

DAPEVO: Deep Adaptive Patch Frame-Event Visual Odometry

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Abstract—Visual odometry is essential for autonomous navigation in GPS-denied environments, yet RGB-based methods remain vulnerable to motion blur, challenging illumination, and dropped frames. Event cameras complement conventional cameras with high temporal resolution and dynamic range, but their asynchronous measurements complicate reliable correspondence estimation. We present DAPEVO, a learned visual odometry system that estimates image and event correspondences independently at shared patch locations and fuses their correlation evidence before motion refinement. Each tracked patch maintains image and event descriptors, and a learned scalar gate combines modality-specific correlation embeddings for each patch-frame edge before a shared recurrent refinement and bundle-adjustment update. DAPEVO also supports event-only observations, enabling continued tracking when RGB frames are sparse or unavailable, while modality-aware keyframe culling preserves scarce frame constraints. On UZH-FPV, when retaining only one in six RGB frames, DAPEVO’s mean absolute trajectory error (ATE) increases by only 36%, from 1.00 to 1.36 m, whereas the ATE of DPVO and RAMP-VO rises by factors of $3.7\times$ and $3.1\times$, respectively. On TartanEvent, DAPEVO similarly remains below 1 m ATE at 3 Hz RGB input, while DPVO and RAMP-VO exceed 9 m. Under degraded RGB input on TartanEvent, DAPEVO achieves an ATE of 0.60 m, compared with more than 4 m for both DPVO and RAMP-VO, while also outperforming event-only DEVO at 0.87 m.

I. INTRODUCTION

Reliable localization in GPS-denied environments is essential for autonomous robots operating indoors, underground, and in planetary exploration settings [1]–[4]. Image-based visual odometry provides rich appearance information, but motion blur, limited dynamic range, and sparse or dropped images can degrade the correspondences required for motion estimation. Event cameras complement conventional cameras with high temporal resolution and high dynamic range [5], providing measurements between image acquisitions and under conditions in which RGB-based tracking becomes unreliable.

The relative usefulness of the two modalities varies spatially and temporally. A visually distinctive image region

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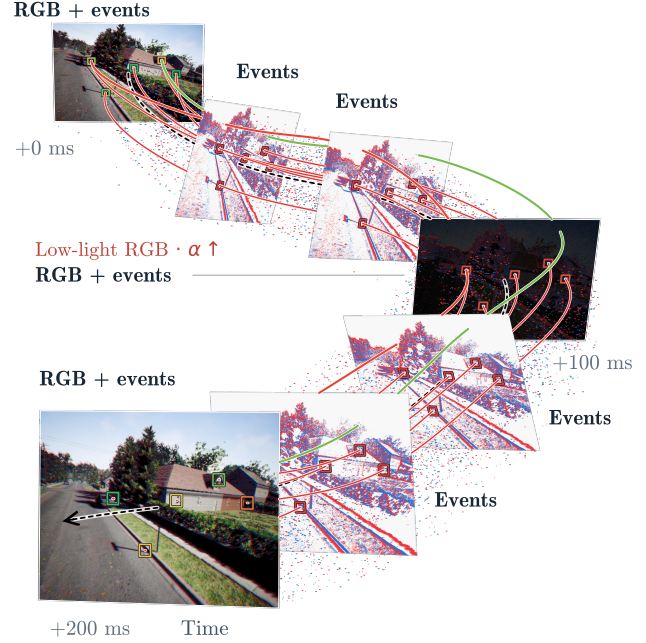


Fig. 1. **Overview of DAPEVO.** Joint RGB–event and event-only observations are processed by separate image and event encoders. Patches with RGB and event descriptors are correlated independently, then adaptively fused by a learned gate before recurrent refinement and bundle adjustment. Patch colors and track lines indicate the event contribution α , from green ($\alpha = 0$) to red ($\alpha = 1$). A low-light augmentation is applied to the central RGB observation to illustrate reduced reliance on degraded frame information. When RGB is unavailable at either correspondence endpoint, $\alpha = 1$, enabling event-only tracking.

may generate few informative events, while degraded image observations may coincide with strong event measurements. A robust image-event estimator must therefore adapt to both the availability and reliability of each modality.

DPVO [6] combines sparse patch tracking with learned correspondence refinement and differentiable bundle adjustment, while DEVO [7] adapts this formulation to event data. RGB–event methods such as EDS [8] and RAMP-VO [9] exploit the complementary sensing modalities. In particular, RAMP-VO asynchronously combines incoming image and event measurements into a shared recurrent feature representation from which matching and context features are decoded. This shared representation enables multimodal estimation, but does not explicitly preserve and weight modality-specific evidence.

This distinction becomes important when one modality becomes unreliable, as its features can introduce ambiguous

correspondences and noisy constraints into the patch graph. Event measurements pose an additional challenge because their differential and motion-dependent nature makes correspondence estimation more difficult than conventional image matching.

We introduce Deep Adaptive Patch Frame-Event Visual Odometry (DAPEVO), a monocular RGB-event odometry method built on DPVO. Co-located image and event descriptors are matched independently, and their correlation embeddings are fused by an edge- and iteration-specific learned gate. When RGB is unavailable, event-only observations remain in the same optimization graph, while modality-aware keyframe culling preserves sparse RGB constraints.

