

Event-based vision and Deep Learning for dynamic scene analysis

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Workshop PPNIV 2022 - Round table

October 23th, 2022, Kyoto, Japan

Applications to Autonomous Vehicles

Conclusion

Event-based camera, Sensing Principle



[Gallego et al., IEEE PAMI 2020]

- Response to brightness changes in the scene asynchronously and independently for every pixel.
- Each event e is a tuple < x, y, t, p >, where (x, y) are the pixel coordinates of events, t is the timestamp of the event, and p = ±1 is the polarity of the event.
- Advantages
 - High Temporal Resolution
 - Low Latency
 - Low Power
 - High Dynamic Range (HDR)
- Challenges
 - Different space-time output
 - Different photometric sensing
 - Noise and dynamic effects

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Commercial and Prototype Event Cameras

Supplier			iniVation			Pro	phesee			Samsung		Cele	Pixel	Insightness
Ca	mera model	DVS128	DAVIS240	DAVIS346	ATIS	Gen3 CD	Gen3 ATIS	Gen 4 CD	DVS-Gen2	DVS-Gen3	DVS-Gen4	CeleX-IV	CeleX-V	Rino 3
	Year, Reference	2008 [2]	2014 [4]	2017	2011 [3]	2017 [67]	2017 [67]	2020 [68]	2017 [5]	2018 [69]	2020 [39]	2017 [70]	2019 [71]	2018 [72]
	Resolution (pixels)	128×128	240×180	346×260	304×240	640×480	480×360	1280×720	640×480	640×480	1280×960	768×640	1280×800	320×262
	Latency (µs)	12µs @ 1klux	12µs @ 1klux	20	3	40 - 200	40 - 200	20 - 150	65 - 410	50	150	10	8	125µs @ 10lux
	Dynamic range (dB)	120	120	120	143	> 120	> 120	> 124	90	90	100	90	120	> 100
	Min. contrast sensitivity (%)	17	11	14.3 - 22.5	13	12	12	11	9	15	20	30	10	15
ns	Power consumption (mW)	23	5 - 14	10 - 170	50 - 175	36 - 95	25 - 87	32 - 84	27 - 50	40	130	-	400	20-70
ti,	Chip size (mm ²)	6.3×6	5×5	8×6	9.9×8.2	9.6×7.2	9.6×7.2	6.22×3.5	8×5.8	8×5.8	8.4×7.6	15.5×15.8	14.3×11.6	5.3×5.3
ica	Pixel size (µm ²)	40×40	18.5×18.5	18.5×18.5	30×30	15×15	20×20	4.86×4.86	9 × 9	9 × 9	4.95×4.95	18×18	9.8×9.8	13×13
cif	Fill factor (%)	8.1	22	22	20	25	20	> 77	11	12	22	8.5	8	22
- e	Supply voltage (V)	3.3	1.8 & 3.3	1.8 & 3.3	1.8 & 3.3	1.8	1.8	1.1 & 2.5	1.2 & 2.8	1.2 & 2.8		1.8 & 3.3	1.2 & 2.5	1.8 & 3.3
LS	Stationary noise (ev/pix/s) at 25C	0.05	0.1	0.1	-	0.1	0.1	0.1	0.03	0.03		0.15	0.2	0.1
IS0	CMOS technology (nm)	350	180	180	180	180	180	90	90	90	65/28	180	65	180
Ser		2P4M	1P6M MIM	1P6M MIM	1P6M	1P6M CIS	1P6M CIS	BI CIS	1P5M BSI			1P6M CIS	CIS	1P6M CIS
	Grayscale output	no	yes	yes	yes	no	yes	no	no	no	no	yes	yes	yes
	Grayscale dynamic range (dB)	NA	55	56.7	130	NA	> 100	NA	NA	NA	NA	90	120	50
	Max. frame rate (fps)	NA	35	40	NA	NA	NA	NA	NA	NA	NA	50	100	30
ra	Max. Bandwidth (Meps)	1	12	12	-	66	66	1066	300	600	1200	200	140	20
ne	Interface	USB 2	USB 2	USB 3		USB 3	USB 3	USB 3	USB 2	USB 3	USB 3			USB 2
Cai	IMU output	no	$1 \mathrm{kHz}$	1 kHz	no	$1\mathrm{kHz}$	$1\mathrm{kHz}$	no	no	$1\mathrm{kHz}$	no	no	no	1 kHz

[Gallego et al., IEEE PAMI 2020]







- (a) Events in space time
- (b) Event frame
- (c) Time surface
- (d) Interpolated voxel-grid
- (e) Motion-compensated event image
- (f) Reconstructed intensity image [Rebecq et al., IEEE PAMI 2019]



Introduction	Event Representations	Algorithms	Applications to Autonomous Vehicles	Conclusion
Algorithms				

DVS128

Micro-

controller

- Feature Detection and Tracking
- Optical Flow Estimation
- 3D reconstruction. Monocular and Stereo
- Pose Estimation and SLAM
- Visual-Inertial Odometry (VIO)
- Image Reconstruction
- Motion Segmentation
- Recognition

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Neuromorphic Control



[Zhu et al., IEEE RAL 2018]



[Rosinol et al., IEEE RAL 2018]

Introduction	Event Representations	Algorithms	Applications to Autonomous Vehicles	Conclusion					
Neuromo	Jeuromorphic Control								

Event-based Vision meets Deep Learning on Steering Prediction for Self-driving Cars [Maqueda et al., IEEE CVPR 2018]



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Introduction	Event Representations	Algorithms	Applications to Autonomous Vehicles	Conclusion	
Motion C	ompensation				

Event-Based Motion Segmentation by Motion Compensation [Stoffregen et al., IEEE ICCV 2019]



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Introduction	Event Representations	Algorithms	Applications to Autonomous Vehicles	Conclusion	
Event Cam	nera Dataset				

DSEC: A Stereo Event Camera Dataset for Driving Scenarios [Gebrig et al., IEEE RAL 2021]



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Introduction	Event Representations	Algorithms	Applications to Autonomous Vehicles	Conclusion	
Object Dete	ction				

Unsupervised Domain Adaptation



[Messikommer et al., IEEE RAL 2021]

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Object Dete	ection				

Object Detection in Adverse Conditions



[Tomy et al., IEEE ICRA 2022]





[Gehrig et al., arXiv 2022]

- Higher resolution sensors significantly increase the required data bandwidth, while burdening downstream tasks
- Higher resolution cameras are also more sensitive to temporal effects such as slow pixel response times
- When used in challenging high-speed scenarios and in low light, lower- resolution sensors often show a better performance while using lower bandwidth



Introduction	Event Representations	Algorithms	Applications to Autonomous Vehicles	Conclusion	
Semantic	Segmentation				

Unsupervised Domain Adaptation



[Sun et al., ECCV 2022]



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Conclusion				

- Event cameras pose a paradigm shift in the way visual information is acquired, so many challenges arise
- Many advantages over frame-based cameras: low latency, low power, high speed and high dynamic range
- Event cameras pose the challenge of rethinking perception, decision and control, especially when using deep learning approaches
- In autonomous vehicles applications, event-based vision will be helpful to catch the dynamic nature of the scene and to increase the robustness against adverse conditions
- Open questions: Event representations, end-to-end Deep Neural Networks architectures, training data, dedicated hardware processing, multi-sensors architecture, etc.