among these, metal-halide perovskites (MHPs) have garnered significant attention due to their high ionic mobility [34], stable and reversible switching under electric fields [35], tunable resistance through compositional engineering [36], and compatibility with cost-effective solution-based processing [37–41]. While lead (Pb)-based MHPs have been widely studied, concerns regarding their toxicity have stimulated efforts to develop environmentally benign alternatives—most notably tin (Sn)-based perovskites—despite their characteristically rapid crystallization kinetics [42–44].

Grain-engineering strategies for Sn-based perovskites have been widely explored. Approaches include: tuning crystallization kinetics through solvent and additive engineering [45], tailoring grain-boundary structures by adjusting film strain, interfacial conditions, and dopant composition [46], applying post-deposition thermal treatments to promote grain coalescence and enlargement [47], and deploying scalable coating/printing techniques—such as slot-die coating—coupled with controlled nucleation triggers to regulate grain formation [48]. As a result of these advances, several studies have successfully incorporated Sn-based perovskites into RSM architectures, exhibiting stable nonvolatile characteristics [49–59]. Nevertheless, studies on Sn-halide perovskite RSMs exhibiting volatile characteristics remain scarce [49, 52, 53, 56, 58, 60–65].

We demonstrate a grain-size-engineered RSM array that uses formamidinium tin iodide (FASnI₃) as the active switching layer. Grain size is controlled across the thin film by a photo-thermochemical treatment with a focused laser, producing lateral structural heterogeneity comprising three spatially distinct domains characterized by different grain sizes and grain-boundary densities. Importantly, this study goes beyond the established grain-size-ion-migration correlation by experimentally disentangling the role of grain-boundary density within an identical device architecture, thereby identifying grain-boundary density as the key microstructural parameter governing volatile threshold switching in FASnI₃-based RSMs. This deliberately engineered morphology enables domain-tailored volatile threshold-switching behavior and short-term neural dynamics, including nonlinear conductance modulation, tunable decay (relaxation) times, integrate-and-fire responses, and improved

signal separability. Leveraging these device-level distinctions, we build a neuromorphic processor for real-time video signal handling in autonomous-driving scenarios. By assigning each physical domain to specific visual features (for example, vehicles, pedestrians, and background), the array performs efficient temporal feature extraction, on-chip data compression, and simplified downstream computation. The architecture delivers high recognition accuracy and demonstrates that grain-morphology engineering provides a scalable, fabrication-friendly route to embed multifunctionality within a single device array, reducing reliance on heterogeneous integration while intrinsically encoding functional diversity through structural design.

2 | Results and Discussion

2.1 | Grain-Size-Controlled RSMs

Grain-size-engineered RSM devices were realized in a 30 × 9 crossbar array with a glass/ITO/FASnI₃/Ag stack (Figure 1a). The bottom electrode pattern comprised 30 parallel ITO lines (100 μm wide) lithographically defined on the glass substrate; fabrication details are given in the Experimental section. The switching medium, an FASnI₃, was deposited by spin coating from a 1.2 M precursor solution of formamidinium iodide (FAI) and tin iodide (SnI₂) in a DMF:DMSO (4:1 v/v) solvent mixture. During spin coating, chlorobenzene (CB) was dispensed as an anti-solvent to promote rapid nucleation and achieve uniform film formation. To improve the chemical robustness of this Sn-based perovskite and to suppress oxidation of Sn²⁺ to Sn⁴⁺, we added tin fluoride (SnF₂) and metallic Sn to the precursor as stabilizing additives. SnF₂ raises the formation energy of Sn vacancies and thereby inhibits vacancy-mediated oxidation pathways [66, 67], whereas excess metallic Sn fosters a comproportionation reaction between Sn²⁺ to Sn⁴⁺, creating a more reducing local environment during film formation [68]. Together, these additives substantially reduce Sn²⁺ oxidation, yielding FASnI₃ films with improved structural integrity and enhanced chemical stability.

After deposition, crystallization was promoted by a photo-thermochemical process. A focused laser beam of three powers was sequentially irradiated onto three spatially separated regions, partitioning the film into domain A (160 mW), domain B (130 mW), and domain C (100 mW) (Figure 1). This laser-based process provides a local thermal-annealing environment comparable to conventional heating—yet faster—and enables precise, complex patterning of RSM elements with distinct perovskite grain sizes [69].

Grain morphologies across the three domains were examined by SEM (Figure 1b). Domain A exhibits the largest average grain size (lowest grain-boundary density), while domains B and C show progressively smaller grains (higher grain-boundary densities) with decreasing laser power. The corresponding grazing incidence x-ray diffraction (GIXRD) patterns corroborate the grain-size-dependent crystallographic characteristics (Figure S1d). Moreover, cross-sectional TEM (Figure S2) confirms that the grain-size variation extends throughout the full film thickness rather than being confined to the surface, and a detailed discussion of how the resulting grain boundary density influences device performance is provided in Note S1 and further addressed