DAPEVO remains competitive under nominal conditions while providing larger gains when RGB observations become sparse or degraded. On UZH-FPV [10], when retaining only one in six RGB frames, DAPEVO increases its ATE by only 36%, whereas the ATE of DPVO and RAMP-VO rises by factors of $3.7\times$ and $3.1\times$, respectively. On TartanEvent [9], DAPEVO remains below 1 m ATE at 3 Hz RGB input, while DPVO and RAMP-VO exceed 9 m. Under degraded RGB input on TartanEvent, DAPEVO achieves an ATE of 0.60 m, compared with more than 4 m for both DPVO and RAMP-VO, while also outperforming event-only DEVO at 0.87 m.

Our contributions are:

- A correspondence-level RGB-event fusion strategy that preserves modality-specific matching evidence and adaptively combines it for each patch-frame edge and recurrent refinement iteration.
- Joint RGB-event and event-only observations within the same optimization graph, together with modality-aware keyframe culling that preserves sparse RGB-bearing constraints, enabling patch tracking and pose updates at a higher rate than the RGB frame rate.
- An evaluation on synthetic and real-world datasets under nominal operation, degraded RGB observations, and reduced RGB frame rates.

II. RELATED WORK

A. Geometric and Learned Visual Odometry

Classical visual odometry estimates geometric constraints through feature matching, as in ORB-SLAM3 [11], or direct photometric alignment, as in DSO [12]. DeepVO [13] regresses camera motion with a recurrent network, whereas D3VO [14] integrates predicted depth, pose, and photometric uncertainty into a direct geometric estimator. RAFT [15] introduced recurrent refinement through correlation lookups for optical flow. DROID-SLAM [16] uses recurrent correspondence refinement and differentiable bundle adjustment, while DPVO [6] introduces a sparse patch representation for efficient visual odometry. DPV-SLAM [17] extends this formulation with loop closure.

B. Event-Based Motion Estimation

Early event-based estimators recover motion and structure through filtering or geometric optimization. Kim et al. [18] jointly estimate motion and structure from monocular events,

while EVO [19] performs event-to-map alignment with parallel mapping. ESVO [20] extends event-based odometry to stereo, and event-inertial approaches combine event tracks with filtering or nonlinear optimization [21], [22].

Learned methods estimate motion directly from event representations or integrate learned correspondence estimation with geometric optimization. Zhu et al. [23] jointly learn optical flow, depth, and egomotion through event motion compensation. DEVO [7] adapts DPVO to event voxel grids and introduces learned event-based patch selection, while DEIO [24] and Stereo-DEVO [25] extend learned event odometry with inertial and stereo measurements.

C. Combining Frames and Events

RGB-event methods exploit the complementary appearance and temporal information provided by the two sensing modalities. Kueng et al. [26] detect features in intensity images and track them asynchronously using events. EDS [8] estimates inter-frame motion from an event-derived brightness-increment residual and explicitly evaluates reduced frame rates. Ultimate SLAM [27] and PL-EVIO [28] combine frame, event, and inertial constraints within geometric estimators.

Learned approaches have also explored recurrent and shared representations for asynchronous multimodal fusion. RAM-Net [29] maintains a recurrent state that can be updated asynchronously by either modality. RAMP-VO [9] extends this formulation to visual odometry using parallel multiscale encoders that integrate frame and event inputs into a shared recurrent representation, from which matching and context features are decoded. It supports asynchronous inputs and reduced RGB frame rates, but does not retain separate image- and event-based correlation evidence through correspondence estimation.

III. METHOD

A. Input Representation and Geometric State

Figure 2 provides an overview of the DAPEVO architecture. At timestamp t , DAPEVO receives a five-bin event voxel grid $\mathbf{V}_t \in \mathbb{R}^{5 \times H \times W}$ and, when available, an RGB image $\mathbf{I}_t \in \mathbb{R}^{3 \times H \times W}$. We refer to observations containing both modalities as *joint frames* and those containing only events as *event-only frames*. Both modalities are assumed to share the same camera intrinsics, as provided by a shared pixel array or a calibrated beamsplitter configuration. Following DEVO [7], events are accumulated into five temporal bins; in contrast to the RGB inputs, *event-only* frames can be instantiated at arbitrary timestamps.

We adopt the patch representation and geometric formulation of DPVO [6], together with the event-based patch selection of DEVO [7]. The geometric state consists of N camera poses $\mathbf{T} \in \text{SE}(3)^N$, one for each frame, and a set of patches $\{\mathbf{P}_k\}_k$, with a fixed number of patches extracted from each incoming frame. Each patch $\mathbf{P}_k \in \mathbb{R}^{4 \times p^2}$ represents a $p \times p$ region in homogeneous coordinates, with its fourth row containing a constant inverse depth d_k shared by all patch elements. As in DPVO, we use $p = 3$.

