

Recent Event Camera Innovations: A Survey

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Abstract. Event-based vision, inspired by the human visual system, offers transformative capabilities such as low latency, high dynamic range, and reduced power consumption. This paper presents a comprehensive survey of event cameras, tracing their evolution over time. It introduces the fundamental principles of event cameras, compares them with traditional frame cameras, and highlights their unique characteristics and operational differences. The survey covers various event camera models from leading manufacturers, key technological milestones, and influential research contributions. It explores diverse application areas across different domains and discusses essential real-world and synthetic datasets for research advancement. Additionally, the role of event camera simulators in testing and development is discussed. This survey aims to consolidate the current state of event cameras and inspire further innovation in this rapidly evolving field. To support the research community, a GitHub page categorizes past and future research articles and consolidates valuable resources.

Keywords: Event cameras · Event-based vision · Neuromorphic vision · Dynamic vision sensors · Low latency · High dynamic range · Low power

1 Understanding Event-based Vision – An Introduction

Event-based vision represents a paradigm shift in visual sensing technology, inspired by the human visual system’s capability (thus also referred to as neuromorphic vision) to detect and respond to changes in the environment. Unlike traditional frame cameras, which capture static images at set intervals, event-based vision utilizes event cameras to continuously monitor light intensity changes at each pixel. These cameras produce “events” only when significant changes occur, generating a dynamic data stream that reflects real-time scene dynamics. Event-based vision mimics the asynchronous nature of human perception, where each pixel independently detects and records changes. This approach provides exceptionally high temporal resolution, essential for accurately capturing fast-moving objects and dynamic scenes without the motion blur typically associated with frame cameras. By focusing solely on changes and excluding static information,



Fig. 1: Publication Trends in Event-based Vision Research.

event cameras manage data more efficiently, significantly reducing redundancy and bandwidth requirements.

The real-time capture and processing of events enable immediate responses to scene changes, making event-based vision particularly suitable for applications that require rapid decision-making. The technology's focus on detecting changes on a logarithmic scale rather than absolute values allows it to handle a wide range of lighting conditions effectively, avoiding common issues like overexposure or underexposure encountered with traditional systems. This adaptability is particularly valuable in environments with challenging lighting conditions in outdoor settings. Moreover, since event cameras process only the changes, they require less data bandwidth and computational power compared to traditional cameras. This efficiency results in significant energy savings, making event-based vision ideal for battery-powered devices and long-term monitoring applications. The asynchronous nature also facilitates efficient data handling and analysis, focusing exclusively on relevant changes and enabling faster more accurate processing.

The distinctive features of event cameras - low latency, high dynamic range, reduced power consumption, and efficient data handling have driven their adoption across various application domains, including object detection [72], moving object segmentation [167–169, 190], object tracking [211, 283], object classification [12, 235], gesture/action recognition [6, 46, 141], flow/depth/pose estimation [11, 174, 175, 301, 302], semantic segmentation [4, 243], video deblurring [107, 139], video generation [145, 258], neural radiance fields (NERF) [119, 217], visual odometry [25, 279, 298, 306], high-resolution video reconstruction [29, 249, 289] and motion capture [90, 166, 274].

This survey aims to provide researchers with a comprehensive understanding of the current state of event cameras. It offers a background on research trends to illustrate the increasing interest in this field (Sec. 2). The survey explains the workings of event cameras (Sec. 3) and contrasts them with traditional frame

cameras (Sec. 4). It studies various event camera models from leading manufacturers, providing a feature-wise comparison to aid in camera selection (Sec. 5). Key milestone works are overviewed to set the stage for future research directions (Sec. 6). Additionally, the survey discusses the diverse application areas of event-based vision, presenting notable works across different domains (Sec. 7). An overview of crucial event-based datasets (Sec. 8) and simulators essential for advancing research and development is also included (Sec. 9).

The objective of this survey is to consolidate event-based vision systems resources, emphasizing technological advancements and practical applications while serving as a thorough guide to the field's features and options. Complementing this survey is a GitHub resource page, which will be regularly updated to provide researchers with the latest developments in event-based vision, facilitating informed decision-making and promoting ongoing innovation.

2 The Rise of Event-based Vision: A Background

The event-based vision research community has seen significant advancements in recent years, as evidenced by the growing number of published papers (see Fig. 1). Starting from a modest number in 2010, the field has expanded, peaking with a substantial increase in scholarly activity by 2023. This notable surge, particularly from 2019 onwards, is attributed to the increased availability of event cameras from various vendors and the introduction of advanced event-based simulators. Major computer vision conferences such as CVPR, ECCV, ICCV, and WACV have observed a significant rise in event-based vision research papers. For instance, the number of event-based vision papers presented at CVPR has grown markedly, from a few in 2018 to a considerable number in 2024. Specialized workshops dedicated to event-based vision have further contributed to disseminating research in this area. This trend illustrates its expanding impact and increasing recognition within the broader computer vision community.

In the late 1990s and early 2000s, notable advancements in neuromorphic vision included the development of a neuromorphic sensor for robots [81], spiking neural controllers [57], biologically inspired vision sensors [237] and an open-source toolkit for neuromorphic vision [104]. Key works also featured a review of artificial human vision technologies [47], an embedded real-time tracking system [140] and a multichip system for spike-based processing [253]. Additionally, the frame-free dynamic digital vision was discussed [44], AER dynamic vision sensors were introduced for a balancing robot [38,39], a dynamic stereo-vision system was developed [225], and activity-driven sensors were introduced [43]. Notably, [19] organized a workshop on biologically motivated vision.