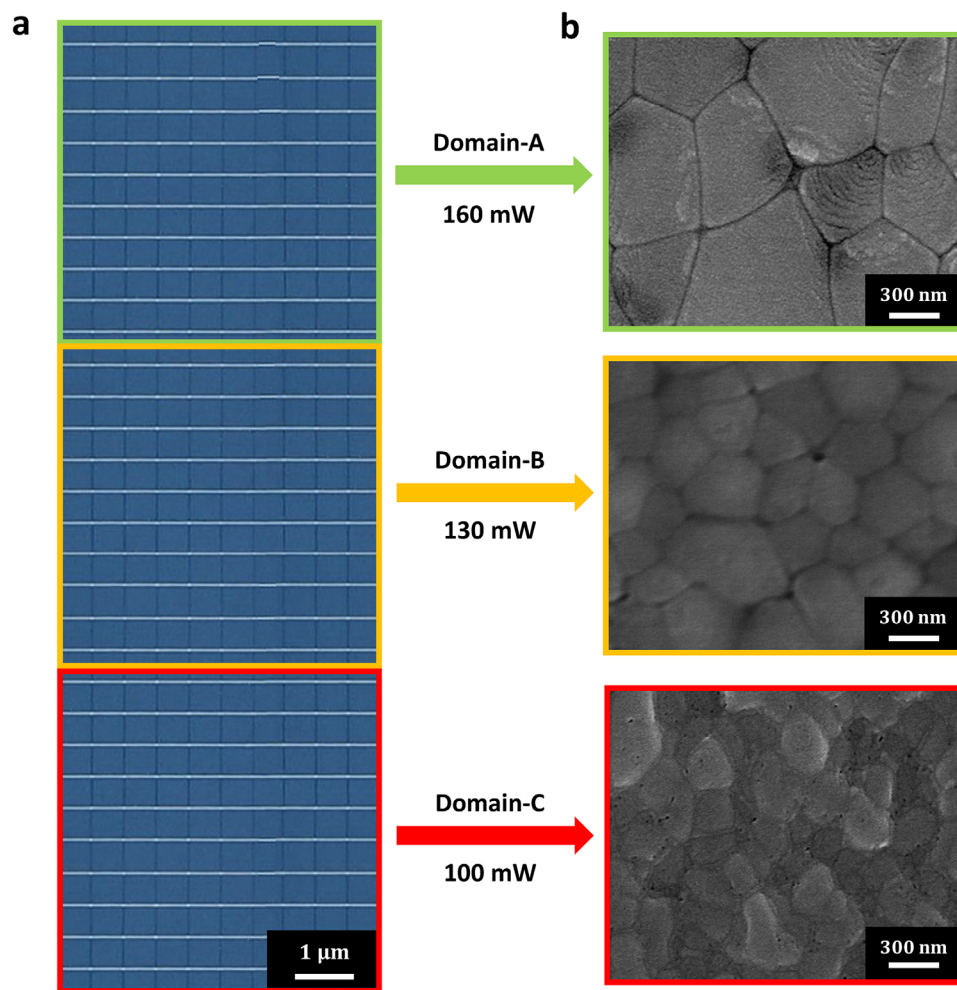


FIGURE 1 | (a) Optical micrographs of grain-size-controlled RSM arrays. (b) SEM images of the FASnI₃ thin films from the same arrays. Domain-A (large grains) is produced by a photo-thermochemical process with a CW laser at 160 mW; Domain-B (medium grains) at 130 mW; and domain-C (small grains) at 100 mW.

in "2.2. Distinct threshold switching behaviors of grain-size-controlled RSMs" section. For reference, morphological changes governed by both laser power and irradiation time per unit area are described in Note S2 and Figure S3. Meanwhile, the measured grain sizes closely match those of control films uniformly annealed at 100, 80, and 60°C, respectively (Figure S1a–c). Collectively, these results demonstrate that spatial modulation of laser power effectively realizes on-substrate thermal gradients, enabling domain-specific grain-size control via the photo-thermochemical process. In addition, the current–voltage (I – V) characteristics of laser-annealed and thermal-annealed films are nearly identical (Figure S4); a detailed discussion is provided in the next section.

The observed grain-size gradient is consistent with von Weimarn's nucleation-and-growth framework, which links the degree of supersaturation to final crystal dimensions [70, 71]. In this picture, low initial supersaturation yields a reduced nucleation rate, so fewer nuclei form and individual crystals have more time and space to grow larger; by contrast, high supersaturation produces rapid nucleation and many small grains within the same crystallization interval. Because raising the temperature typically increases solute solubility

and thus lowers the relative supersaturation in solution-based systems, thermal gradients provide an effective means to tune supersaturation during film formation. This temperature-dependent control of supersaturation therefore plays a central role in driving the evolution of grain size across the film [72–74].

The nucleation rate (V_1) can be described by classical nucleation theory [70] as:

$$V_1 = kA \cdot \exp\left(-\frac{\Delta G^*}{k_B T}\right)$$

where k is a rate constant, A is a pre-exponential factor related to molecular diffusion, k_B is Boltzmann's constant, T is the absolute temperature, and ΔG^* is the critical free energy barrier for nucleation. For a spherical perovskite nucleus [75], ΔG^* is given by:

$$\Delta G^* = \frac{16\pi\gamma^2\Omega^3}{3k_B T^2\sigma^2}$$

where γ is the surface energy of the critical nucleus, Ω is the molecular volume of the crystalline phase, and σ is the

supersaturation ratio. These expressions reveal that:

$$V_1 \propto \exp\left(-\frac{1}{\sigma^2}\right)$$

indicating that even a slight decrease in supersaturation produces a substantial reduction in the nucleation rate. This suppression of nucleation density facilitates the growth of larger grains, consistent with the experimentally observed trend from domain C to domain A.