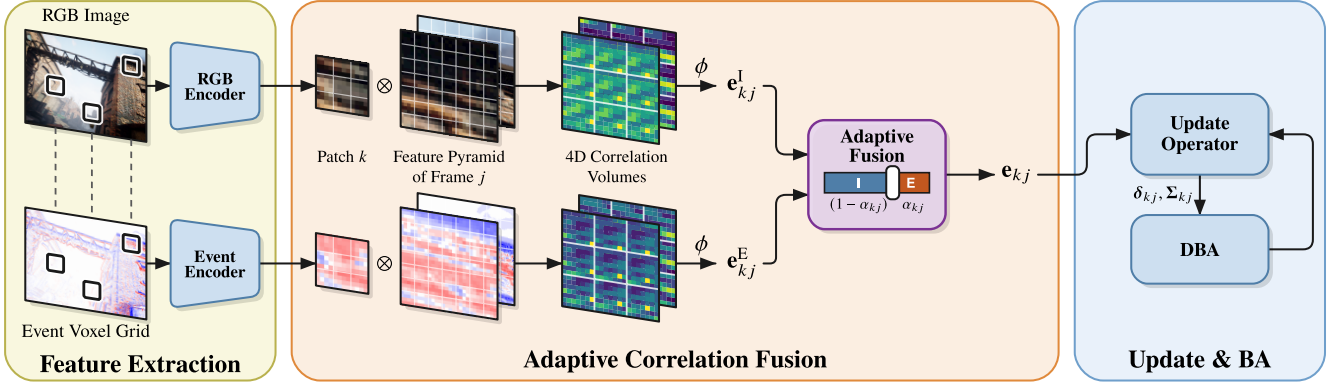


Fig. 2. **DAPEVO architecture.** Images and event voxel grids are processed by separate matching encoders. Each patch k is associated with image and event matching features $\mathbf{g}_k^I$ and $\mathbf{g}_k^E$. For each patch-frame edge (k, j) , image and event correlations are computed independently and mapped to embeddings $\mathbf{e}_{kj}^I$ and $\mathbf{e}_{kj}^E$. A learned gate predicts an edge-specific weight α_{kj} to fuse the two embeddings. When RGB images are unavailable, only the event embedding is used. The resulting embedding $\mathbf{e}_{kj}$ is processed by the recurrent update operator to predict correspondence corrections and confidence weights, which are then used by differentiable bundle adjustment (DBA) to jointly refine camera poses and patch depths.

Patches and frames form a bipartite patch graph, with an edge $(k, j) \in \mathcal{E}$ connecting patch k , extracted from frame i , to a target frame j . As in DPVO [6], patch k is reprojected from its source frame i onto frame j according to

$$\mathbf{P}'_{kj} = \omega_{ij}(\mathbf{T}, \mathbf{P}_k), \quad (1)$$

where ω_{ij} denotes the geometric reprojection from frame i to frame j .

B. Feature Extraction

RGB images and event voxel grids are processed by separate matching and context encoders. The matching encoders produce 128-channel feature maps at 1/4 of the input resolution. A second level at 1/16 resolution is obtained by average pooling, forming a two-level matching feature pyramid for each modality that provides the target-frame features used for correlation. The matching features of patch k are cropped from the corresponding 1/4-resolution feature maps of its source frame i using bilinear sampling. For a patch k extracted from a joint frame, this yields modality-specific matching features

$$\mathbf{g}_k^I, \mathbf{g}_k^E \in \mathbb{R}^{128 \times p \times p}, \quad (2)$$

where $\mathbf{g}_k^I$ and $\mathbf{g}_k^E$ denote the image and event matching features, respectively. For a patch extracted from an event-only frame, only $\mathbf{g}_k^E$ is available.

The context encoders produce 384-channel feature maps at 1/4 of the input resolution. For each patch k extracted from frame i , an event context feature $\mathbf{u}_k^E \in \mathbb{R}^{384}$ is sampled at the patch center from the event context feature map of frame i . If i is joint, an image context feature $\mathbf{u}_k^I \in \mathbb{R}^{384}$ is sampled at the same location from the corresponding image context feature map. The context feature associated with patch k is then defined as

$$\mathbf{u}_k = \begin{cases} \mathbf{u}_k^I + \psi([\mathbf{u}_k^I; \mathbf{u}_k^E]), & \text{if } i \text{ is joint,} \\ \mathbf{u}_k^E, & \text{if } i \text{ is event-only,} \end{cases} \quad (3)$$

where $[\cdot; \cdot]$ denotes concatenation and ψ is a two-layer multilayer perceptron (MLP) with a ReLU nonlinearity. When i is joint, $\mathbf{u}_k^I$ provides the base representation, while event information is incorporated through a learned residual. The resulting context feature $\mathbf{u}_k$ is computed once when the patch is instantiated and shared across all edges associated with that patch.

C. Adaptive Correlation Fusion

Following DPVO [6] and DEVO [7], each pixel of patch k is correlated with a 7×7 neighborhood centered at its current reprojection in the target frame j , independently at both levels of the corresponding matching feature pyramid, as illustrated in Fig. 2. This produces a $p \times p \times 7 \times 7$ correlation volume at each pyramid level and for each modality. The two levels are flattened and concatenated, yielding

$$\mathbf{c}_{kj}^I, \mathbf{c}_{kj}^E \in \mathbb{R}^{2p^2 \cdot 7^2} = \mathbb{R}^{882}. \quad (4)$$

While image and event features remain in separate modality-specific feature spaces, their correlation volumes provide a common representation of matching evidence. We therefore use a shared correlation encoder ϕ to map the two correlation vectors to modality-specific embeddings,

$$\mathbf{e}_{kj}^I = \phi(\mathbf{c}_{kj}^I), \quad \mathbf{e}_{kj}^E = \phi(\mathbf{c}_{kj}^E), \quad \mathbf{e}_{kj}^I, \mathbf{e}_{kj}^E \in \mathbb{R}^{384}. \quad (5)$$

An edge-specific fusion weight $\alpha_{kj} \in [0, 1]$ is predicted from the two embeddings as

$$\alpha_{kj} = \gamma([\mathbf{e}_{kj}^I; \mathbf{e}_{kj}^E]), \quad (6)$$

where γ denotes a learned linear layer followed by a sigmoid activation.