From the early 2010s to 2020, notable advancements included the exploration of asynchronous event-based binocular stereo-matching [216], embedded neuromorphic vision for humanoid robots [10], multi-kernel convolution processor module [21], high-speed vision for microparticle tracking [181], temporally correlated features extraction [14,137], and an algorithm for recognition [158]. Researchers advanced techniques in event-based visual flow [11], SLAM [267]/

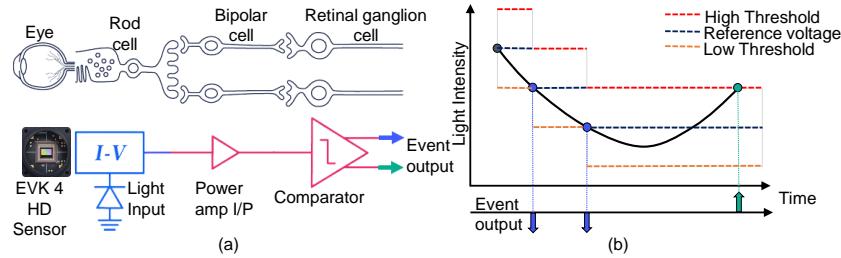


Fig. 2: Working Mechanism of Event Cameras: (a) Independent pixel operation converting light into voltage signals for detecting intensity changes. (b) Event generation as a function of logarithmic light intensity over time.

3D SLAM [266], a robotic goalie with rapid reaction times [42], and a review on retinomorphic sensors [199]. Additionally, a multi-kernel algorithm for high-speed visual features tracking [125], continuous-time trajectory estimation [173], lifetime estimation of events and visual tracking [172], stereo matching [56], and spiking neural network model of 3D perception [185] were explored during the mid-2010s. Innovations such as event-driven classifier [240], spatiotemporal filter for reducing noise [112], low-latency line tracking [54], graph-based object classification [12], and gait recognition [262] emerged. The late 2010s saw comprehensive surveys on event-based vision [61] and neuromorphic vision for autonomous driving [28] along with spatiotemporal feature learning for neuromorphic vision sensing [13]. The rapid advent of event cameras and simulators in the early 2020s significantly impacted the field, leading to milestone achievements as discussed in Sec. 6.

3 How Event Cameras Work: An Inside Look

Event-based vision fundamentally differs from traditional frame-based vision in the way they process a scene. Inspired by the human retina, where the rod, bipolar, and retinal ganglion cells detect and transmit visual signals independently (see Fig. 2 (a)), the purpose of each pixel in the sensor is to capture any change in visual information of the scene asynchronously. This autonomous principle of the sensor leads to a unique and efficient way of processing visual data in real-time. The working mechanism of an event camera involves several key steps. Each pixel operates independently, continuously, and asynchronously processing incoming light. Light photons hitting photodiodes in each pixel are converted into electrical current and transformed into a voltage signal. This generated voltage is compared to a reference voltage at each pixel continuously to detect logarithmic changes in light intensity.

As illustrated in Fig. 2 (b), every time the voltage difference exceeds a predefined threshold, an event $\langle x, y, p, t \rangle$ is triggered, recording the pixel coordinates (x, y) , the time of change t , and the polarity $p \in \{-1, +1\}$, denoting an increase

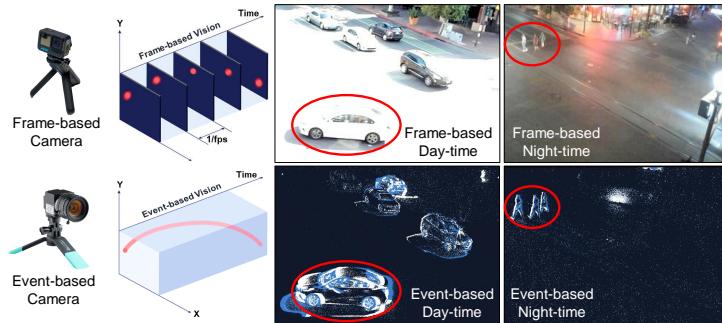


Fig. 3: Comparison of Frame vs. Event Cameras: The top row shows common issues like motion blur and visibility in frame-based images, while the bottom row shows event-based images with reduced motion blur and better visibility in challenging lighting.

or decrease of light intensity. These events are output as they occur, reflecting the changes in the scene over time through a continuous data stream rather than a series of static frames. The stream can be visualized as a two-channel representation in a 3D space. Here, two dimensions constitute the spatial component capturing the location of the event in image coordinates and the third dimension represents its temporal coordinates, indicating precisely when the event occurred. This spatial-temporal representation minimizes data redundancy and enables efficient processing of dynamic aspects of the scene through its sparse structure.

4 Event Camera vs. Frame Camera: A Comparison

Event cameras offer several advantages over traditional frame cameras due to their unique operating principles. Each pixel in an event camera records changes the moment they are detected, allowing for the capture of fast-moving objects and dynamic scenes, thus achieving high temporal resolution ($>10,000$ fps). Motion blur, a common issue in frame-based systems [40], occurs when objects move rapidly during the camera's exposure time, causing them to appear smeared across the image. However, unlike frame cameras, where every pixel must wait for a global exposure time of the frame, event cameras respond immediately to changes in the scene. This immediate response helps event cameras demonstrate low latency and significantly reduce motion blur, as shown in Fig. 3. This capability is critical in applications requiring real-time monitoring and rapid response, such as robotics and autonomous driving [55, 187].

While modern frame cameras can achieve high frame rates, they come at the cost of large bandwidth and storage requirements, which can be limiting. By only recording changes in the scene, event cameras produce less data than traditional frame cameras. This reduction in data bandwidth makes event cameras ideal for applications with limited bandwidth or storage capacity. The focus on changes

rather than absolute light levels further ensures that only the relevant information is captured, reducing redundancy. These advantages are most important for embedded and edge device systems, which often have limited processing power, memory, and storage capabilities, and benefit greatly from efficient and reduced data output [75, 120, 134, 219, 238].