In addition to nucleation, the crystal growth rate (V_2) also depends on supersaturation. According to the Burton–Cabrera–Frank (BCF) theory [76], V_2 exhibits a supersaturation-dependent transition: at low supersaturation, the growth rate increases quadratically ($V_2 \propto \sigma^2$), corresponding to parabolic growth, whereas at high supersaturation, V_2 increases linearly ($V_2 \propto \sigma$), indicating a diffusion-limited regime [75]. Importantly, the nucleation rate (V_1) is far more sensitive to changes in supersaturation than the crystal growth rate (V_2) [77, 78], supporting the conclusion that temperature-induced suppression of nucleation is the dominant factor governing grain-size modulation. Based on this theoretical framework, the largest grain observed in domain A (highest laser power) and the smallest in domain C (lowest laser power) can be clearly attributed to the temperature-dependent suppression of supersaturation and nucleation.

To complete the device architecture, a top Ag electrode was deposited by thermal evaporation through a shadow mask patterned with 9 vertical lines, each 300 μm wide. This process yields a 10×9 crossbar array within each of the three grain domains (Figure 1a), enabling direct comparative analysis of resistive switching performance as a function of grain size on the same device platform.

2.2 | Distinct Threshold Switching Behaviors of Grain-Size-Controlled RSMs

To investigate the effect of grain boundary density on the electrical characteristics of grain-size-controlled RSM devices, direct current (DC) voltage sweeps were performed on devices located within three distinct domains exhibiting different grain morphologies (Figure 1b). During the measurements, the top Ag electrode was positively biased, while the bottom ITO electrode was grounded. The dominant switching mechanism is attributed to electrochemical metallization (ECM), driven by Ag^+ ion migration from the top electrode, leading to the formation of conductive filaments [79]. For reference, the evidence supporting the predominance of the ECM mechanism is provided in Note S3 and Figure S5. As shown in Figure 2a, all devices exhibit volatile threshold switching behavior, irrespective of domain size. When the applied voltage increases from 0 to 2 V, the device transitions from a high resistance state (HRS) to a low resistance state (LRS), resulting in a sharp increase in current. This transition voltage is defined as the forward threshold voltage (V_{th}^{f}). Conversely, as the applied voltage is swept back toward 0 V, the device returns to the HRS, accompanied by a sudden reduction in current; the voltage at which this transition occurs is defined as the reverse threshold voltage (V_{th}^{r}).

Representative I - V traces show a clear, systematic dependence of threshold voltage on grain size. Measured forward threshold voltages (V_{th}^{f}) for domains A, B, and C are 1.40, 1.31, and 1.21 V, respectively, corresponding to progressively smaller grains. For completeness, additional I - V characteristics measured under sequential forward and reverse bias sweeps for each domain are exhibited in Figure S5. This trend indicates that devices with smaller grains, and therefore higher grain-boundary density, switch from HRS to an LRS at lower voltages, supporting lower-power operation. In addition, grain-size-dependent variations in film thickness—stemming from crystallization kinetics that couple lateral grain growth with vertical film growth [80, 81]—further contribute to the lower threshold voltage in domain-C, since smaller-grain regions form relatively thinner active layers, as shown in Figure S2. We attribute this behavior to preferential Ag^+ migration along grain boundaries, which offer lower activation-energy pathways than intra-grain regions [82–84]. This mechanism of grain-boundary-mediated ion migration has been extensively validated through both experimental observations and theoretical studies, demonstrating that Ag^+ ions preferentially migrate along grain boundaries, which in turn promotes the formation of conductive filaments at reduced operating voltages [85–90]. The high grain-boundary density in domain C facilitates energetically favorable pathways for filament formation, thereby lowering the threshold voltage required for switching. These results verify that the photo-thermochemical process affords precise control over grain morphology and thereby enables the implementation of three distinct volatile threshold-switching behaviors within a single array. For comparison, I - V responses of laser-annealed and conventionally thermally annealed films are nearly identical (Figure S4). Moreover, devices fabricated within the same domain show strong device-to-device and cycle-to-cycle uniformity (Figure S6), underscoring the reproducibility and robustness of the approach. A comparative summary of key electrical performance metrics for representative perovskite-based RSMs is provided in Table S1.

2.3 | Short-Term Dynamics of Grain-Size-Controlled RSMs

The distinct volatile threshold switching behaviors observed in the grain-size-controlled RSMs reproduce key short-term dynamical features of biological neural systems, such as nonlinearity, relaxation time, signal separability, and integrate-and-fire responses. These properties closely resemble short-term plasticity (STP) in biological synapses, where transient conductance modulation enables the encoding and processing of temporal information. In biological neurons, the arrival of an action potential at the presynaptic terminal opens voltage-gated Ca^{2+} channels, leading to neurotransmitter release [91, 92]. The neurotransmitters subsequently bind to ligand-gated ion channels on the postsynaptic membrane, inducing Na^+ influx and signal transmission. In our devices, analogous functionality is captured through the postsynaptic current (PSC) [93–97], whose amplitude depends on the degree of active-metal-ion diffusion within the switching medium in response to an applied voltage pulse [93, 98].