If either i or j is event-only, image matching is unavailable and only the event correlation embedding $\mathbf{e}_{kj}^E$ is computed. The correlation embedding used by the recurrent update operator is therefore

$$\mathbf{e}_{kj} = \begin{cases} (1 - \alpha_{kj})\mathbf{e}_{kj}^I + \alpha_{kj}\mathbf{e}_{kj}^E, & \text{if } i \text{ and } j \text{ are joint,} \\ \mathbf{e}_{kj}^E, & \text{otherwise.} \end{cases} \quad (7)$$

Since α_{kj} is recomputed at each recurrent iteration, the fusion adapts independently for each edge and refinement step.

D. Update Operator and Differentiable Bundle Adjustment

Following DPVO [6] and DEVO [7], correspondence refinement and geometric optimization are performed by the recurrent update operator and differentiable bundle adjustment. DAPEVO retains these components unchanged, replacing the single-modality correlation input with the fused embedding $\mathbf{e}_{kj}$ from (7). The update operator predicts 2D flow revisions $\{\delta_{kj}\}_{kj}$ and confidence weights $\{\Sigma_{kj}\}_{kj}$, which the bundle adjustment uses to jointly refine camera poses and patch depths.

E. Event-Only Tracking and Keyframe Management

DAPEVO supports event-only tracking between RGB observations, allowing the tracking rate to exceed the RGB frame rate. During initialization, only joint frames are used, while incoming event-only frames are discarded. After initialization, both joint and event-only frames are processed.

To preserve joint observations when RGB frames are sparse, we introduce a modality-aware variant of the DPVO [6] keyframe-culling criterion, which we refer to as *subgraph culling*. Projected motion is evaluated with respect to the nearest preceding and following frames that share the modalities available in the candidate. For a joint candidate, the nearest joint frames are used, whereas for an event-only candidate, the nearest frames are used regardless of type, since event information is available in every frame. The candidate is removed when the mean bidirectional projected motion falls below 15 feature-map pixels for joint frames or 25 pixels for event-only frames. These thresholds should be adjusted when using different input resolutions.

F. Training

DAPEVO is trained in two stages using the supervision and recurrent optimization framework of DPVO [6]. In the first stage, the event matching and context encoders and the event-based patch scorer are trained while the pretrained DPVO update operator remains frozen. This stage learns event representations that are compatible with the update operator originally trained on image features.

In the second stage, the pretrained image branch is combined with the learned event branch and the two feature extractors are frozen. The context-fusion MLP ψ and correlation gate γ are then optimized to combine the modality-specific representations. The recurrent update operator is subsequently fine-tuned jointly with the fusion modules.

To prevent the fusion mechanism from collapsing to the generally stronger image representation under nominal conditions, training includes modality-specific input corruption and modality dropout. Image corruption comprises low-light augmentation, noise, blur, and occlusion, whereas event corruption comprises temporal dropout, event thinning, and noise. Modality dropout additionally removes the correlation evidence of either modality, exposing the recurrent update operator to single-modality observations during training.

IV. EXPERIMENTS

A. Implementation Details

DAPEVO is trained on the TartanEvent training set [9], [30]. The event branch is trained for 100,000 iterations, with the first 1,000 iterations using the structure-only warm-up of DPVO [6]. The subsequent fusion stage is trained for 60,000 iterations. The final layer of the context-fusion MLP ψ is initialized to zero, while the correlation gate γ is initialized with zero weights and bias -2 , yielding $\alpha_{kj} \simeq 0.12$ and an initially image-dominant representation.

During fusion training, image corruption is applied to 50% of sequences and event corruption to 15%, while the remaining 35% are left unmodified. Image and event correlation volumes are independently dropped in 5% of training sequences for each modality. After 8,000 fusion-training iterations, the recurrent update operator is unfrozen and optimized with a learning rate ten times lower than that of the fusion modules.

The network is trained on a single RTX8000 GPU using the same training hyperparameters from DPVO and DEVO. All experiments use the default DPVO configuration [6], with 96 patches extracted per input frame.

In addition, we optimize the runtime of the existing DPVO codebase, without changing its network structure. Batched aggregation over patch and frame-pair groups replaces generic scatter operations and reuses indexing layouts between graph changes. Static half precision and compilation reduce conversion and kernel-launch costs. The correlation kernel stages overlapping neighborhoods in shared memory and uses channels-last vectorized feature loads.

Using its default configuration, these optimizations reduce DPVO processing time on the Quadro RTX 8000 from 55.8 to 23.8ms per input frame. Under the same configuration, DAPEVO requires 36.5ms per frame when every input contains both RGB and events, corresponding to a 53% overhead over optimized DPVO. On an RTX 5090, optimized DPVO and DAPEVO require 7.5 and 10.2ms per frame, respectively, corresponding to a 36% overhead.

B. Experimental Setup

We evaluate DAPEVO on synthetic and real-world event-camera benchmarks with synchronized RGB images and events. TartanEvent [9] provides synthetic events, images, and ground-truth trajectories generated from TartanAir [30]; we use its 32-sequence validation split and the monocular test split of the ECCV 2020 SLAM Competition [9], [30]. We additionally evaluate on UZH-FPV [10] for aggressive quadrotor motion, the HKU monocular [28], [31] sequences under challenging illumination and high-dynamic-range conditions, and the four indoor-flying sequences of MVSEC [32].