Furthermore, event cameras operate effectively across a wide range of lighting conditions. Focusing on logarithmic changes in light intensity allows them to avoid issues like overexposure, underexposure, and sudden changes in lighting conditions that commonly affect traditional cameras. Event sensors' high dynamic range (>120 dB) far exceeds the dynamic range exhibited by high-quality frame cameras that do not exceed 95 dB [91]. This makes them suitable for environments with challenging lighting (see Fig. 3), such as outdoor scenes with varying illumination. Their exceptional low light cutoff (0.08 Lux) has prompted further explorations in various low-light applications [159, 278, 288]. Overall, these advantages make event cameras a compelling choice for diverse applications.

5 Event Camera Models: An Overview

In 2017, pioneering works [6, 175] utilized early event cameras like the DVS 128 [93] and DAVIS 240 [92], laying the groundwork for advanced applications in the field. Since then, event camera technology has advanced significantly, with prominent manufacturers such as iniVation [101], Prophesee [207], Lucid Vision Lab (TRT009S-EC, TRT003S-EC) [124], Celepixe (CeleX5-MIP, CeleX-V), and Insightness (SiliconEye Rino 3 EVK) [103] introducing innovative event camera models. Among these, iniVation and Prophesee have emerged as leaders, with models such as the DAVIS 346 [97], Prophesee EVK4 [203], and DAVIS 240 [92] gaining prominence in the research community. This section reviews various event cameras from iniVation and Prophesee.

iniVation is a leading company in neuromorphic vision systems, known for its bio-inspired technology that provides ultra-low latency, high dynamic range, and low power consumption. Their current product lineup includes the DVXplorer [98] with VGA resolution, 110 dB dynamic range, and 165 million events per second, the DVXplorer Lite [99] with QVGA resolution, 110 dB dynamic range, and 100 million events per second, the DAVIS 346 [97], a prototype offering concurrent QVGA+ resolution and up to 12 million events per second, and the DAVIS 346 AER [94], which provides both event and frame output with a 120 dB dynamic range. Moreoever, the DVXplorer S Duo [100] integrates an event-based sensor with a global-shutter color image sensor, powered by an Nvidia Jetson Nano SOM. Also, their Stereo Kit [102] includes two devices, lenses, tripods, and other accessories for advanced stereo vision exploration. Note that some earlier products, such as the DVXplorer Mini, DVS 240, DAVIS 240, eDVS, DVS 128, DVL-5000, have been discontinued by iniVation and are no longer available. Additionally, iniVation offers software solutions like DV [95] for user-friendly visualization, DV-Processing [96] for C++/Python-based processing, and

Table 1: Comprehensive Comparison of Event Cameras Manufactured by iniVation.

	DVXplorer S Duo	DVXplorer Micro	DVXplorer	DVXplorer Lite	DAVIS346	DAVIS346 AER
Device Attributes						
Power Output						
Spatial Resolution	640 x 480	640 x 480	640 x 480	320 x 240	320 x 240	320 x 240
Temporal Resolution	65 - 200 μ s	65 - 200 μ s	65 - 200 μ s	65 - 200 μ s	1 μ s	1 μ s
Max Throughput	30 MEPS	450 MEPS	165 MEPS	100 MEPS	12 MEPS	12 MEPS
Latency	<1 ms	<1 ms	<1 ms	<1 ms	<1 ms	<1 ms
Dynamic Range	90 dB - 110 dB	90 dB - 110 dB	90 dB - 110 dB	90 dB - 110 dB	120 dB	120 dB
Contrast Sensitivity	13% - 27.5%	13% - 27.5%	13% - 27.5%	13% - 27.5%	14.3% - 22.5%	14.3% - 22.5%
Pixel pitch	9 μ m	9 μ m	9 μ m	18 μ m	18.5 μ m	18.5 μ m
Spatial Resolution	1920 x 1080 HD	-	-	-	346 x 260	346 x 260
Frame Rate	Up to 30 fps	-	-	-	Up to 40 fps	Up to 40 fps
Dynamic Range	71.4 dB	-	-	-	55 dB	55 dB
PPS	-	-	-	-	4.2 %	4.2 %
Dark Signal	-	-	-	-	18000 e-/s	18000 e-/s
Readout Noise	-	-	-	-	55 e-	55 e-
Pixel Pitch	3 μ m	-	-	-	18.5 μ m	18.5 μ m
Dimensions (H x W x D)	32 x 80 x 92	24 x 27.5 x 29.7	40 x 60 x 25	40 x 60 x 25	40 x 60 x 25	40 x 78.5 x 25
Lens mount	S-mount	CS-mount	CS-mount	CS-mount	CS-mount	CS-mount
Mounting options	2-side Whitworth 1/4" 20 female and M3 mounting points	4x M2 mounting points	4-side Whitworth 1/4" 20 female and M3 mounting points			
Connectors	USB 3.0 C-Mini HDMI	USB 3.0 micro B port	USB 3.0 micro B port	USB 3.0 micro B port	USB 3.0 micro B port	USB 3.0 micro B port
Case materials	Anodized aluminum	Engineering plastic	Anodized aluminum	Engineering plastic	Anodized aluminum	Anodized aluminum
Weight (without lens)	220 g	10 g	100 g	75 g	100 g	120 g
Power consumption	7W - 12 W	-	-	-	<180 mA @ 5 VDC (USB)	<180 mA @ 5 VDC (USB)
Sensor Technology	-	90 nm BSI CIS	-	-	0.18 μ m 1P6M MM CIS	0.18 μ m 1P6M MM CIS
Sensor Supply voltage	-	12 V, 1.8 V and 2.8 V	-	-	1.8 V and 3.3 V	1.8 V and 3.3 V
Other Features	-	-	6-axis IMU (Gyro + Accelerometer), up to 8 kHz sampling rate Support multi-camera time synchronization			
	on-board processing (Nvidia Jetson Nano)	-	-	-	-	-

ROS integration, alongside a low-level library for event camera usage. Tab. 1 summarizes the key characteristics and features of iniVation’s event cameras.

Table 2: Comprehensive Comparison of Event Cameras Manufactured by Prophesee.