Upon application of a single voltage pulse (1.2 V, 2 ms), conductive filaments nucleate within the RSM, and the PSC rises

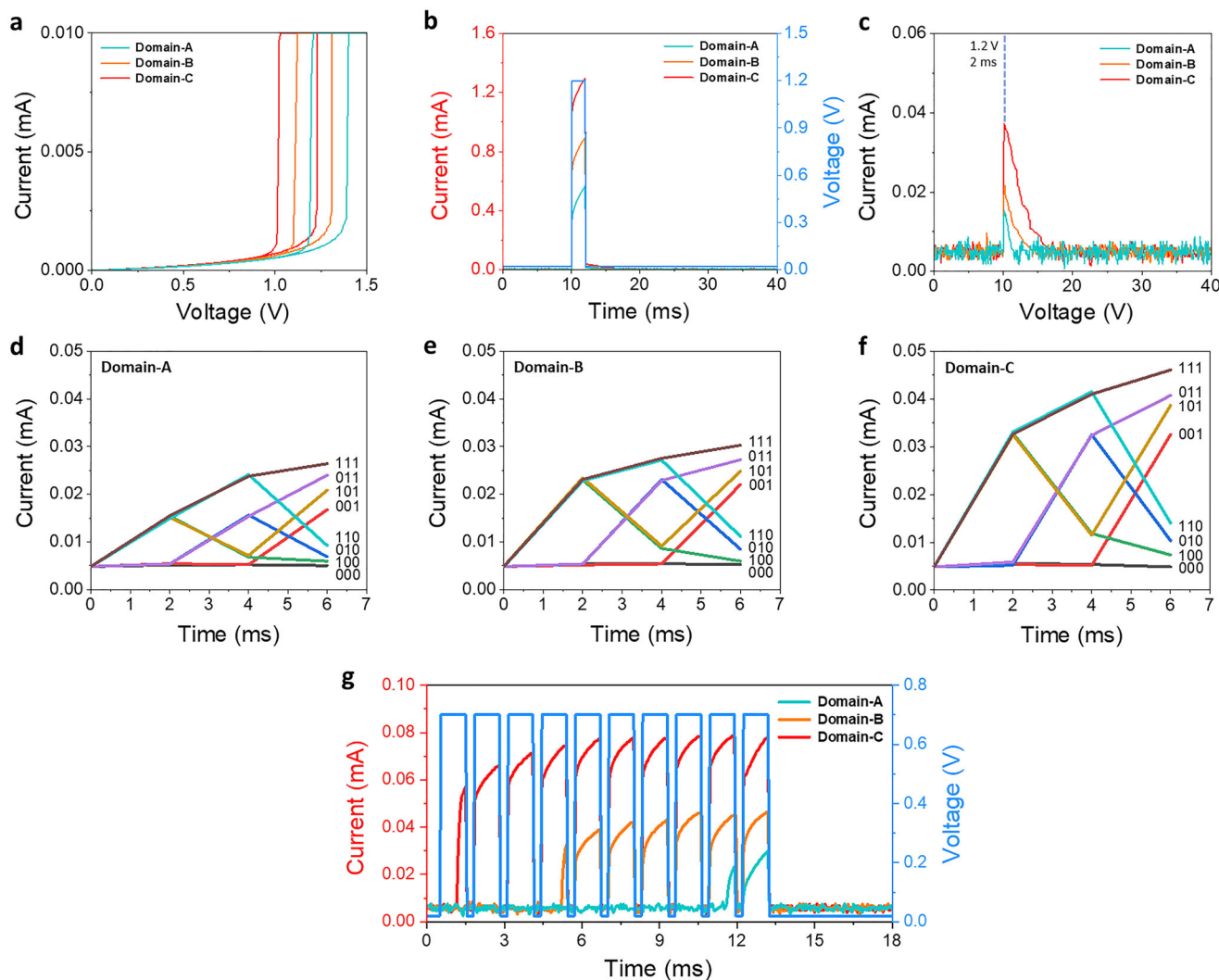


FIGURE 2 | Electrical characteristics of the grain-size-controlled RSM arrays. (a) Representative I - V curves measured in domains-A, B, and C, exhibiting distinct volatile threshold switching modes. (b–g) Short-term neural dynamics: (b) PSC responses to a single voltage pulse (1.2 V, 2 ms), representing domain-dependent nonlinear increase and rapid decay. (c) Decay times of PSC for domains-A, -B, and -C, illustrating the correlation between grain-boundary density and temporal dynamics. (d–f) Signal separability across (d) domains-A, (e) -B, and (f) -C, in response to eight distinct input pulse streams ([000] to [111]). (g) Integrate-and-fire behavior under repetitive subthreshold voltage pulses (0.7 V, 1 ms), with spike generation occurring once in domain-A, six times in domain-B, and nine times in domain-C.

gradually and nonlinearly, irrespective of domain size; removal of the pulse returns the PSC rapidly to baseline, consistent with STP (Figure 2b). The PSC increment varies systematically with local grain-boundary density: devices in domain A (few grain boundaries, limited Ag^+ pathways) show the smallest increase, whereas devices in domain C (many grain boundaries, facile Ag^+ diffusion) show the largest. This domain dependence also governs the decay time, defined as the interval for the PSC to return to its baseline. Decay times of 2.7, 4.0, and 6.9 ms are measured for domains-A, B, and C, respectively (Figure 2c). Thus, tuning grain-boundary density differentiates short-term dynamics across the array, yielding distinct short-, intermediate-, and long-term responses. Nonlinear PSC evolution and corresponding decay times under multiple pulse stimulations (3, 6, and 9 pulses) are provided in Figure S7. In addition, the correlation between the pulse interval time and the corresponding PSC responses under two consecutive pulse stimulation—commonly evaluated

through the paired-pulse facilitation (PPF) effect—is represented in Figure S8.