We report absolute trajectory error (ATE) after Sim(3) alignment on TartanEvent and UZH-FPV. For TartanEvent, we additionally report the area under the empirical cumulative distribution of sequence ATE over $[0, 1]$ m (AUC). On HKU, UZH FPV and MVSEC, we report mean position error (MPE), defined as the mean position error normalized by

TABLE I

TARTANEvent VALIDATION RESULTS UNDER NOMINAL AND DEGRADED RGB INPUT.

Method	Input	Nominal RGB		Degraded RGB	
		AUC $\uparrow$	ATE [m] $\downarrow$	AUC $\uparrow$	ATE [m] $\downarrow$
DPVO [6]	I	0.83	0.17	0.14	4.96
DEVO [7]	E	0.56	0.87	0.56	0.87
RAMP-VO [9]	I+E	0.85	0.15	0.14	7.01
Feature fusion	I+E	0.78	0.22	0.50	1.68
DAPEVO	I+E	0.85	0.15	0.63	0.60

the ground-truth trajectory length, expressed as a percentage. Following PL-EVIO [28], HKU trajectories are aligned using the first 5 s, and the resulting transformation is held fixed for the remainder of the trajectory. For DPVO, DEVO, RAMP-VO and DAPEVO, this alignment additionally estimates the global scale. Additionally, in the following tables *fail* denotes a failure explicitly reported by the original source. The cited evaluations do not specify a numerical failure threshold.

C. Benchmark Comparison

TartanEvent. Under nominal RGB input, DAPEVO and RAMP-VO achieve identical ATE and AUC at the reported precision (Table I). This is consistent with evaluation in the noise-free synthetic training domain, where reliable image correspondences may limit the benefit of adaptive fusion. To isolate the fusion architecture, we train a *Feature Fusion* variant using the same data, augmentations, and optimization protocol as DAPEVO. It concatenates image and event features from separate convolutional stems, then uses a shared encoder to produce joint patch descriptors and a single correlation volume. Its ATE is 0.22 m under nominal RGB input and 1.68 m under degradation, compared with 0.15 m and 0.60 m for DAPEVO. The 64.3% reduction under degradation supports the benefit of separate correlations and adaptive fusion beyond the training protocol; Sec. IV-D examines this condition further.

UZH-FPV. DAPEVO achieves the lowest average MPE on UZH-FPV, reducing the error to 0.46 from 0.52 for DPVO and 0.53 for DEVO (Table II). For comparability with published results, Table II uses the sequence subset adopted in prior evaluations; the reduced-frame-rate experiments in Sec. IV-D instead evaluate all UZH-FPV sequences.

HKU Monocular. The HKU monocular sequences expose a different behavior, as summarized in Table III. DAPEVO and DPVO have similar median errors across trials, with average median MPEs of 0.19 and 0.21 respectively, but their mean errors differ markedly: 0.19 for DAPEVO versus 2.32 for DPVO. The discrepancy is dominated by occasional high-error DPVO trials, most notably on d2l2, where its mean/median MPE reaches 22.55/0.30 compared with 0.19/0.19 for DAPEVO. DAPEVO therefore maintains comparable nominal accuracy while exhibiting substantially greater consistency across repeated trials under the challenging illumination conditions represented in this benchmark.

MVSEC. DAPEVO achieves an average MPE of 0.19%,

TABLE II

MPE [%] ON INDOOR UZH-FPV. ALL RESULTS ARE FROM [7], [28], EXCEPT FOR DPVO AND DAPEVO. BEST RESULTS ARE BOLD.

	VINS-Mono [33]	Ultimate SLAM [27]	PL-EVIO [28]	DEVO [7]	DPVO [6]	DAPEVO
Loop closure	$\checkmark$	$\checkmark$	$\checkmark$	$\times$	$\times$	$\times$
fwd_3	0.65	<i>fail</i>	0.38	0.37	0.32	0.38
fwd_5	1.07	<i>fail</i>	0.90	0.40	0.24	0.25
fwd_6	0.25	<i>fail</i>	0.30	0.31	0.42	0.39
fwd_7	0.37	<i>fail</i>	0.55	0.50	0.23	0.19
fwd_9	0.51	<i>fail</i>	0.44	0.61	0.57	0.56
fwd_10	0.92	<i>fail</i>	1.06	0.52	0.58	0.54
45deg_2	0.53	<i>fail</i>	0.55	0.72	0.81	0.69
45deg_4	1.72	9.79	1.30	0.45	0.62	0.43
45deg_9	1.25	4.74	0.76	0.89	0.93	0.73
Avg.	0.81	<i>fail</i>	0.69	0.53	0.52	0.46

TABLE III

HKU MONOCULAR MPE [%]. DPVO/DAPEVO REPORT MEAN/MEDIAN OVER FIVE TRIALS; OTHER RESULTS ARE FROM [28] AND USE AN IMU.

I: IMAGES; E: EVENTS.

