Deep Event Visual Odometry

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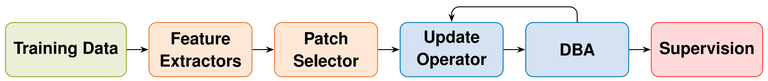
Motivation

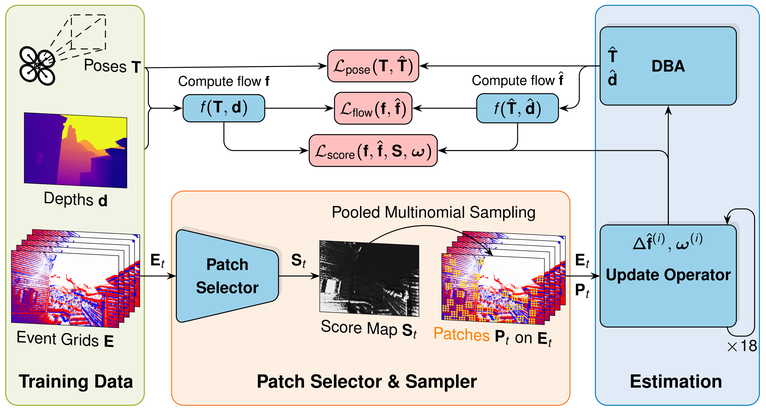
Event cameras offer the exciting properties of high temporal resolution, high dynamic range, and low latency. This makes them ideally suited for camera pose tracking during high-speed motion and in HDR lighting conditions. However, existing event-based monocular visual odometry approaches demonstrate limited performance on recent benchmarks.

We propose **Deep Event VO (DEVO)**, the first monocular event-only VO system with strong performance on seven real-world benchmarks.

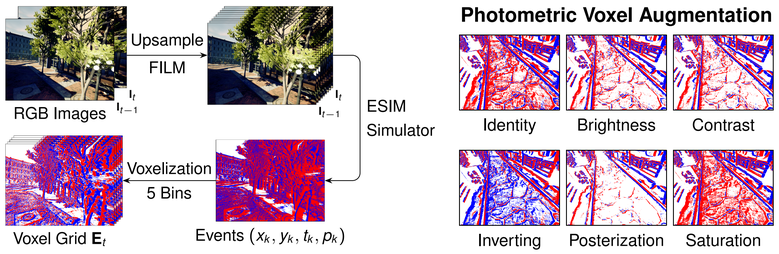


- **Supervised training** using camera poses and depths.
- Novel **patch selector** predicts a score map to highlight optimal coordinates for pose and optical flow estimation.
- Recurrent **update operator** refines optical flow estimates and updates poses and depths using **differentiable bundle adjustment (DBA)**.

Method

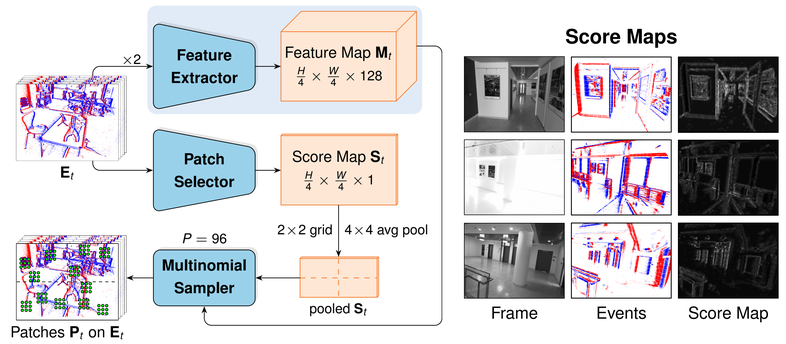


Training Data Generation



Photometric Voxel Augmentation

Patch Selector & Sampler



Loss Functions

Pose Loss

$$\mathcal{L}_{\text{pose}} = \sum_{(i,j)\, i \neq j} \left\| \log_{\text{SE3}} \left(\left(\mathbf{T}_j^{-1} \mathbf{T}_i \right)^{-1} \left(\hat{\mathbf{T}}_j^{-1} \hat{\mathbf{T}}_i \right) \right) \right\|$$

ground truth pose $\mathbf{T}$
estimated pose $\hat{\mathbf{T}}$

Flow Loss

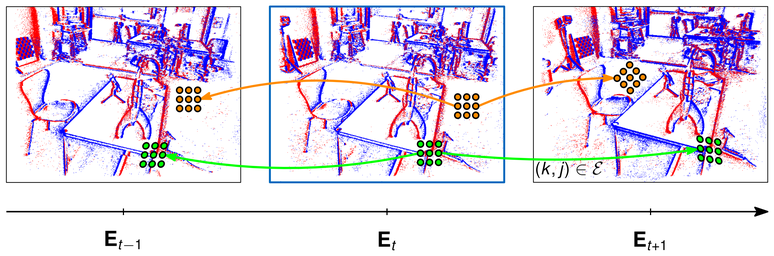
$$\mathcal{L}_{\text{flow}} = \sum_{(k,j) \in \mathcal{E}} \underbrace{\min \left\| \left(\mathbf{f}_{kj} - \hat{\mathbf{f}}_{kj} \right) \right\|}_{=: r_{kj} \text{ (flow residual)}}$$