Signal separability was assessed by applying eight pulse sequences (Figure 2d–f)—[000], [001], [010], [100], [011], [101], [110], and [111]—where “0” denotes no pulse and “1” denotes a single pulse (1.2 V, 2 ms). Each sequence produces a distinct terminal PSC, confirming separability. The PSC gain for a given sequence increases from domain A to C (Figure 2d–f), consistent with the grain-boundary-mediated diffusion pathway density. These results indicate that grain-boundary engineering can tune separability for time-dependent signal processing tasks. Further details are discussed in the next section.

Leveraging the devices’ nonlinear dynamics, we next evaluated integrate-and-fire behavior. In biological neurons, temporally clustered inputs accumulate; when the integrated membrane

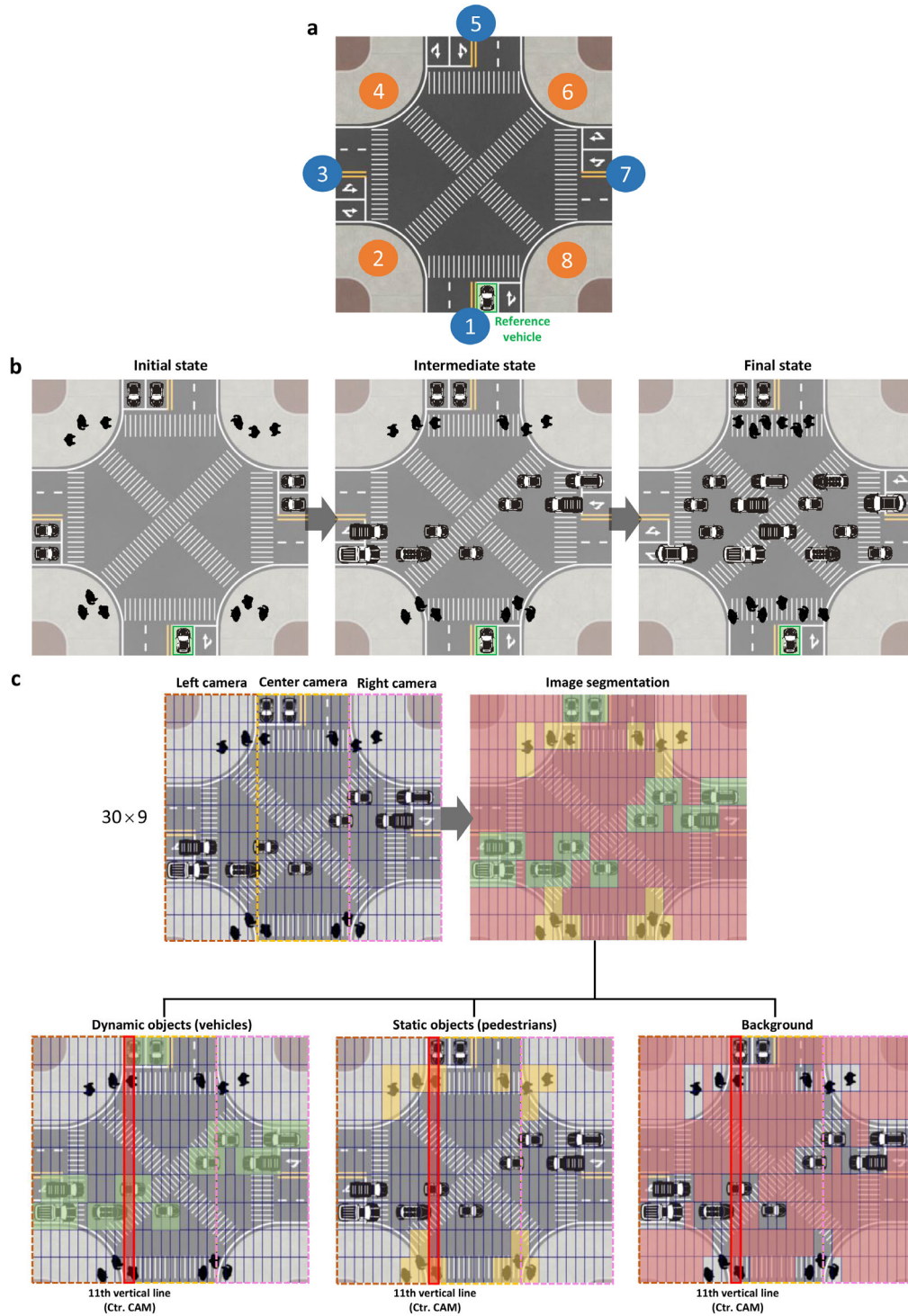


FIGURE 3 | Neuromorphic computing system based on a grain-size-controlled RSM array for autonomous driving. (a) Schematic diagram of a four-way intersection with traffic signals, segmented into eight spatial areas for scenario generation. (b) Temporal evolution of scenario-1 represented by initial, intermediate, and final states, with the field of view of the reference vehicle highlighted (green square). (c) Pixelated 30×9 matrix input representing the