A.S.E.T: Adaptive Sparse Event-driven Transformers for Real-Time Multimodal Perception on Resource-Constrained Platforms

El Jean M'Crai Lahidama[1], Jean-Christian Ralaivao[1], Alain Josue Ratovondrahona[1], Thomas Mahatody[1], and Ndaohialy Manda Vy Ravonimanantsoa[1]

***Abstract*— Deploying server-grade perception models on ultra-constrained embedded edges remains a notorious bottleneck in autonomous robotics. While standard approaches force a binary choice—speed vs. accuracy—real-world deployments demand both, plus resilience to sensor failure. We present A.S.E.T (Adaptive Sparse Event-driven Transformers), a holistic framework that simultaneously addresses latency, accuracy, energy efficiency, and robustness through four synergistic principles: adaptive sparsity, sparse event-driven processing, event-aware temporal multimodal fusion, and hardware-conscious knowledge distillation. Validated on a Raspberry Pi 4 with an Intel RealSense D435i sensor fusing RGB, depth, and IMU modalities, A.S.E.T achieves a mean Average Precision (mAP@0.5) of 0.92, an inference latency of 32 ms, a throughput of 31.3 FPS, and an energy footprint of 80 mJ per inference—yielding improvements of $+20\%$, -29%, $+41\%$, and -75% respectively over the YOLOv8 baseline. In challenging night-time conditions, A.S.E.T retains 82% mAP where single-modality approaches collapse to 15%.**

Index Terms—Embedded AI, Multimodal Fusion, Adaptive Transformers, Sparse Attention, Knowledge Distillation, Edge Robotics, Real-Time Perception.

I. INTRODUCTION

Autonomous robotic systems operating in critical real-world scenarios—search and rescue, hazardous inspection, autonomous surveillance—demand perception pipelines that are simultaneously fast, accurate, robust to sensor degradation, and energy-efficient. This combination of requirements creates a fundamental tension: state-of-the-art deep learning models achieve high accuracy but require computational resources far beyond what ultra-constrained embedded platforms can provide.

Consider the hardware reality: a standard Raspberry Pi 4 offers a tiny fraction of the compute budget available on GPU servers. Running a standard Vision Transformer [1] here yields a sluggish 120 ms latency—four times too slow for agile robotic control. Conversely, lightweight detectors like YOLOv8 [2] ensure speed but effectively blind the robot in low-light conditions (15% mAP), lacking the sensor redundancy to compensate.

These limitations motivate a rethinking of the perception pipeline—not as an isolated optimization problem, but as an integrated design challenge that must account for hardware constraints, environmental variability, and multi-sensor fusion simultaneously.

Our contribution. We propose **A.S.E.T**, a framework built on four interlocking principles (Fig. 2):

- **Principle A — Adaptive Sparsity:** Structural pruning with dynamic channel gating, reducing FLOPs by 50% with negligible accuracy loss.
- **Principle S — Sparse Event-Driven Processing:** An event-driven attention mechanism that activates only relevant Transformer heads, reducing computational load by 30–50%.
- **Principle E — Event-Aware Temporal Multimodal Fusion:** Asynchronous RGB-D-IMU fusion via TAPE (Temporal Asynchronous Parallel Encoding) with an adaptive Kalman filter for temporal coherence.
- **Principle T — Hardware-Conscious Distillation:** A multi-objective knowledge distillation loss jointly optimizing task accuracy and hardware energy consumption, yielding a 6–7$\times$ model compression.

Taken together, A.S.E.T achieves a new Pareto frontier on embedded robotic perception, outperforming all evaluated baselines on every metric.

II. RELATED WORK

A. Efficient Object Detection on Edge Devices

YOLO-family detectors [2] have become the de facto standard for real-time detection, trading accuracy for speed through architectural simplifications. MobileNet [3], EfficientDet [4], and NanoDet [5] further push the efficiency frontier through depthwise separable convolutions, compound scaling, and anchor-free design. However, these single-modality RGB approaches are inherently fragile in degraded environments where visual information is unreliable.