	EVK 4 HD	EVK3	EVK3 - HD	VisionCam EB	SilkyEvCam VGA	SilkyEvCam HD
Device Attributes						
Power Output						
Spatial Resolution	1280 x 720	320 x 320	1280 x 720	640 x 480	640 x 480	1280 x 720
Optical Format	1/2.5"	1/5"	1/5"	3/4"	3/4"	1/2.5"
Max. Bandwidth	1.6 Gbps	-	1.6 Gbps	1 Gbps	-	-
Typical Latency	220 μ s	<150 μ s	220 μ s	220 μ s	200 μ s	<100 μ s
Dynamic Range	>80 dB	>120 dB	>80 dB	>120 dB	>120 dB	>120 dB
Contrast Sensitivity	25%	25%	25%	25%	25%	25%
Pixel Size	4.86 x 4.86 μ m	6.3 x 6.3 μ m	4.86 x 4.86 μ m	15 x 15 μ m	15 x 15 μ m	4.86 x 4.86 μ m
Low light cutoff	0.08 lux	0.05 lux	0.08 lux	0.08 lux	0.08 lux	0.08 lux
Dimensions (H x W x D) mm	30 x 30 x 36	108 x 76 x 45	108 x 76 x 45	105 x 50 x 50 (30 + lens tube 27 - 80 mm)	30 x 30 x 36	30 x 30 x 36
DoF	47.7°	76°	81.5°	-	70°	47.7°
Lens Mount	C/CS mount	M12 S-Mount	C/CS with S-mount	C-S Mount	C/CS Mount	C/CS Mount
Mounting Options	4x M2 front + 2x M2.6 back fixing points	Optical Flex module C-Module	M12 S-Mount	6 x M4	M12 S-Mount	M12 S-Mount
Connectors	USB 3.0 Type-C	USB 3.0 Micro-B and SMA	USB 3.0 Micro-B	M12 - 17 Pin	USB 3.0 Type-C	USB 3.0 Type-C
Case Material	Aluminum alloy	PCBs only	PCBs only	-	Aluminum alloy	Aluminum alloy
Weight	40g	-	-	180 g without lens	102.6 g	72.5 g
Power Consumption	0.5W powered via USB	powered via USB	4.5W powered via USB	-	USB Power (VBUS)	USB Power (VBUS)
Sensor Tech	IMX636	GenX320 CCAM5 module, CM2 Flex Optical Module	IMX636	PPSSMVCD (Gen3.1 VGA sensor)	IMX636	PPSSMVCD (Gen3.1 VGA sensor)
Other Features	-	Synchronization interface	-	Programmable with dual-core ARM Cortex-A15 1 x eSD Card > 32 GB	-	-
				METAVISION Intelligence Suite - SDR support by PROPHESEE		

Prophesee offers evaluation kits for exploring event-based vision, including USB cameras and embedded starter kits. USB cameras feature the Metavision EVK4-HD [203] with the IMX636 sensor (1280x720px) [208], providing high dynamic range (>120 dB) and low pixel latency (<100 μ s), the Metavision EVK3- GENX320 with the GenX320 sensor (320x320px) [201], known for ultra-low power consumption (down to 36 μ W) and high dynamic range (>120 dB), and the Metavision EVK3-HD [202] with the IMX636 sensor and USB 3.0 con-

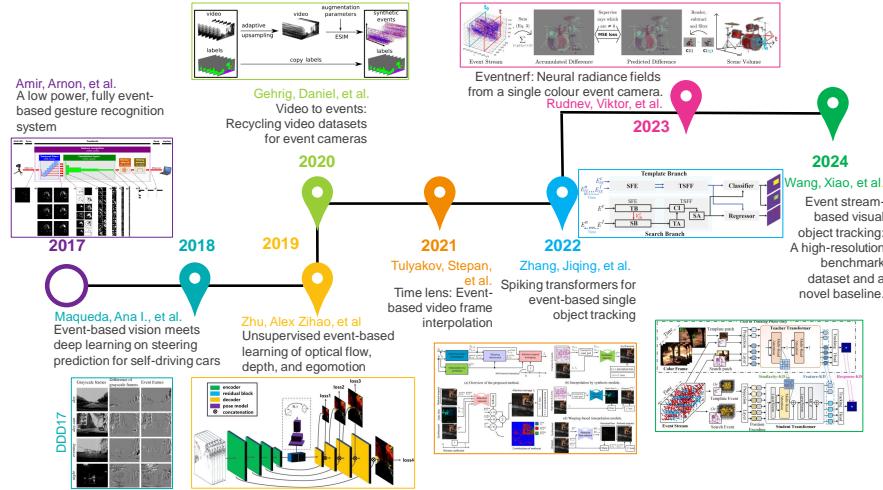


Fig. 4: Key Milestone Papers and Works in Event-based Vision.

nnectivity. Embedded starter kits include the Metavision Starter Kit-AMD Kria KV260 [205], combining IMX636 [236] and GenX320 sensors for FPGA-based development, and the Metavision Starter Kit-STM32F7 [206], optimized for the STM32-F7 MCU with the GenX320 sensor for low-power applications. The Metavision SDK [204] offers a comprehensive suite of tools, including visualization applications, programming guides, and APIs in C++ and Python for custom solution development and sample recordings. Tab. 2 summarizes the key characteristics and features of Prophesee's event cameras.

6 Pioneering Progress: Milestones in Event-based Vision

In this section, significant milestone works in event-based vision from 2017 to 2024 (July) are reviewed, highlighting key advancements that have shaped the field, as illustrated in Fig. 4. In 2017, [6] introduced a low-power, fully event-based gesture recognition system using the TrueNorth processor, achieving real-time accuracy with minimal power. [175] released a comprehensive dataset and simulator, combining global-shutter and event-based sensors to advance algorithms for robotics and vision applications. [129] developed the CIFAR10-DVS dataset, converting CIFAR-10 images into event streams, offering a valuable benchmark for event-driven object classification, utilizing a repeated closed-loop smooth (RCLS) movement of frame-based images.