intermediate state of scenario-1, segmented into vehicles, pedestrians, and background, and binarized as filled (1) or blank (0) pixels. (d) Optical microscope image of grain-size-controlled RSM implemented on a 30×9 crossbar array, where the pulse streams generated in (c) are applied to rows as input. Domains-A, -B, and -C correspond to the 1st-10th, 11th-20th, and 21st-30th rows, respectively. The 1st-3rd, 4th-6th, and 7th-9th columns represent the initial, intermediate, and final states of each scenario, respectively. Within each state group, the columns from left to right correspond to the left, center, and right cameras (CAM). Finally, nine output values (in columns) are obtained via multiply-accumulate (MAC) operations. (e) PSC responses of the corresponding rows under the intermediate state of scenario-1, obtained from preprocessed pixel-based input pulses represented in (c), reflecting domain-dependent signal separability. (f) Schematic of the 9×5 single-layer perceptron (SLP) model used for training and recognition, with inputs corresponding to column-wise accumulated PSC values from the RSM array. (g) Recognition accuracy as a function of training epochs, achieving 98.9% accuracy after 20 epochs.

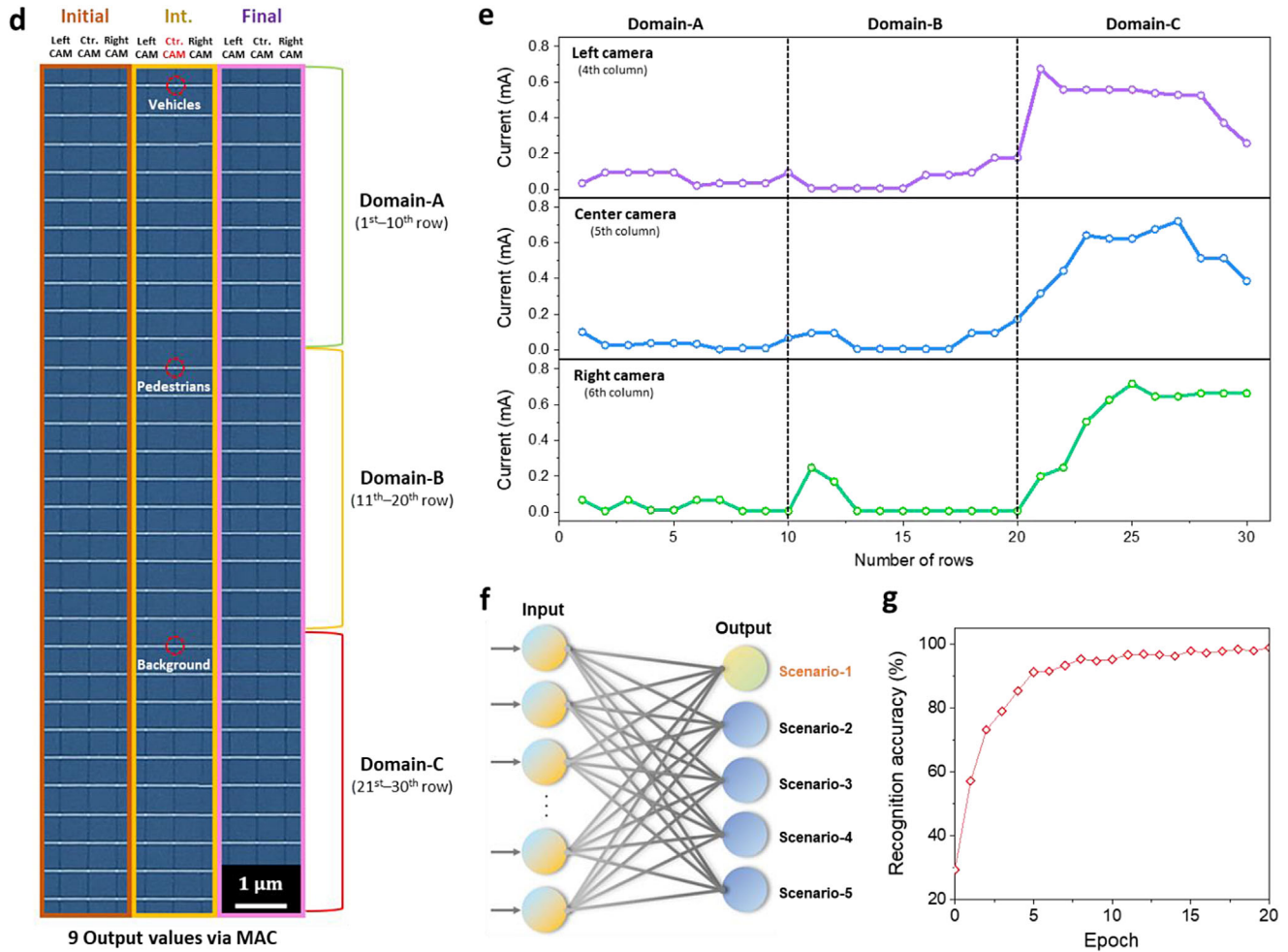


FIGURE 3 | (Continued)

