Real-Time Optical Flow for Vehicular Perception with Low- and High-Resolution Event Cameras

IEEE Transactions on Intelligent Transportation Systems (vol. 23, Sept. 2022)

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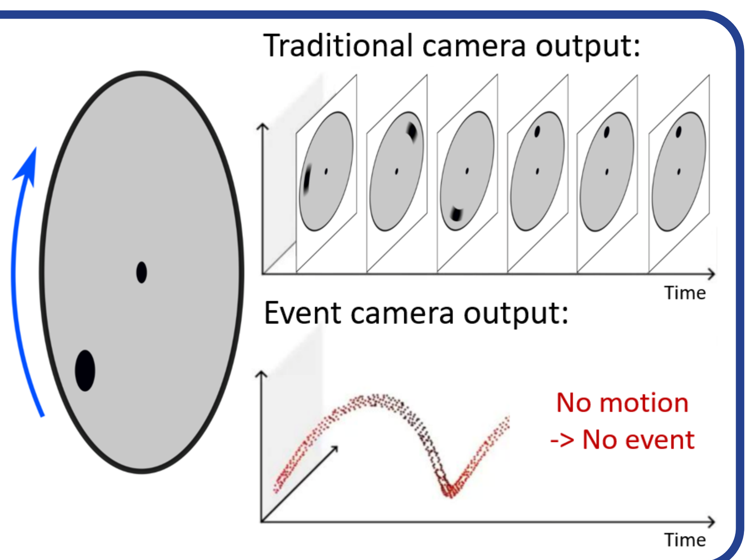
Event cameras are emerging sensors which only react to brightness changes, and output them as a fully asynchronous stream of data. They offer many advantages: high dynamic range, low latency, and no motion blur

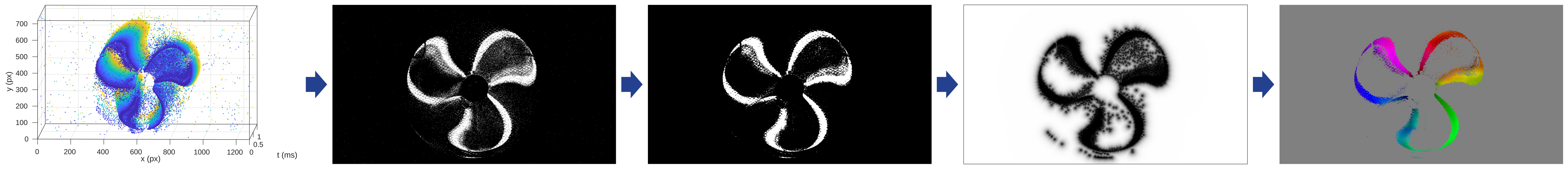


Motivation: Current event-based optical flow methods only produce accurate results for low-resolution sensors, and do not consider the real-time constraint

Goal: Propose a novel method for computing accurate event-based optical flow in **real-time** for both low- and **high-resolution** cameras

Proposed solution: A lightweight pipeline, which converts events to pseudo-images, and computes image-based optical flow