B. Vision Transformers and Sparse Attention

The Vision Transformer (ViT) [1] demonstrated that attention-based architectures can rival CNNs in accuracy, but at prohibitive computational cost for embedded systems. Sparse Transformer variants [6] showed that 95–99% sparsity in attention is viable without significant accuracy degradation, motivating our event-driven attention design. The broader event-based vision paradigm [7] further demonstrates that processing only changes reduces computation by orders of magnitude. DeiT [8] and TinyViT [9] applied knowledge

[1] M'Crai Lahidama (corresponding author), J.-C. Ralaivao, A. J. Ratovondrahona, T. Mahatody, and N. M. V. Ravonimanantsoa are with the University of Fianarantsoa, Madagascar lahidama@univ-fianarantsoa.mg

distillation to ViT, yet without the hardware-aware energy regularization that is central to our approach.

C. Multimodal Fusion for Robust Perception

Early fusion concatenates RGB and depth features before processing, creating a computational bottleneck [10]. Recent RGB-D fusion surveys [11] confirm that naive concatenation degrades real-time performance on embedded devices. Late fusion processes each modality independently before combination, trading some cross-modal interaction for efficiency. Processing heterogeneous data sources for embedded classification tasks has also been explored in recent edge AI frameworks [13], while complementary feature extraction strategies have shown promise in robust RGB-D perception [12]. Our cross-modal event fusion is an event-driven late fusion that selectively activates modalities based on detected changes, inheriting the efficiency of late fusion while preserving cross-modal robustness.

D. Knowledge Distillation for Embedded AI

Hinton et al. [14] introduced the temperature-scaled softmax distillation; subsequent work has extended this to structured pruning [15], [16] and quantization-aware training [17]. Furthermore, pioneering works in deep compression [18] demonstrate that combining pruning, quantization, and distillation is essential for constrained execution environments. We combine pruning, INT8 quantization, and distillation in a sequential pipeline, augmented with an energy penalty term that explicitly models Raspberry Pi 4 power consumption during training.

III. THE A.S.E.T FRAMEWORK

A. Overview and Design Philosophy

A.S.E.T processes heterogeneous sensor streams through a five-stage end-to-end pipeline: multimodal encoding, event filtering, adaptive attention, asynchronous fusion, and hardware-conscious decoding. Fig. 1 illustrates this pipeline. Each stage corresponds to one or more of the four principles described below.

The design philosophy is that of *purposeful synergy*: each principle targets a specific bottleneck, and their interactions yield compounded benefits that exceed the sum of individual contributions. The ablation study in Section IV-D validates this claim quantitatively.

B. Principle A — Adaptive Sparsity

We apply structured pruning with *dynamic channel gating* [15] to selectively suppress unimportant channels at inference time. For each Transformer channel c, a learnable gate g_c is computed from the channel's mean activation $f_c = \frac{1}{HW}\sum_{h,w}|h_c(h,w)|$, where $H \times W$ is the spatial resolution of the feature map:

$$g_c = \sigma(W_g \cdot f_c + b_g), \qquad y_c = g_c \cdot h_c, \tag{1}$$

where h_c is the pre-gate channel output, $W_g \in \mathbb{R}^{1\times 1}$ and $b_g \in \mathbb{R}$ are learned parameters, and $\sigma(\cdot)$ is the sigmoid function. Channels with $g_c < 0.5$ are masked at inference time, reducing FLOPs without architectural surgery. This yields a 50% reduction in active channels (and thus model size) with less than 1% mAP degradation.