In 2018, [161] enhanced steering prediction for self-driving cars by adapting deep neural networks for event data. [235] introduced HATS, a feature representation and machine learning architecture that improved object classification accuracy and released the first large real-world event-based dataset. [300] unveiled the multivehicle stereo event camera dataset (MVSEC), offering syn-

chronized event streams and IMU data for 3D perception tasks. [212] developed ESIM, an open-source simulator for generating high-quality synthetic event data, while [301] also introduced EV-FlowNet, a self-supervised framework for optical flow estimation from event streams. In 2019, [302] proposed an unsupervised learning framework for predicting optical flow and depth from event streams using discretized volume representation. [213] developed a method to reconstruct high-quality videos from event data with a recurrent neural network for object classification and visual-inertial odometry. [189] introduced the event-based double integral (EDI) model to generate sharp, high-frame-rate videos from a single blurry frame and event data, addressing motion blur. Additionally, [214] improved intensity image and color video reconstruction using a recurrent network trained on simulated data.

In 2020, [196] released a high-resolution (1Mpx) dataset and a recurrent architecture with temporal consistency loss, improving object detection. [68] converted conventional video datasets into synthetic event data for detection and segmentation tasks, enhancing model training, while [224] developed a neural network for fast and efficient image reconstruction from event data. In 2021, [71] introduced the high-resolution DSEC stereo dataset to improve autonomous driving under challenging lighting conditions. [85] developed the v2e toolbox for generating realistic synthetic DVS events from intensity frames, enhancing object detection, particularly at night. [251] proposed Time Lens, a frame interpolation method that improves image quality and handles dynamic scenarios. [298] presented an event-based stereo-visual odometry system with real-time robustness. [113] introduced the N-ImageNet dataset to support fine-grained object recognition with event cameras.

In 2022, [283] introduced STNet, a spiking transformer network for single-object tracking that combines global spatial and temporal cues for superior accuracy and speed. [241] developed EFNet, a two-stage restoration network utilizing cross-modal attention, setting new benchmarks in motion deblurring with the REBlur dataset. [222] proposed AEGNN, which reduce computational complexity and latency by processing events as sparse, evolving spatiotemporal graphs. [249] presented Time Lens++, enhancing frame interpolation with parametric non-linear flow and multi-scale fusion. In 2023, [217] introduced Event-NeRF, which uses a single-color event stream to achieve dense 3D reconstructions with high-quality RGB renderings. [72] developed recurrent vision transformers (RVT), reaching state-of-the-art object detection performance with reduced inference time and parameter efficiency. [89] introduced Ev-NeRF, adapting neural radiance fields to event data for improved intensity image reconstruction under extreme conditions.

In 2024, [261] introduced high-resolution data and hierarchical knowledge distillation to enhance speed and accuracy in visual object tracking. [2] (SEVD) provided synthetic multi-view data for robust traffic participant detection, while [252] (eTraM) offered 10 hr of event-based traffic monitoring data, showcasing the effectiveness of event cameras in diverse scenarios. These milestones demonstrate the rapid progress and growing potential of event-based vision technologies.

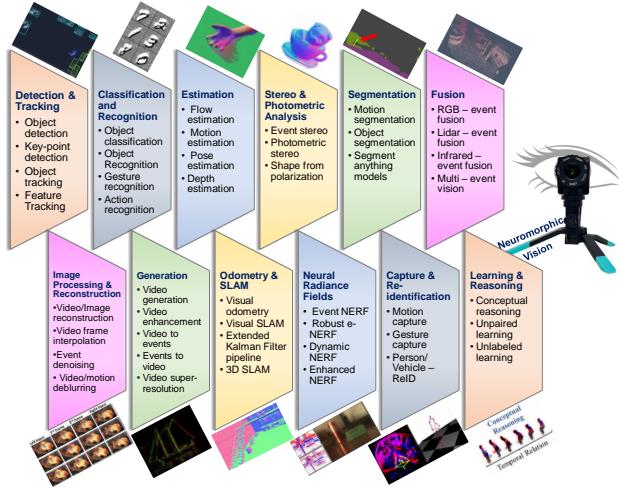


Fig. 5: Showcasing Broad Applications and Notable Works in Event-based Vision Research.

7 Event Cameras in Action: Diverse Tasks and Impacts

Event-based vision is revolutionizing numerous fields by introducing new capabilities across a wide range of tasks, including detection, tracking, classification, recognition, and estimation. This section highlights key tasks, as illustrated in Fig. 5, and explores its significant impact across different application domains. In detection and tracking, event cameras with high temporal resolution and low latency have driven advancements in object detection, key-point detection, and tracking. Innovations such as scene-adaptive sparse transformers [194], spiking [283] and recurrent vision transformers [72], and self-supervised learning [66] have enhanced accuracy in these areas, benefiting applications in surveillance and autonomous driving [26]. In classification and recognition, event cameras have markedly improved object classification, gesture and gait recognition, and action recognition, particularly in dynamic or complex scenes. Their ability to capture detailed temporal information boosts object classification through histograms of averaged time surfaces [235] and space-time event clouds [260].

Furthermore, event cameras greatly enhance estimation tasks such as optical flow, motion/pose, and depth estimation. The high-speed and low-latency characteristics of event cameras allow for precise calculation of motion, orientation, and depth, which are essential for understanding scene dynamics and improving 3D perception. Key advancements include progressive spatiotemporal alignment for motion estimation [86], globally optimal contrast maximization [142], and tangentially elongated Gaussian belief propagation for optical flow [226]. These developments are crucial for applications in robotics, augmented reality, and autonomous navigation. In stereo and photometric analysis, event-based vision supports advanced techniques like event stereo [32], photometric stereo [280],

Table 3: Event-based Vision Applications with Related Notable Research Papers.