	Ultimate SLAM [27]	PL-EIO [28]	PL-EVIO [28]	DPVO [6]	DAPEVO
	Mean / Median				
Input	I+E	E	I+E	I	I+E
Loop clos.	$\checkmark$	$\checkmark$	$\checkmark$	$\times$	$\times$
hdr1	2.44	0.67	0.17	0.11 / 0.12	0.12 / 0.12
hdr2	1.11	0.45	0.12	0.17 / 0.16	0.15 / 0.15
hdr3	0.83	0.74	0.19	0.27 / 0.27	0.26 / 0.25
hdr4	1.49	0.37	0.11	0.18 / 0.18	0.15 / 0.16
d2l1	1.00	0.78	0.14	0.20 / 0.20	0.21 / 0.21
d2l2	0.79	0.44	0.12	22.55 / 0.30	0.19 / 0.19
l2d1	0.84	0.42	0.13	0.90 / 0.31	0.28 / 0.28
l2d2	1.49	0.73	0.16	0.17 / 0.16	0.16 / 0.16
dark1	3.45	0.64	0.43	0.12 / 0.12	0.12 / 0.12
dark2	0.63	0.30	0.47	0.20 / 0.19	0.20 / 0.21
aggr. hdr	2.30	0.62	1.97	0.65 / 0.28	0.21 / 0.19
Avg.	1.49	0.56	0.36	2.32 / 0.21	0.19 / 0.19

close to RGB-only DPVO at 0.17% and below event-only DEVO at 0.46% (Table IV). The evaluated learned methods outperform the classical baselines, and incorporating events preserves comparable RGB frame-based accuracy.

TartanEvent 2020 Competition. Generalization to the held-out ECCV 2020 SLAM Competition split is evaluated in Table V. DAPEVO achieves an average ATE of 0.19 m, improving over DPVO at 0.21 m but remaining behind RAMP-VO at 0.17 m. DAPEVO ranks second in average ATE and attains the best or tied-best result on seven of the sixteen sequences. This evaluation provides an additional comparison on trajectories not contained in the TartanEvent validation split, but remains within the same noise-free synthetic domain used for training, where reliable RGB observations may limit the benefit of adaptive modality weighting.

D. Robustness to RGB Degradation and Reduced Frame Rate

We evaluate DAPEVO under two conditions that reduce the reliability or availability of image-based correspon-

TABLE IV

MVSEC INDOOR-FLYING MPE [%]. BEST/SECOND-BEST RESULTS ARE BOLD/UNDERLINED.

	ORB-SLAM3 [11]	VINS-Fusion [34]	ESVIO [35]	Ultimate SLAM [27]	PL-EVIO [28]	ESVO [20]	EVO [19]	DPVO [6]	DEVO [7]	DAPEVO
IF1	5.31	1.50	0.94	fail	1.35	4.00	5.09	0.16	0.26	0.16
IF2	5.65	6.98	1.00	fail	1.00	3.66	fail	0.15	0.32	<u>0.16</u>
IF3	2.90	0.73	0.47	fail	0.64	1.71	2.58	0.08	0.19	0.08
IF4	6.99	3.62	5.55	2.77	5.31	fail	fail	0.30	1.08	<u>0.36</u>
Avg.	5.21	3.21	1.99	fail	2.08	fail	fail	0.17	0.46	<u>0.19</u>

TABLE V

ECCV 2020 SLAM COMPETITION MONOCULAR WITH SIMULATED EVENT ATE [M]. DAPEVO: MEDIAN OF FIVE TRIALS; BASELINES: [9]. CHECKMARKS DENOTE GLOBAL OPTIMIZATION OR LOOP CLOSURE. AMONG OTHER METHODS, BEST /SECOND-BEST RESULTS ARE BOLD/UNDERLINED.

	ORB-SLAM3 [11]	COLMAP [36]	DROID-SLAM [16]	DSO [12]	DROID-VO [16]	DPVO [6]	RAMP-VO [9]	DAPEVO
Input Loop clos.	I ✓	I ✓	I ✓	I ×	I ×	I ×	I+E ×	I+E ×
ME00	13.61	15.20	0.17	9.65	0.22	<u>0.16</u>	0.20	0.14
ME01	16.86	5.58	0.06	3.84	0.15	0.11	0.04	<u>0.08</u>
ME02	20.57	10.86	0.36	12.20	0.24	<u>0.11</u>	0.10	0.14
ME03	16.00	3.93	0.87	8.17	1.27	0.66	<u>0.46</u>	0.41
ME04	22.27	2.62	1.14	9.27	1.04	<u>0.31</u>	0.16	0.35
ME05	9.28	14.78	0.13	2.94	0.14	0.14	<u>0.13</u>	0.07
ME06	21.61	7.00	1.13	8.15	1.32	0.30	0.12	<u>0.21</u>
ME07	7.74	18.47	0.06	5.43	0.77	0.13	<u>0.12</u>	0.11
MH00	15.44	12.26	0.08	9.92	0.32	0.21	0.36	0.28
MH01	2.92	13.45	0.05	0.35	0.13	0.04	0.06	0.03
MH02	13.51	13.45	0.04	7.96	0.08	0.04	0.04	0.04
MH03	8.18	20.95	0.02	3.46	0.09	0.08	0.04	<u>0.05</u>
MH04	2.59	24.97	0.01	fail	1.52	<u>0.58</u>	0.41	0.78
MH05	21.91	16.79	0.68	12.58	0.69	0.17	0.25	<u>0.21</u>
MH06	11.70	7.01	0.30	8.42	0.39	<u>0.11</u>	<u>0.11</u>	0.10
MH07	25.88	7.97	0.07	7.50	0.97	0.15	0.07	<u>0.08</u>
Avg.	14.38	12.50	0.33	fail	0.58	0.21	0.17	<u>0.19</u>

dences: degraded RGB observations and reduced RGB frame rates.