potential exceeds a threshold, an action potential is produced. To reproduce this effect, we applied a train of ten subthreshold voltage pulses (0.7 V amplitude, 1 ms duration) with a 0.3 ms interpulse interval, conditions under which an individual pulse cannot nucleate a conductive filament. As plotted in Figure 2g, the number of successful firing events increases with grain-boundary density: domains A, B, and C exhibit 1, 6, and 9 spikes, respectively. Spike amplitudes likewise grow from domain A to C, consistent with the nonlinear PSC behavior shown in Figure 2b and confirming that grain-boundary density controls both firing probability and strength. Unless stated otherwise, read measurements were taken at 0.02 V. Additional integrate-and-fire tests across varied pulse amplitudes, durations, and interpulse intervals (Figure S9) further demonstrate the devices' tunable response to diverse temporal input patterns.

2.4 | Time-Dependent Signal Processing for Autonomous Driving

A neuromorphic computing system for autonomous driving was implemented using a 30×9 crossbar array of grain-size-controlled RSM devices that modulate short-term dynamics. Autonomous vehicles typically employ three forward-facing cameras (left, center, right) [99], whose video streams are processed in parallel

for real-time perception and adaptive control [100]. To meet the resulting demand for fast, accurate video processing, we exploit the domain-dependent volatile response of the RSM array to extract and compress temporal features from frame sequences representing five road scenarios, each evolving through initial, intermediate, and final states.

For dataset generation, a signalized four-way intersection was modeled with the reference vehicle highlighted by a green-framed area (Figure 3a). The scene was partitioned clockwise into eight areas (areas 1–8) (Figure 3a): odd indices denote road segments and even indices denote sidewalks. Scenarios are defined from the forward view of the reference vehicle in area 1 and include combinations of vehicle motion (e.g., straight, left turn) and pedestrian crossings. As an example, scenario-1 comprises vehicles proceeding straight through areas-3 and -7, with pedestrians crossing from areas 2→8 and 4→6 (Figure 3b). Temporal evolution is delineated into three discrete states—initial, intermediate, and final. Additional scenarios are presented in Figure S10. Each state-specific frame is pixelated to a 30×9 matrix; three 10×9 submatrices correspond to the left, center, and right cameras. An intermediate-state example for scenario 1 is shown in Figure 3c. Frames are then segmented to classify pixels as vehicles, pedestrians, or background [101, 102], followed by binarization (object pixels filled “1”

nonobject pixels blank “0”): “1” denotes a single pulse (1.2 V, 2 ms) and “0” denotes no pulse. The binary pixels are grouped vertically in sets of nine and applied to the array in Figure 3d as input (row). A detailed explanation of the pulse streams corresponding to each column of the pixelated matrix is provided in Figure S11.

Devices in domains A, B, and C are mapped to vehicle, pedestrian, and background pixels, respectively. This assignment follows our measurements showing that domain C devices (higher grain-boundary density) exhibit larger conductance modulation under identical pulses than domain A devices (Figure 2d–f). Mapping the relatively less dynamic background to domain C enhances sensitivity to subtle changes and improves recognition accuracy [103, 104]. As an illustrative intermediate-state line (11th column from the center camera; red guide in Figure 3c), the pulse streams [100001100], [010000001], and [001110010] are applied to the 1st, 11th, and 21st rows in the 5th column for vehicle, pedestrian, and background pixels, respectively (red circles, Figure 3d). For reference, Figure S12 displays the current responses for eight exemplar 9-bit pulse sequences, each containing a single zero—[111111110], [111111101], [111111011], [11110111], [11101111], [11011111], [11011111], and [10111110]—whose signal content is closely similar, thereby demonstrating that the system preserves input distinguishability despite device-level variability. The input-mapping procedure is detailed in Figure S13, and additional state matrices are provided in Figure S14. The corresponding PSC responses for scenario-1 (intermediate state) appear in Figure 3e, exhibiting domain-dependent terminal PSC values consistent with the separability trends in Figure 2d–f. Rows and columns correspond to the top Ag and bottom ITO electrodes, respectively. Columnwise multiply-accumulate (MAC) operations sum the PSC values to generate nine outputs per scenario (three object states $\times$ three viewing angles).

A total of 5000 datasets were prepared (1000 per scenario), with 4000 used for training and 1000 reserved for testing. The nine device outputs served as inputs to a 9×5 single-layer perceptron (SLP) (Figure 3f). Training and inference were conducted through on-chip learning, where synaptic weights were iteratively updated using backpropagation [83]. Detailed simulation parameters are provided in the Experimental Section. After 20 training epochs, the classifier reached a recognition accuracy of 98.9% (Figure 3g). These results confirm that the domain-specific volatile responses of the grain-size-engineered RSM array enable reliable temporal-feature extraction from complex video inputs, delivering intrinsic data compression and substantially reduced computational overhead, critical characteristics for energy-efficient neuromorphic hardware in autonomous-driving systems. For reference, the simulation workflow codes are provided in Note S4.