Our Real-Time Event-Based Optical Flow (RTEF) Pipeline



1) Events are split into bins of a few milliseconds

2) For a given bin, events are accumulated into a binary image

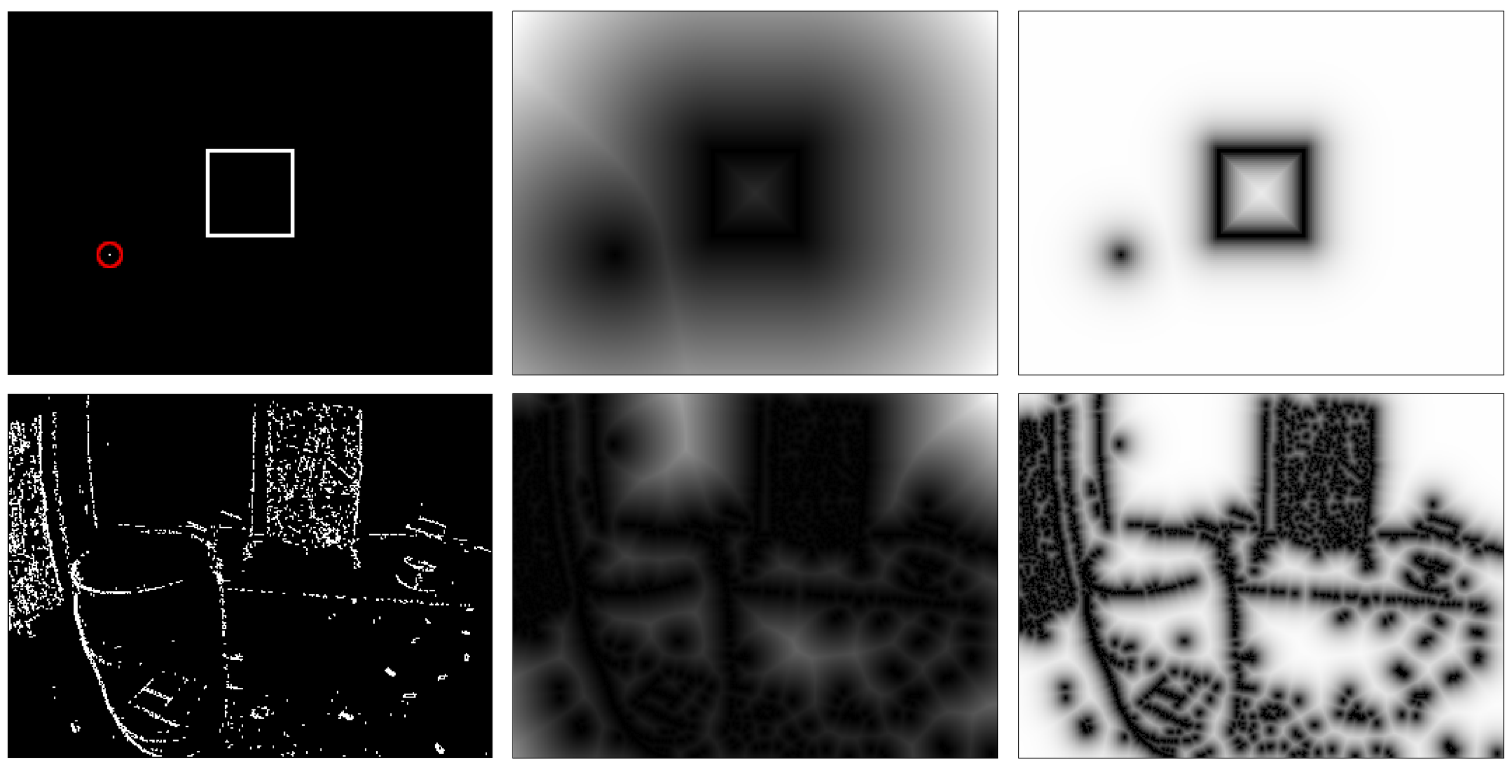
3) A denoising step is then applied, to only keep the most predominant edges

4) The image is densified (see ⊛ below), which is necessary for optical flow computation