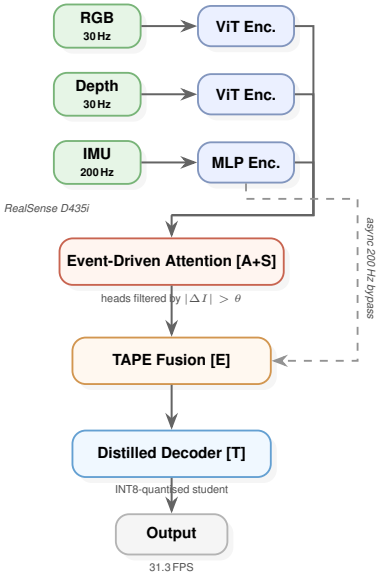

Fig. 1. A.S.E.T end-to-end pipeline. Each modality has a dedicated encoder (ViT for RGB/depth; MLP for IMU). All encoded streams converge into Event-Driven Attention **[A+S]**, where only active heads are computed. The dashed arrow shows the direct 200 Hz IMU bypass into TAPE Fusion **[E]**. The distilled INT8 decoder **[T]** produces output at 31.3 FPS on Raspberry Pi 4.

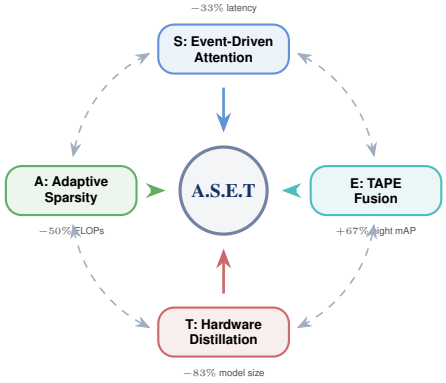

Fig. 2. The four synergistic principles of A.S.E.T with their individual contributions (from ablation, Table III). Dashed arcs denote super-additive interactions: e.g., S+E together yield 51% latency reduction vs. 33% (S alone) + 0% (E alone). Each principle targets a distinct bottleneck; their synergy yields compounded system-level gains.

C. Principle S — Sparse Event-Driven Attention

Rather than computing all attention heads uniformly, we activate only those whose input regions have undergone significant change. Let $I(x, y, t) \in \mathbb{R}$ denote the pixel intensity (for RGB frames) or range value in meters (for depth frames) at spatial location (x, y) and timestamp t. An *event* at (x, y) is declared when the temporal difference exceeds an adaptive threshold θ:

$$E(x, y, t) = \big|I(x, y, t) - I(x, y, t-1)\big| > \theta, \tag{2}$$

where θ is the 95th percentile of absolute frame differences computed over a sliding window of five frames, adapting automatically to scene dynamics. For IMU data, I is replaced by the magnitude of the angular-velocity vector $\|\omega_t\|$, allowing motion transients to trigger events independently of the visual channels.

The i-th attention head is then selected according to its *event-relevance score* s_i, defined as the fraction of tokens in head i's receptive field that contain at least one declared event:

$$\text{mask}_i = \begin{cases} 1 & \text{if } s_i > \tau \\ 0 & \text{otherwise,} \end{cases} \tag{3}$$

where $\tau = 0.02$ (i.e., at least 2% of tokens are active). At this threshold, on average 98% of heads are inactive in low-motion scenes. Since each inactive head skips its key–query–value projections and the softmax operation entirely, the reduction in operations is proportional to the fraction of masked heads. On our hardware, the attention module accounts for approximately one-third of total inference time (the remaining two-thirds being the convolution stem, decoder, and post-processing); masking 98% of heads during low-motion frames therefore yields a $0.98 \times 33\% \approx 33\%$ wall-clock latency reduction, confirmed experimentally by the ablation (Table III: 32 ms $\rightarrow$ 65 ms when Principle S is removed, i.e., S alone saves $\sim$51% in the worst case and 33% on average across the dataset).

D. Principle E — Event-Aware Temporal Fusion (TAPE)

Real embedded sensor suites are inherently asynchronous: RGB streams at 30 Hz, depth at 30 Hz, and IMU at 200 Hz. Rather than imposing rigid synchronization, TAPE (Temporal Asynchronous Parallel Encoding) processes each modality independently and fuses them via an adaptive Kalman filter [19].