3 | Conclusions

We present a time-dependent signal-processing platform based on a grain-size-controlled RSM array incorporating a FASnI_3 perovskite thin film. Controlled spatial modulation of grain-boundary density is achieved through a photo-thermochemical process, producing structurally heterogeneous domains across

the array. This engineered heterogeneity yields domain-dependent volatile threshold-switching behaviors and short-term neural dynamics. Devices with higher grain-boundary density exhibit lower threshold voltages, stronger PSC responses, and extended decay times, consistent with enhanced Ag^+ migration along grain boundaries. These tunable properties enable distinct signal separability and adaptable integrate-and-fire functionality, allowing multiple computational roles to coexist within a single device array. Exploiting these domain-specific dynamics, we implement a real-time signal-processing system for video analysis in autonomous-driving scenarios. Spatial mapping of inputs to corresponding device domains facilitates efficient temporal-feature extraction, intrinsic data compression, and optimized MAC operations. The resulting system achieves a 98.9% recognition accuracy, underscoring the scalability and functional versatility of the grain-size-controlled RSM array. In summary, this work establishes a neuromorphic hardware architecture in which multifunctionality and temporal processing are intrinsically encoded in the device structure itself, eliminating the need for complex heterogeneous integration and paving the way for scalable, energy-efficient computing platforms.

4 | Experimental Section

4.1 | Preparation of Sn-Halide Perovskite

High-purity SnI_2 (99.985%) and FAI (99.99%) were sourced from Alfa Aesar and Greatcell Solar Materials, respectively. SnF_2 (99%), metallic Sn (powder, 99.5%), DMF (anhydrous), and DMSO (anhydrous) were purchased from Sigma-Aldrich. To prepare the FASnI_3 precursor solution (1.2M), FAI (206.4 mg), SnI_2 (447.0 mg), SnF_2 (18.8 mg), and metallic Sn (5 mg mL^{-1}) were dissolved in a solvent mixture of DMF and DMSO with a volume ratio of 4:1.

4.2 | Fabrication of Grain-Size-Controlled RSM

A 30×9 crossbar array configuration was employed to fabricate the grain-size-controlled RSM with a glass/ITO/ FASnI_3 /Ag structure. Initially, ITO-coated glass substrates were thoroughly cleaned using ultrasonication in an acetone and isopropyl alcohol (IPA) solution for 20 min, followed by drying with nitrogen gas. To form the bottom electrode, a layer of photoresist (PR) AZ5214 was spin-coated onto the ITO-coated glass at 1000 RPM for 1 min. The coated substrate was then soft baked at 100°C for 5 min. A patterned mask containing 30 lines, each 100 μm wide, was placed over the PR layer before exposure to UV light for 7 s. Afterward, the PR was developed in AZ 300 MIF solution for 1 min, rinsed with deionized water, and hardened at 120°C for 5 min. The patterned PR-coated ITO was subsequently etched for 20 min using CH_4 gas in a reactive ion etcher (RIE) with a gas flow rate of 90 sccm and a reflective power of 300 W. Finally, any remaining PR was eliminated using an acetone-IPA mixture. Next, the FASnI_3 perovskite precursor solution (1.2M) was filtered through a 0.2- μm PTFE filter and deposited onto the patterned ITO-coated glass substrate via spin-coating at 8000 RPM for 60 s. During this process, 250 μL of CB (anti-solvent, Sigma-Aldrich) was applied to the perovskite layer at 12 s. For photo-thermochemical process,

the films were exposed to CW laser (532 nm wavelength, laser beam with objective lens (numerical aperture of 0.055), beam diameter of 25 μm , and scan rate of 5 mm s^{-1}) with various power (160, 130, and 100 mW). Lastly, the top electrode, consisting of a 150 nm Ag layer, was deposited via thermal evaporation (KVE-TG2000) using a shadow mask containing 9 lines, each 300 μm wide. To protect the device from oxidation, a glass encapsulation process was employed.

4.3 | Characterization

Surface morphology was characterized using a field-emission SEM (Nova Nano SEM 450, FEI). Grazing-incidence x-ray diffraction (GIXRD) measurements were conducted on a SmartLab diffractometer (Rigaku) with an incidence angle fixed at 0.3° to minimize diffraction contributions from the underlying electrode. Cross-sectional microstructural analysis was performed using a transmission electron microscope (JEM-2010, JEOL).

4.4 | Electrical Measurements

The electrical properties of the grain-size-controlled RSMs were characterized through I - V measurements and conductance stability assessments using a Keithley 2600 sourcemeter. Short-, mid-, and long-term memory behaviors of the artificial neuron, including integrate-and-fire dynamics, signal separability, and decay times, were evaluated with a Series-300 potentiostat under controlled voltage-pulse stimulation. In all measurements, a positive voltage bias or pulse train was applied to the top Ag electrode, while the bottom ITO electrode was held at ground potential. All experiments were conducted at room temperature under ambient conditions using a probe station housed within a light-shielded enclosure. To prevent oxidation of the switching medium during measurement, encapsulated RSM devices were employed throughout the characterization process.

4.5 | Simulation of Neural Networks

On-chip training was simulated using Python and NumPy. For the neuromorphic computing framework, an SLP with a 9×5 architecture was employed to classify datasets representing five distinct road scenarios. Synaptic weights were updated via the backpropagation algorithm, and the softmax function was used as the activation function. Final recognition accuracy was determined by averaging the outcomes of 30 independent simulations, each initialized with a different random seed.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Supporting File: smll73909-sup-0001-SuppMat.pdf.