ground truth optical flow $\mathbf{f}$
estimated optical flow $\hat{\mathbf{f}}$

Score Loss

$$\mathcal{L}_{\text{score}} = \frac{1}{|\mathcal{E}|} \sum_{(k,j) \in \mathcal{E}} s_k r_{kj} \underbrace{\left(1 - \alpha \ln \omega_{kj} \right)}_{\text{“inverted” weight}} - \ln \mathbf{S}[\mathbf{P}]$$

score value s_k
flow residual r_{kj}
sampled values $\mathbf{S}[\mathbf{P}]$



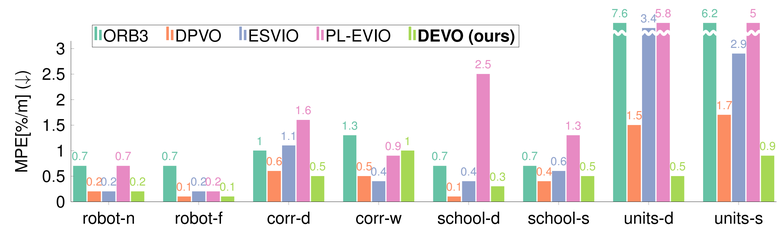
Results

Method	Modality	indoor forward 3	5	6	7	9	10	indoor 45 deg 2	4	9
ORB-SLAM3	Stereo VIO	0.55	1.19	–	**0.36**	0.77	1.02	2.18	1.53	**0.49**
VINS-Fusion	Stereo VIO	0.84	–	1.45	0.61	2.87	4.48	–	–	–
VINS-Mono	Mono VIO	0.65	1.07	**0.25**	0.37	0.51	0.92	**0.53**	1.72	1.25
DPVO	Mono VO	–	–	–	–	–	–	–	–	–
USLAM	Mono EVIO	–	–	–	–	–	–	–	9.79	4.74
PL-EVIO	Mono EVIO	0.38	0.90	0.30	0.55	**0.44**	1.06	0.55	1.30	0.76
EVO	Mono EO	–	–	–	–	–	–	–	–	–
DPVO†	Mono EO†	0.52	0.42	0.55	–	0.45	0.54	–	1.21	–
DEVO (ours)	Mono EO	**0.37**	**0.40**	0.31	0.50	0.61	**0.52**	0.72	**0.45**	0.89

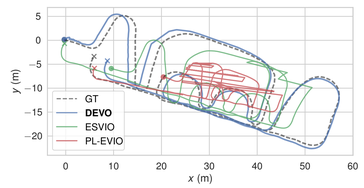
Evaluation on UZH-FPV Drone Racing Dataset with MPE[%/m] (↓), highlighting **Top1** and Top2. DPVO† is a re-trained DPVO model on E2VID reconstructions.

Results

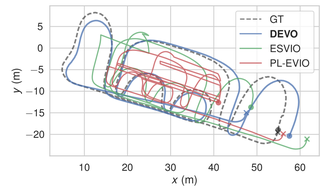
Quantitative Evaluation on VECtor Benchmark



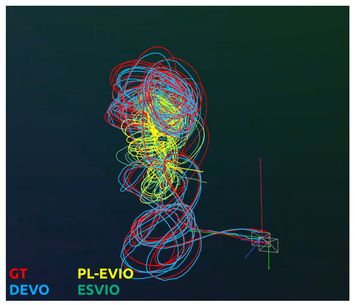
VECtor units-dolly



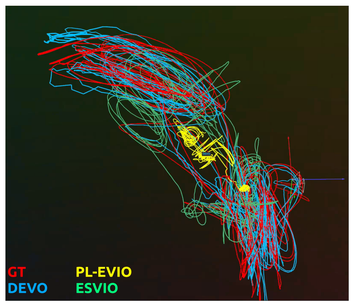
VECtor units-scooter



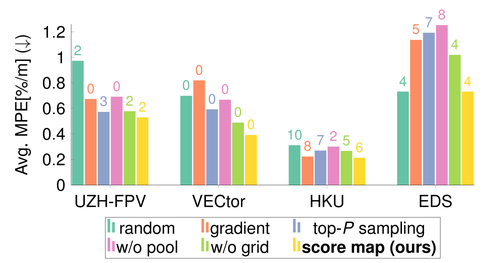
HKU aggressive_rotation



HKU hdr_dark_normal



Ablation Study



Ablation Study on Patch Selection and Sampling. DEVO trained with various patch selection methods and evaluated on four real-world benchmarks. Numbers near the bars indicate the total number of failures.

Conclusion

- DEVO demonstrates that **supervised learning** on simulated events of TartanAir dataset enables strong generalization to real-world event VO benchmark.
- We introduce a novel **patch selection** mechanism specifically tailored towards event data, which increases the accuracy and robustness of DEVO.

More Info

Paper, Code, Model, . . .