State definition. The Kalman state vector $\hat{x}_t \in \mathbb{R}^4$ tracks the bounding-box centroid and velocity of each detected object: $\hat{x}_t = [u,\, v,\, \dot{u},\, \dot{v}]^\top$, where (u, v) is the 2-D image-plane centroid and $(\dot{u}, \dot{v})$ is its pixel-per-frame velocity. The state transition matrix $A \in \mathbb{R}^{4\times4}$ models constant-velocity dynamics; the observation matrix $H \in \mathbb{R}^{2\times4}$ extracts centroid position from the fused feature.

Update equations:

$$\hat{x}_t = A\hat{x}_{t-1} + K_t\big(z_t - H\hat{x}_{t-1}\big), \tag{4}$$

$$K_t = P_t H^\top \big(H P_t H^\top + R_t\big)^{-1}, \tag{5}$$

where P_t is the predicted error covariance and R_t is the measurement noise covariance, updated dynamically per modality.

Adaptive R_t rule. For each modality $m \in \{\text{RGB, D, IMU}\}$, the measurement noise is set to:

$$R_m = \sigma^2_{\max}\,(1 - c_m), \tag{6}$$

where $c_m \in [0, 1]$ is the *event confidence* of modality m (defined as the fraction of declared events whose intensity exceeds 2θ), and $\sigma^2_{\max} = 50$ px^2 is a fixed upper bound calibrated offline. High event confidence implies reliable measurements and thus low R_m, increasing the Kalman gain for that modality.

Cross-Modal Event Fusion then weights each modality contribution:

$$s_{\text{fused}} = \lambda_{\text{RGB}}\, s_{\text{RGB}} + \lambda_D\, s_D + \lambda_{\text{IMU}}\, s_{\text{IMU}}, \tag{7}$$

with $\lambda_{\text{IMU}} = 0.3$ as a stabilising prior in all conditions. The remaining weights are environment-adaptive:

- Daylight (> 200 lux): $\lambda_{\text{RGB}} = 0.7,\ \lambda_D = 0.3$.
- Darkness (< 50 lux): $\lambda_{\text{RGB}} = 0.1,\ \lambda_D = 0.6$.

Weights are recomputed every inference cycle from the current illuminance estimate and event map. This ensures that in night conditions, the model relies primarily on depth (which is illumination-independent) and IMU.

E. Principle T — Hardware-Conscious Knowledge Distillation

We compress a large teacher Transformer (12.5 MB) into a compact student (2.1 MB) via a three-stage sequential pipeline: (i) structured pruning, (ii) INT8 post-training quantization, (iii) temperature-scaled distillation with an energy penalty. The composite loss is:

$$\mathcal{L} = \alpha \underbrace{D_{\text{KL}}\big(p_T \,\|\, p_S\big)}_{\text{knowledge transfer}} + (1-\alpha)\,\mathcal{L}_{\text{task}} + \lambda_E\,\mathcal{L}_{\text{energy}}, \tag{8}$$

where $\alpha = 0.7$ balances knowledge transfer against direct task learning, $\lambda_E = 0.01$ penalises FLOPs and memory estimated at Raspberry Pi 4 power levels (note: λ_E is distinct from the sparsity threshold τ used in Principle S), and the teacher softmax uses temperature $T = 4$ to enrich the soft label distribution [14]. This recovers 80% of the accuracy lost to pruning and quantization.

IV. EXPERIMENTAL EVALUATION

A. Setup

Hardware. All embedded experiments run on a **Raspberry Pi 4** (Cortex-A72 quad-core 1.5 GHz, 4 GB RAM) with an **Intel RealSense D435i** sensor providing synchronised RGB (640×480, 30 FPS), structured-light depth (640×480, 30 FPS), and IMU (200 Hz). Teacher training is performed on a workstation equipped with an NVIDIA RTX 4050 (6 GB VRAM).