5) Optical flow can finally be computed, using an image-based algorithm

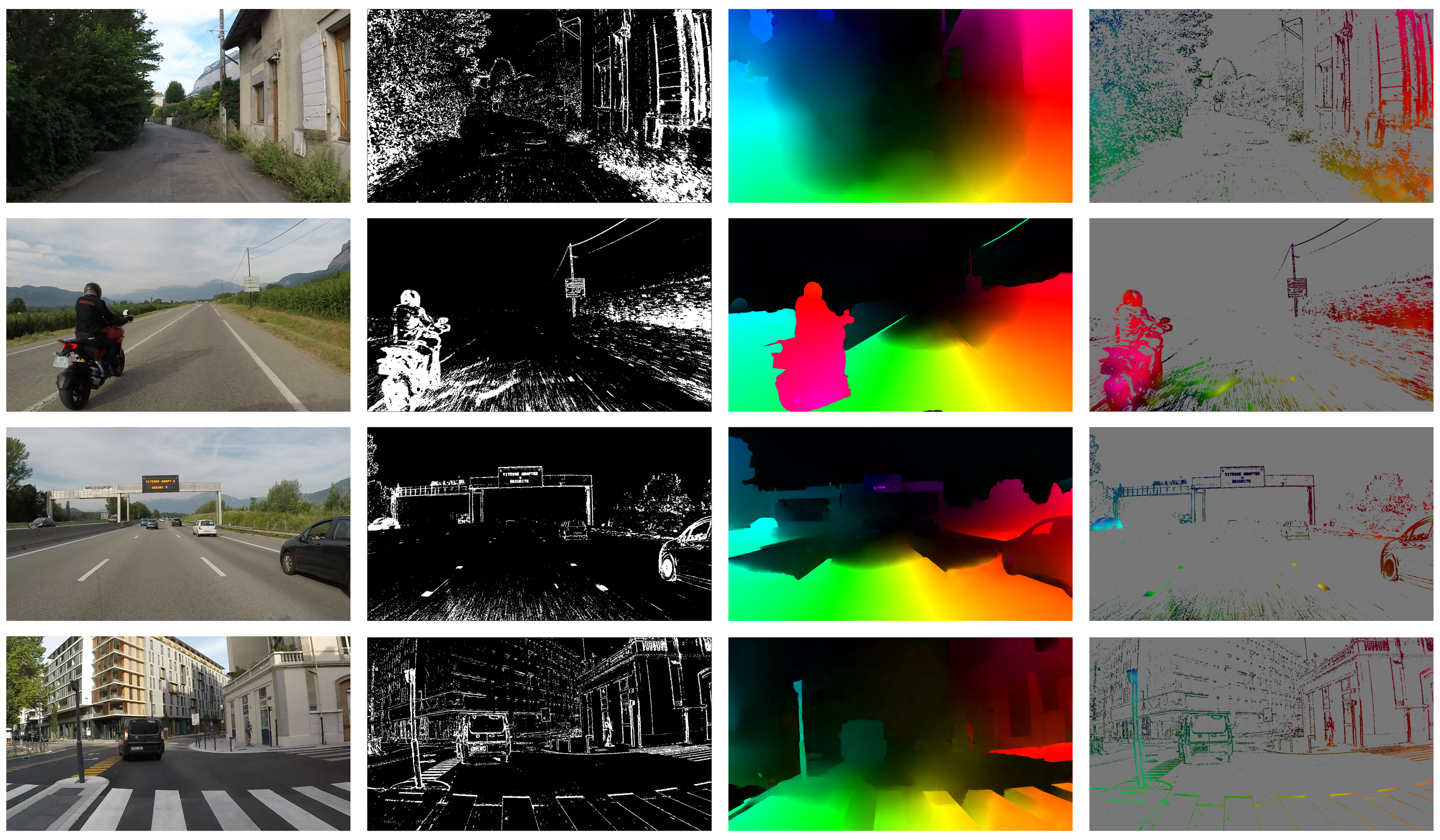
⊛ Core component: proposed robust densification

- The edge images obtained at step 3) are only binary representations, unsuitable for image-based optical flow computation
- The use of a distance transform, as proposed by Almatrafi et al. [1], allows for densification, but:
  - a single noisy event can impact a large part of the image;
  - dense texture areas become "dark blobs"
- Our solution: a novel inverse exponential distance transform, which densifies the image while keeping the textures and limiting the impact of noise



The base image, as obtained after step 3) | The original distance transform, as proposed by [1] | Our inverse exponential distance transform

Qualitative results on Prophesee's 20-minute-long driving sequence



Reference image | Edge image | Image-based flow (RAFT) | Our flow

Quantitative results on the MVSEC Dataset

Method	Indoor flying 1		Indoor flying 2		Indoor flying 3		Outdoor day 1		Outdoor day 2	
	AEE (px)	% outliers	AEE (px)	% outliers	AEE (px)	% outliers	AEE (px)	% outliers	AEE (px)	% outliers
RTEF (ours)	0.52	0.1	0.98	5.5	0.71	2.1	0.53	0.2	0.74	1.2
EV-FlowNet [2]	0.56	–	0.66	–	0.59	–	0.68	–	0.82	–
FireFlowNet [3]	0.97	2.6	1.67	15.3	1.43	11.0	1.06	6.6	–	–