	Applications	Taks	Related Papers
Event-based Vision	Detection and Tracking	Object detection	[2, 70, 72, 130, 164, 177, 194–196, 221, 223, 248, 252, 271, 292, 299, 309, 310]
		Key-point detection	[31, 66, 84, 87, 148, 160]
		Object tracking	[8, 58, 230, 261, 283, 285, 304, 309]
		Feature tracking	[69, 74, 127, 132, 165, 228, 306]
Classification and Recognition	Classification and Recognition	Object classification	[45, 235]
		Object recognition	[22, 34, 113, 114, 133, 254, 277, 293, 309]
		Gesture recognition	[6, 260]
		Gait recognition	[262]
Estimation	Estimation	Action recognition	[67, 197, 246, 295]
		Optical flow estimation	[62, 63, 122, 126, 146, 154, 155, 188, 192, 198, 226, 232, 233, 255]
		Motion/Pose estimation	[51, 64, 86, 105, 142, 143, 162, 180, 182, 183, 193, 215, 218, 307]
		Depth estimation	[36, 62, 179, 231, 282]
Stereo and Photometric Analysis	Stereo and Photometric Analysis	Event stereo	[7, 32, 149, 171, 179, 250, 263, 286, 297]
		Photometric stereo	[280]
		Shape from Polarization	[163, 176]
		Semantic segmentation	[16, 109, 121, 243]
Segmentation	Segmentation	Motion/Object segmentation	[128, 168, 239, 298]
		Segment Anything Models	[30]
		Frame/RGB – Event	[127, 186, 248, 249, 273, 284, 299]
		Lidar/Infrared – Event	[18, 37, 73, 220, 245, 294]
Reconstruction and Image Processing	Reconstruction and Image Processing	Motion reconstruction	[106]
		Video reconstruction	[53, 147, 213, 264, 268, 275, 303, 308]
		Image reconstruction/restoration	[78, 134, 136, 151, 178, 191, 224, 259]
		Video frame interpolation	[35, 82, 115, 123, 150, 186, 242, 249, 251, 269, 270, 276, 281, 289]
Fusion	Fusion	Event denoising	[3, 9, 48, 49, 76, 265, 287]
		Motion/Video deblurring	[33, 52, 107, 116, 117, 139, 241, 272, 289, 290, 296]
		Video generation/enhancement	[135, 256, 258, 305]
		Video to events	[68, 291]
Generation	Generation	Video/Event Super-resolution	[79, 80, 88, 110, 131, 153]
		Odometry and SLAM	[83, 143, 144, 170, 220, 311]
		SLAM	[27, 65, 77, 108, 210]
		NERF	[23, 89, 152, 157, 209, 217]
Capture and Re-Identification	Capture and Re-Identification	Motion capture	[166, 274]
		Person Re-ID	[1, 24]
		Conceptual reasoning	[295]
		Unsupervised learning	[62, 118, 302]
Learning and Reasoning	Learning and Reasoning	Unlabeled and unpaired event data	[257]

and shape from polarization [176], offering high-resolution depth maps and detailed surface properties. For segmentation tasks, including semantic segmentation [243], motion/object segmentation [239], and segment anything models [30], event cameras excel in dynamic and high-speed scenes, enabling precise scene understanding and object isolation. The fusion of event-based data with traditional frame-based [273], lidar, or infrared data [73, 294] further enhances applications such as environmental mapping by combining complementary information.

Event-based vision significantly advances reconstruction and image processing tasks, contributing to video reconstruction [268, 303], image reconstruction [191, 259], video frame interpolation [150, 281], event denoising [9], and motion deblurring [33, 241]. In generation-related tasks, it aids in video generation and enhancement [145, 258], video-to-events conversion [68], and super-resolution [88, 153], facilitating high-quality content creation and analysis. For odometry and SLAM, event-based vision plays a crucial role in visual odometry [311] and simultaneous localization and mapping [27], providing accurate navigation and mapping capabilities. Tab. 3 highlights notable works using event cameras across various tasks and application domains, underscoring the transformative impact of event-based vision in addressing complex challenges and driving innovation.

Table 4: Summary of Real-world Event-based Datasets.