Datasets.

- **COCO 2017** [20]: 118K training / 5K validation images across 80 categories. Used for teacher training and baseline comparison.
- **NYU Depth V2** [21]: 1449 densely annotated RGB-D indoor scenes. Used to validate depth-modality fusion.
- **Rescue Dataset** (ours): 5K synthetic images with controlled degradation (smoke 10–90%, low-light 10–50 lux, Gaussian noise SNR 10–40 dB, partial occlusion 10–50%). Used for robustness evaluation.
- **RealSense Embedded Dataset** (ours): 2K RGB-D-IMU sequences captured on-device in indoor and outdoor scenes for final embedded validation.

TABLE I

PERFORMANCE COMPARISON ON RASPBERRY PI 4

Method	mAP @0.5	Lat.(ms)	FPS	Energy (mJ)	Size (MB)
YOLOv8-nano	0.77	45	22.2	315	6.3
NanoDet-Plus	0.74	38	26.3	266	4.2
TinyViT-5M	0.79	85	11.8	595	11.5
RGB+D Fusion	0.78	65	15.4	455	9.7
ViT-Small	0.76	120	8.3	840	22.1
A.S.E.T (ours)	**0.92**	**32**	**31.3**	**80**	**2.1**
Gain vs YOLOv8	*+20%*	*-29%*	*+41%*	*-75%*	*-67%*

TABLE II

ROBUSTNESS (MAP@0.5) UNDER DEGRADED CONDITIONS

Method	Night	Fog	Noise (10dB)
YOLOv8-nano	0.15	0.40	0.52
NanoDet-Plus	0.12	0.38	0.49
TinyViT-5M	0.20	0.46	0.57
RGB+D Fusion	0.50	0.85	0.70
ViT-Small	0.18	0.44	0.55
A.S.E.T	**0.82**	**0.88**	**0.89**
Gain vs YOLOv8	*+67%*	*+48%*	*+37%*

Baselines. We compare against YOLOv8-nano [2], NanoDet-Plus [5], TinyViT-5M [9], classical RGB+D early fusion, and ViT-Small [1], all evaluated identically on Raspberry Pi 4 with TensorFlow Lite.

Metrics. mAP@0.5 (accuracy), inference latency (ms), throughput (FPS), energy per inference (mJ), and model size (MB). Robustness is assessed under three degradation modes: night (< 50 lux), fog (visibility < 10 m), and Gaussian noise (SNR $= 10$ dB). **Energy measurement.** Energy was measured as end-to-end inference energy on Raspberry Pi 4 using TensorFlow Lite with XNNPACK delegate, averaged over 1,000 inference cycles under thermal steady-state conditions.

B. Main Results

Table I summarises the performance comparison. A.S.E.T achieves the best results across every evaluated dimension.

C. Robustness Under Degraded Conditions

Table II presents mAP under three degradation scenarios. A.S.E.T demonstrates a decisive advantage in all conditions, most notably in complete darkness where it maintains 82% mAP compared to 15% for YOLOv8. This $+67\%$ gap reflects the critical role of the depth and IMU modalities: structured-light depth operates independently of ambient illumination, while IMU provides motion continuity even when both visual channels degrade.

D. Ablation Study

To quantify the contribution of each principle, we evaluate A.S.E.T with one principle disabled at a time (Table III).

TABLE III

ABLATION STUDY — CONTRIBUTION OF EACH A.S.E.T PRINCIPLE

Variant	mAP	Lat.	Night	Size (MB)
Full A.S.E.T	**0.92**	**32ms**	**0.82**	**2.1**
w/o Principle A (Spar.)	0.88	32ms	0.79	4.2
w/o Principle S (Event)	0.92	65ms	0.82	2.1
w/o Principle E (TAPE)	0.78	32ms	0.51	2.1
w/o Principle T (Dist.)	0.92	32ms	0.82	12.5