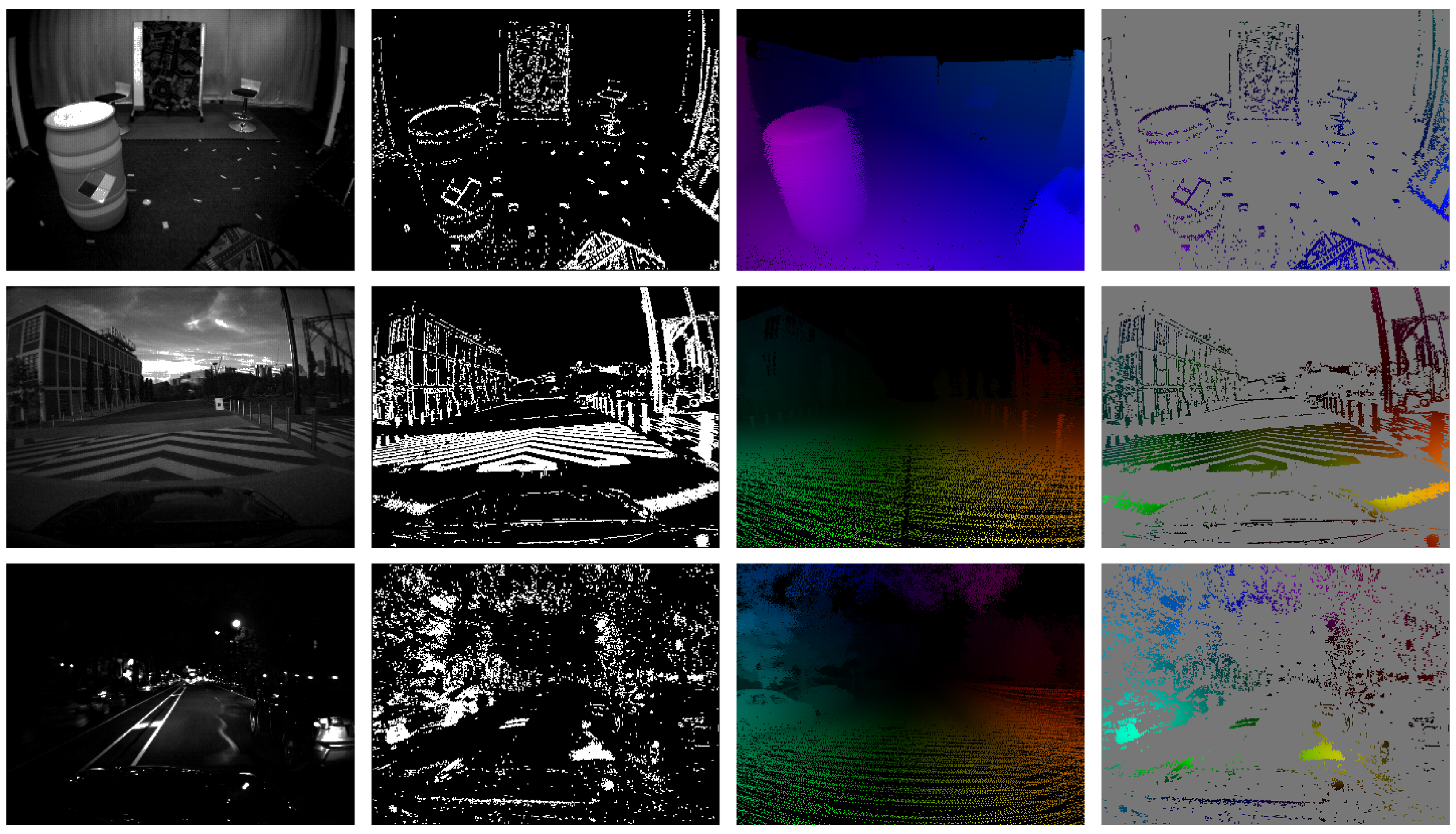
Table 1. Raw errors on the optical flow

RTEF (ours)	EV-FlowNet [2]	FireFlowNet [3]
250Hz	125Hz	262Hz

Table 2. Execution speed

Compared to the state of the art, our method combines both the high accuracy of EV-FlowNet and the high speed of FireFlowNet

Qualitative results on the MVSEC Dataset



Grayscale image | Edge image | GT flow | Our flow

References

[1] M. Almatrafi, R. Baldwin, K. Aizawa, and K. Hirakawa. Distance surface for event-based optical flow. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 42(7):1547–1556, Jul. 2020.

[2] T. Stoffregen, C. Scheerlinck, D. Scaramuzza, T. Drummond, N. Barnes, L. Kleeman, and R. Mahony. Reducing the sim-to-real gap for event cameras. In *Proceedings of the European Conference on Computer Vision*, pages 534–539, 2020.

[3] F. Paredes-Vallés and G. C. H. E. de Croon. Back to event basics: Self-supervised learning of image reconstruction for event cameras via photometric constancy. *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 3446–3455, Jun. 2021.

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