Year	Dataset Name	Event Modality Used	Subject/Object Classes	Labeling	Tasks	Dataset Description
2024	EventVOT [261]	Prophesee EVK4 HD	UAV's, Pedestrians, Vehicles, Ball sports	Yes, Manual	Object tracking	Large-scale, high-resolution, visual object-tracking dataset
2024	eTraM [252]	Prophesee EVK4 HD	Vehicles, Pedestrians, Micro-mobility	Yes, Manual, 2D BB	Object detection, tracking	High-resolution, large-scale, fixed Traffic perception dataset for traffic monitoring
2024	SeAct [295]	DAVIS346	Human actions like sit, catch, throw, vomit, handshake	Yes	Action recognition	Event-text action recognition dataset
2023	PEDRo [17]	DAVIS346	Persons	Yes, Manual, 2D BB	Object detection	A large person detection dataset recorded with a moving camera
2022	DVS-Lip [247]	DAVIS346	Different sequences containing all words in English vocabulary	Yes	Gesture recognition	Lip-reading dataset with over 100 classes, 40 speakers, 10K lip utterances in the English language
2022	EVIMo2 [20]	Prophesee Gen3 DVS Gen2	Moving objects	Yes, Automatic	Motion Segmentation, Recognition	Indoor dataset with moving objects, 3D motion of the sensor, object motion and structure, masks and optical flow
2021	DSEC [71]	Prophesee Gen 3.1	Driving scenarios with diverse illumination during day & nighttime	Yes	Stereo matching	High-resolution stereo dataset for driving scenarios
2020	GEN1 [41]	Prophesee Gen 1	Cars, Pedestrians	Yes, Manual, 2D BB	Object detection, tracking, flow estimation	Large event-based automotive (cars and pedestrians) detection dataset
2020	1 Mpx [196]	Prophesee 1 Mpx	Pedestrians, two-wheelers, cars, trucks, buses, traffic signs, traffic lights	Yes, Automatic, 2D BB	Object detection	High-resolution large-scale automotive detection dataset (25M BB, 14 hr)
2019	ASL-DVS [12]	DAVIS240c	24 classes of hand gesture correspond to 24 letters (A-Y, excluding J)	Yes	Gesture recognition	Dataset for American Sign Language (ASL) recognition
2019	EV-IMO [169]	DAVIS346	Moving objects	Yes, Automatic	Motion segmentation, visual odometry, optical flow, stereo	Indoor dataset with moving objects, 3D motion of the sensor, 3D object and structure, and object masks
2018	N-Cars [235]	Prophesee Gen 1	Cars	Yes, 2D BB, Semi-automatic	Object Classification	Large real-world event-based dataset for object classification
2018	MVSEC [300]	DAVIS346B	Poses and depth	Yes	Feature tracking, visual odometry, depth estimation	Synchronized stereo pair dataset recorded from a handheld rig, hexacopter, top of a car, on a motorcycle, in different illumination levels
2017	DIDD17 [15]	DAVIS346B	Vehicle speed, driver steering etc.,	Yes	Steering angle prediction	Driving recordings in highways, city during day, evening, night, dry, and wet weather conditions
2017	DvsGesture [6]	DVS128	11 hand and arm gesture classes	Yes	Gesture recognition	Gesture dataset comprising 11 hand gesture categories from 29 subjects under 3 illumination conditions
2017	Event Camera Dataset [175]	DAVIS 240C	Object rotation, translation, person walking and running, etc.,	Yes	Pose estimation, visual odometry, SLAM	The object's motion captured in outdoor and indoor scenarios with varying speed and DoFs

8 Data for Innovation: Event-based Vision Datasets

Event-based vision datasets are crucial for advancing the field by providing resources for training and evaluating algorithms. Real-world datasets, captured with event cameras, cover diverse scenarios, while synthetic datasets from simulators offer controlled data for experimentation. This section reviews prominent datasets, summarized in Tab. 4 and Tab. 5, with a detailed list available on the GitHub page.

8.1 Real-world Datasets

The EventVOT [261] dataset offers high-resolution visual object tracking data using the Prophesee EVK4 HD camera, covering diverse target categories such as UAVs, pedestrians, vehicles, and ball sports across various motion speeds and lighting conditions. eTraM [252] dataset provides a comprehensive traffic monitoring dataset with 10 hr of data from the Prophesee EVK4 HD camera, including 2M bounding box annotations across eight traffic participant classes. SeAct [295] introduces a semantic-rich dataset for event-text action recognition, collected with a DAVIS 346 camera and enhanced with GPT-4 generated action captions. DVS-Lip [247] is a lip-reading dataset recorded with the DAVIS 346 camera, featuring 100 words and fine-grained movement information. DSEC [71] provides stereo data for driving scenarios, including lidar and GPS measurements, with 53 sequences collected under various illumination conditions. GEN1 [41] offers a large-scale automotive detection dataset with over 39 hr of data collected in different driving conditions.

The 1 MPX [196] dataset includes high-resolution data from a 1-megapixel event camera, providing 25M bounding boxes for object detection in automotive scenarios. N-Cars [235] features recordings of urban environments for object

Table 5: Summary of Synthetic Event-based Datasets.

Year	Dataset Name	Event Modality Used	Subject/Object Classes	Labeling	Task	Dataset Description
2024	SEVD [2]	CARLA DVS	Car, truck, van, bicycle, motorcycle, pedestrian	Yes, Automatic labeling, 2D and 3D BB	Object detection, tracking	Multi-view ego and fixed perception dataset for traffic monitoring
2024	Event-KITTI [294]	V2E	Vehicles, pedestrians, cyclists, etc.,	Yes	Object Detection, tracking	An event-based version of KITTI using the V2E for daytime images and a noise model for nighttime images of corresponding daytime
2023	ESfP Synthetic [176]	ESIM	Scenes consisting of a textured mesh illuminated with a point light source	Yes, ground-truth surface normal from renderer	Object reconstruction	Data for Surface normal estimation using event-based shape from polarization
2022	N-EPIC-Kitchens [197]	ESIM	8 action classes (Put, take, open, close, wash, cut, mix, pour)	Yes	Action Recognition	Event-based camera extension of the large-scale EPIC-Kitchens dataset
2021	N-ImageNet [113]	Samsung DVS Gen3	1000 Object Classes (same as ImageNet)	Yes	Object Recognition	Event-based version of the original ImageNet dataset.
2017	CIFAR10-DVS [129]	DVS camera	10 Object Classes (airplane, automobile, bird, cat, deer, dog, frog, horse, ship, truck)	Yes	Object Classification	Event-based representations of the original CIFAR-10 images
2015	N-MNIST [184]	DVS camera	10 classes of digits (0-9)	Yes	Object Classification	An event-based version of the original MNIST dataset
2015	N-Caltech-101 [184]	ATIS image sensor	101 Object Classes (animals, vehicles, etc..)	Yes	Object Classification	Event-based version of the traditional Caltech101 dataset
2015	MNIST-DVS [229]	DVS camera	10 classes of digits (0-9)	Yes	Object Classification	An event-based version of the original MNIST dataset

classification, capturing 80 min of video with an ATIS camera. MVSEC [300] includes synchronized stereo data for 3D perception across varied environments, while DDD17 [15] provides both event and frame-based driving data with over 12 hr of recordings. DvsGesture [6] is a gesture recognition dataset with 1,342 instances of 11 hand and arm gestures recorded under different lighting conditions using the DVS 128 camera. Moreover, the Event Camera Dataset [175] offers data for pose estimation, visual odometry, and SLAM using a DAVIS camera.