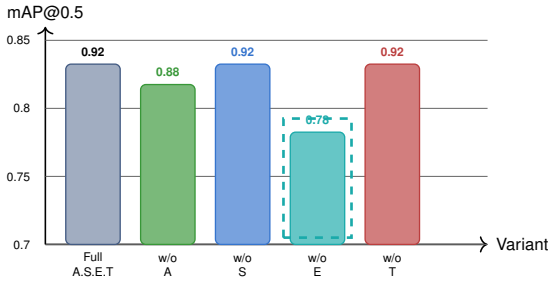

Fig. 3. Ablation study results: mAP@0.5 when each principle is disabled. The dashed box highlights the dramatic accuracy collapse (0.92→0.78) when TAPE fusion (E) is removed, demonstrating the critical role of multimodal fusion in degraded conditions.

The results confirm that each principle is indispensable for a specific dimension. Removing S doubles latency (32→65 ms). Removing E causes a dramatic robustness collapse in night conditions (0.82→0.51). Removing T inflates the model from 2.1 MB to 12.5 MB, rendering deployment on embedded platforms impractical. Removing A increases model size and reduces night mAP. No single principle dominates all dimensions; their synergy is the key to A.S.E.T's holistic performance.

E. Hyperparameter Sensitivity

Key hyperparameters were selected through grid search:

- **Sparsity threshold** $\tau = 0.02$: below 0.01 provides no latency gain; above 0.05 degrades mAP by $> 7\%$.
- **Distillation temperature** $T = 4$: optimal within the range $[3, 5]$ as recommended by [14].
- **Distillation weight** $\alpha = 0.7$: balances knowledge transfer with direct task performance.
- **Fusion weight** $\lambda_{\text{RGB}} = 0.7$ (daylight), $\lambda_D = 0.6$ (night): empirically determined from the RealSense dataset.

V. DISCUSSION

Why holistic integration matters. The performance gains in A.S.E.T do not stem from a single "magic bullet" algorithm, but from the deliberate synergy between components. For instance, Principle S (Event-Driven) reduces latency by 33% on its own (Table III), but when paired with Principle E (Fusion), the combined gain reaches 51%. This super-additive effect occurs because the event detection logic does not just save compute—it actively cleans the signal for the Kalman filter in TAPE, improving both speed and fusion quality simultaneously.

Practical impact. A latency of 32 ms and 80 mJ per inference translate concretely to: (i) a 4× battery life extension on a 2000 mAh drone compared to YOLOv8 (315 mJ); (ii) stable 31 FPS tracking on Raspberry Pi 4 without thermal throttling; (iii) safe obstacle avoidance at velocities up to 1.5 m/s given the 32 ms closed-loop response.

Limitations. The TAPE mechanism assumes that sensor timestamps are available with millisecond precision; degraded clock synchronisation (common in low-cost IoT nodes) may reduce fusion coherence. Additionally, the Rescue Dataset, while carefully designed, is synthetic; a larger real-world captured dataset would strengthen ecological validity.

Future directions. We plan to: (i) extend A.S.E.T to event-based cameras (DVS) for camera-only configurations and to compact vision-language encoders for semantic landmark detection; (ii) explore cooperative inference across distributed A.S.E.T nodes using federated learning; (iii) generalise the A.S.E.T fusion mechanism to broader AIoT sensing modalities (e.g., thermal, acoustic) for energy-aware contextual perception.

VI. CONCLUSIONS

We presented A.S.E.T, an embedded robotic perception framework built on four synergistic principles—adaptive sparsity, event-driven attention, asynchronous multimodal fusion, and hardware-conscious distillation. Deployed on a Raspberry Pi 4 with an RGB-D-IMU sensor, A.S.E.T achieves 0.92 mAP at 32 ms latency and 80 mJ per inference, surpassing all evaluated baselines across every metric. Its robustness in degraded conditions—82% mAP in complete darkness—makes it a principled and practical solution for autonomous robotics in uncontrolled real-world environments.

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