Degraded RGB observations. We construct a degraded variant of the TartanEvent validation set, denoted *TartanDark*, by applying darkening gamma correction and adding gaussian noise to every image while leaving the event stream unchanged. All methods are evaluated on the same degraded sequences, and results are averaged over five trials. Table I compares performance on the original and degraded observations. When the RGB observations are degraded, the performance of the RGB-dependent methods deteriorates substantially, whereas DAPEVO maintains an AUC of 0.63 and an ATE of 0.60m. It also improves over event-only DEVO, indicating that the remaining RGB information continues to provide useful correspondence constraints despite the degradation. These results support the use of adaptive correlation fusion rather than committing to either modality globally.

Reduced RGB frame rate. We next evaluate robustness to temporally sparse RGB observations by progressively

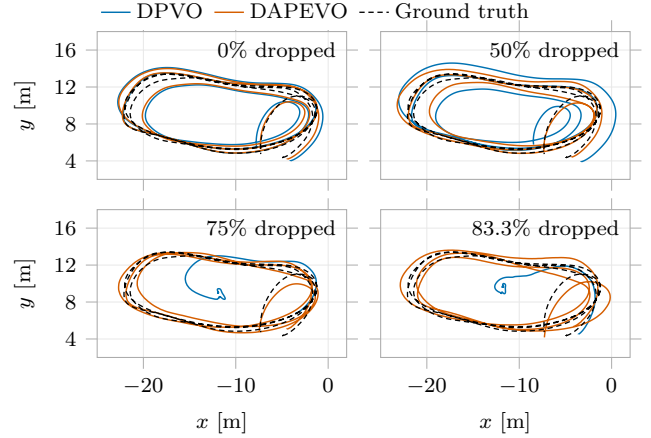


Fig. 3. X-Y trajectories on UZH-FPV indoor_45_13 at increasing image-drop rates. As the drop rate increases, DPVO exhibits substantial trajectory deviation, whereas DAPEVO remains closely aligned with the ground truth.

TABLE VI

TARTANEVENT VALIDATION AUC AND ATE [M] AT REDUCED RGB RATES. DAPEVO EVENT VOXEL GRIDS REMAIN AT 30 HZ.

RGB rate	DPVO [6]		RAMP-VO [9]		DAPEVO	
[Hz]	AUC ↑	ATE ↓	AUC ↑	ATE ↓	AUC ↑	ATE ↓
30	0.83	0.17	0.85	0.15	0.85	0.15
15	0.80	0.39	0.74	0.45	0.79	0.21
10	0.77	0.45	0.66	1.32	0.77	0.29
6	0.48	1.70	0.39	3.33	0.73	0.31
5	0.34	3.64	0.27	4.45	0.69	0.35
3	0.09	9.58	0.08	9.97	0.58	0.82

subsampling the image stream while retaining event measurements between consecutive frames. On TartanEvent, the RGB rate is reduced from 30 to 3 Hz, while DAPEVO processes event voxel grids at a fixed rate of 30 Hz. As shown in Table VI, all methods perform similarly at the nominal frame rate, but their behavior diverges as RGB observations become less frequent. At 6 Hz, DAPEVO obtains an ATE of 0.31 m, compared with 1.70 m for DPVO and 3.33 m for RAMP-VO. At 3 Hz, DAPEVO remains below 1 m ATE (0.82 m), whereas DPVO and RAMP-VO reach 9.58 m and 9.97 m, respectively. The corresponding AUC remains 0.58 for DAPEVO, compared with 0.09 and 0.08 for DPVO and RAMP-VO.

We further evaluate robustness to reduced RGB frame rates on the real-world UZH-FPV sequences. Figure 4 reports the mean ATE as the proportion of dropped RGB frames increases from 0 to 83.3%. DAPEVO's mean ATE increases from 1.00 to 1.36 m, compared with increases from 1.25 to 4.63 m for DPVO and from 1.49 to 4.62 m for RAMP-VO. Figure 3 compares trajectories on indoor_45_13 at RGB frame-drop rates of 0, 50, 75, and 83.3%. DAPEVO follows the ground-truth trajectory more closely, whereas DPVO exhibits substantial trajectory deviations. Together, these results support the benefit of incorporating intermediate event-only observations when RGB measurements become temporally sparse.

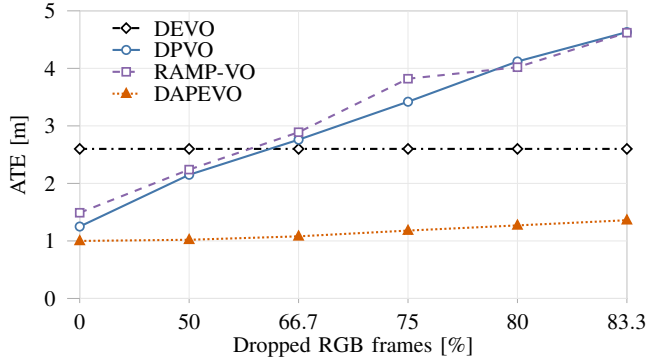


Fig. 4. UZH-FPV ATE averaged over five trials per sequence and all sequences. Equally spaced markers denote retaining every k th RGB frame, $k = 1, \dots, 6$; labels give the corresponding drop percentages.

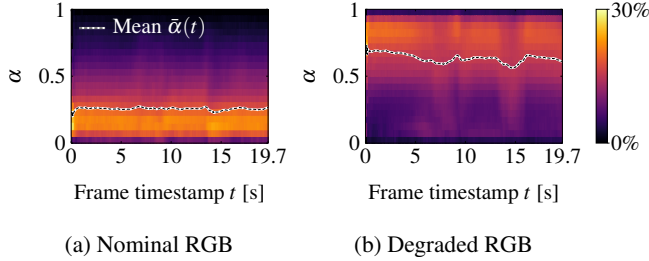


Fig. 5. Temporal distribution of the event-fusion weight α on TartanEvent *japanesealley/Hard/P005*. Columns show normalized edges fractions in 0.05-wide bins; we exclude edges whose reprojections fall out-of-frame. Dashed curves show the mean. Larger α favors events, while smaller α favors RGB.