8.2 Synthetic Datasets

The SEVD [2] dataset provides a comprehensive synthetic event-based vision dataset using multiple DVS cameras within the CARLA simulator. It captures multi-view data across various lighting and weather conditions for ego and fixed traffic perception, including RGB imagery, depth maps, optical flow, and segmentation annotations to facilitate diverse traffic monitoring. The Event-KITTI [294] dataset extends the KITTI by generating event streams from daytime and synthesizing nighttime images, aiding in scene flow analysis and motion fusion. The ESfP-Synthetic [176] dataset focuses on shape from polarization by rendering scenes with a polarizer and using ESIM to simulate events.

The N-ImageNet [113] dataset, derived from ImageNet using a moving event camera setup, serves as a benchmark for fine-grained object recognition, addressing artifacts from monitor refresh mechanisms. The CIFAR10-DVS [129] dataset converts CIFAR-10 into event streams, offering an intermediate difficulty dataset for event-driven object classification through realistic image movements. Lastly, the N-MNIST and N-Caltech [184] datasets convert MNIST and Caltech101 into spiking neuromorphic datasets using a pan-tilt camera platform, facilitating studies on neuromorphic vision and sensor motion. These synthetic datasets have collectively advanced event-based vision, supporting diverse applications.

9 Simulating Reality: The Event-based Simulators

Event-based simulators are crucial for advancing event-based vision systems, providing synthetic data for algorithm validation and application exploration in a controlled, cost-effective manner. Notable simulators include the DAVIS

Table 6: Summary of Open-source Event Camera Simulators.

Simulator	Open Source	Programming Language	Input	Output	Dependencies	Description	Related Resources
ESIM	Yes	C++	Arbitrary 3D camera motion, initial images	Event streams, standard images, IMU data, ground truth	OpenGL Renderer, UnrealCV Renderer	Simulates arbitrary camera motion in 3D scenes, while providing events, standard images, inertial measurements, with ground-truth	[60, 212]
DAVIS Simulator	Yes	Python	Camera trajectory, Blender scenes, render configurations	Event streams, camera calibration, ground truth, intensity images, depth map	Blender	Generates synthetic datasets using Blender for prototyping vision algorithms or event-based feature tracking algorithms	[59, 175]
v2e	Yes	Python	RGB or grayscale videos, image sequences	Event frame videos (.h5 format)	PyTorch, OpenCV, Python packages	Synthesizes event data from any real (or synthetic) conventional frame-based video, using pre-trained DVS pixel model	[85, 227]
ICNS Simulator	Yes	Python/C++/Matlab	Videos, Blender-generated scenes, camera trajectories	Event streams, camera calibration, ground truth, intensity images	Blender	An extended DVS pixel simulator for neuromorphic benchmarks which simulates latency and the event structure	[111, 244]
V2CE Toolbox	Yes	Python	RGB or grayscale videos, image sequences	Event streams	PyTorch	Converts RGB or grayscale videos to event streams. Trained on MVSEC dataset, optimized for DAVIS 340k cameras (340x260[px])	[50, 291]
DVS-Voltmeter	Yes	Python	High frame-rate videos	Event streams	PyTorch, OpenCV	Stochastic DVS simulator, incorporating voltage variations, randomness from photon reception, and noise effects.	[138, 156]
CARLA DVS Camera	Yes	Python/C++	Synchronous frames from a video within CARLA	Event streams (carla.DVSEventArray)	CARLA simulator, Python packages	Emulates microsecond dynamics asynchronously, providing microsecond temporal resolution.	[234]
Prophesee	Yes	Python	Image (png/jpg) or video (mp4/avi)	Event-based frame/video	Mitavision SDK, Python packages	Transforms frame-based images or videos into event-based counterpart	[200]
VtoE	Yes	Python	High frame-rate videos	Event streams	PyTorch, OpenCV	Stochastic DVS simulator, incorporating voltage variations, randomness from photon reception, and noise effects.	[138, 156]
VISTA	Yes	Python/C++	Synchronous frames from a video within VISTA	Event streams	VISTA simulator, Python packages	Synthesizes event data locally around RGB data given a viewpoint and timestamp with video interpolation and event emission model	[5]

Simulator [175], which generated event streams, intensity frames, and depth maps with high temporal precision through time interpolation. The ESIM [212] extended this by offering an open-source platform for modeling camera motion in 3D scenes, producing events and comprehensive ground truth data.

The v2e simulator [85] converted conventional video frames into realistic event-based data, addressing non-idealities such as Gaussian event threshold mismatch. The ICNS simulator [111] enhanced noise accuracy by integrating real pixel noise distributions. The DVS-Voltmeter [138] used a stochastic approach to simulate realistic events, incorporating voltage variations and noise effects from high-frame-rate videos. The V2CE Toolbox [291] improved video-to-event conversion with dynamic-aware timestamp inference. Additionally, the CARLA DVS camera [234] implementation simulates event generation with high-frequency execution to emulate microsecond resolution and adjust sensor frequency based on scene dynamics, while Prophesee Video to Event Simulator [200] provides a Python script for converting frame-based videos into event-based counterparts. Together, these simulators are essential for developing and testing event-based vision systems, driving innovation in the field. Tab. 6 summarizes the most commonly used event-based simulators.

10 Conclusion

Event cameras have significantly impacted visual sensing technology and this survey outlines their evolution, explains their operational principles, and highlights how they differ from traditional frame-based cameras. It reviews various models and key milestones, offering a comprehensive overview of event-based vision as it stands today. The diverse applications of event cameras across different fields demonstrate their flexibility and potential. The importance of real-world and synthetic datasets in advancing the field is emphasized, along with the role of simulators in improving testing and development. As research progresses, consolidating and sharing knowledge will be essential for addressing new challenges and promoting further innovation. The GitHub page provided will be a valuable resource for the research community, offering access to past research and continuously updated with ongoing research and other relevant materials.

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