E. Ablation studies

Adaptive Correlation Fusion We first assess whether observation-dependent fusion improves performance beyond a fixed modality weighting. Figure 5 shows the distribution of the adaptive fusion weight α_{kj} for the same sequence under nominal and degraded RGB input. The mean event-fusion weight increases from approximately 0.25 under nominal conditions to 0.6-0.7 under degradation, indicating greater reliance on event correspondences as image quality deteriorates. This raises the question of whether the benefit comes from adapting the weight to individual observations or simply shifting the overall balance between modalities.

To distinguish these effects, we replace α_{kj} with four alternatives: 0 (RGB-only correlations), 1 (event-only correlations), 0.5 (equal weighting), and a condition-specific constant equal to the mean weight predicted by the adaptive model, denoted *Dataset Mean*. The latter tests whether a global modality balance derived from the adaptive model is sufficient to recover its performance. All variants are evaluated on the TartanEvent validation split under both nominal and degraded RGB input.

Table VII shows that under nominal conditions, RGB-only matching achieves the lowest ATE, while adaptive fusion remains close in both ATE and AUC. Under degraded RGB input, adaptive fusion achieves an ATE of 0.60 m and an AUC of 0.63, compared with 0.73 m and 0.59 for

TABLE VII

FUSION-WEIGHT ABLATION ON TARTANEVENT VALIDATION. *Dataset Mean* fixes α to the adaptive model’s mean over the considered dataset.

α	Nominal RGB		Degraded RGB	
	AUC $\uparrow$	ATE [m] $\downarrow$	AUC $\uparrow$	ATE [m] $\downarrow$
0.0 (RGB only)	0.87	0.13	0.19	5.04
Dataset Mean	0.84	0.16	0.57	0.99
0.5	0.82	0.19	0.57	0.99
1.0 (events only)	0.58	0.96	0.59	0.73
Adaptive	0.85	0.15	0.63	0.60

TABLE VIII

CULLING ABLATION ON TARTANEVENT VALIDATION AT 5 Hz RGB.

JOINT FRAMES: FRACTION OF RETAINED KEYFRAMES WITH BOTH MODALITIES.

Method	Threshold (joint, evt-only)	AUC $\uparrow$	ATE [m] $\downarrow$	Joint frames
Original [6], [7]	(15, 15)	0.57	0.70	0.20
Original [6], [7]	(15, 25)	0.64	0.71	0.57
Subgraph	(15, 15)	0.66	0.39	0.54
Subgraph	(15, 25)	0.69	0.35	0.74

event-only matching, corresponding to a 17.8% reduction in ATE. The Dataset Mean variant yields an ATE of 0.99 m, showing that replacing observation-dependent weights with their condition-specific average does not preserve the benefit. Together, these results support adapting the fusion weight across observations to retain useful image information while increasing reliance on events when image correspondences become unreliable.

Keyframe management. We next evaluate the proposed modality-aware keyframe management against the original culling strategy used by DPVO and DEVO. The comparison is performed on the TartanEvent validation split with the RGB frame rate reduced to 5 Hz, such that joint RGB-event observations are substantially less frequent than event-only observations. Table VIII compares the original and proposed subgraph-based strategies using equal culling thresholds for both observation types, (15,15), and the modality-specific thresholds (15,25) used in DAPEVO. The original strategy retains only 20% joint keyframes with equal thresholds, whereas the proposed strategy increases this fraction to 54%. With modality-specific thresholds, the fraction of retained joint keyframes further increases to 74%. This preservation of frame-bearing keyframes translates into improved trajectory accuracy: the proposed strategy with (15,25) increases AUC from 0.64 to 0.69 and reduces ATE from 0.71 m to 0.35 m relative to the corresponding original culling strategy.

Patch selection strategy. DAPEVO uses the event-based patch scorer introduced in DEVO to select patch locations shared by both modalities. Because DPVO reports random patch sampling as its strongest selection strategy, we verify that replacing it with the DEVO event scorer does not degrade the underlying frame-based pipeline. We evaluate DPVO with the DEVO event scorer, and find that the event-based patch selection does not degrade RGB frame-only tracking; instead, AUC increases from 0.83 to 0.86 and ATE

decreases from 0.17 m to 0.14 m. Consequently, the use of the event scorer is not responsible for a loss in the underlying frame-based performance and provides a suitable common patch-selection mechanism for the two modalities.

V. DISCUSSION AND CONCLUSION

We presented DAPEVO, an image-event visual odometry method that fuses modality-specific evidence at the patch-correlation level while maintaining a shared geometric state. Event-only observations are incorporated into the same optimization graph, while modality-aware keyframe management preserves joint observations required for frame-based correlations. Experiments under reduced RGB frame rates show that intermediate event observations substantially improve robustness as frame observations become sparse, on both synthetic and real-world data. Under challenging illumination, adaptive correlation fusion reduces the dependence on unreliable RGB frame information while retaining useful visual constraints, outperforming either modality alone. Together, these results demonstrate the benefit of performing image-event fusion at the correspondence level and adapting the contribution of each modality to the available observations.

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