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Event Camera and LiDAR Fusion: A Novel Hybrid Imaging System for Robust Autonomous Perception

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Abstract: Event cameras represent a transformative advancement in visual sensing technology, drawing inspiration from biological retinas to capture brightness changes asynchronously at the pixel level. Unlike conventional frame-based cameras that suffer from motion blur and limited dynamic range, event sensors achieve microsecond temporal resolution and exceptional performance, exceeding 120 dB dynamic range. This novel hybrid perception system synergistically combines event-based vision with LiDAR sensing to overcome individual sensor constraints while leveraging their complementary strengths. The fusion architecture addresses fundamental challenges in autonomous perception through sophisticated temporal synchronization, noise filtering, and heterogeneous data representation strategies. Applications span diverse domains from high-speed drone navigation and advanced driver assistance systems to robotic manipulation and space missions. The hybrid system demonstrates superior performance in challenging scenarios, including extreme lighting variations, rapid motion, and feature-poor environments where traditional sensors fail. Through continuous-time estimation frameworks and neural fusion models, the system maintains robust operation across the full spectrum of real-world conditions. This technological convergence opens new possibilities for autonomous systems to operate in previously inaccessible domains, establishing a foundation for next-generation perception capabilities that match biological vision's adaptability while maintaining the precision required for autonomous operation.

Keywords: Event-Based Vision, LiDAR Fusion, Neuromorphic Sensing, Autonomous Navigation, High Dynamic Range Imaging.

INTRODUCTION

The evolution of autonomous systems has been fundamentally constrained by the limitations of conventional sensing modalities. As these systems are deployed in increasingly complex and dynamic environments, the demand for robust, high-performance perception capabilities has never been more critical. Traditional frame-based cameras, while ubiquitous in current autonomous systems, suffer from motion blur during rapid movements and exhibit poor performance under extreme lighting conditions. Similarly, LiDAR sensors, despite providing accurate depth information, operate at relatively low temporal resolutions (10-20 Hz) and produce sparse point clouds that may miss critical dynamic events.

Event cameras represent a paradigm shift in visual sensing, drawing inspiration from biological retinas to capture brightness changes asynchronously at the pixel level. Unlike conventional cameras that capture entire frames at fixed intervals, event cameras respond only to changes in the visual scene, achieving microsecond temporal resolution, exceptional dynamic range exceeding 120 dB, and immunity to motion blur. Recent surveys have highlighted the growing adoption of event-based vision in FPGA implementations, where processing architectures can achieve throughputs of up to 100 million events per second while maintaining power consumption below 5 watts (Kryjak, T. 2024). These characteristics make event cameras ideally suited for scenarios where traditional sensors fail, such as high-speed motion tracking or operation under extreme lighting variations. The implementation of event processing on FPGAs has demonstrated particular advantages in reducing latency to sub-millisecond levels, with some architectures achieving end-to-end processing delays as low as 200 microseconds for optical flow computation (Kryjak, T. 2024).

This research proposes a novel hybrid perception system that synergistically combines event-based vision with LiDAR sensing to create a robust, high-speed, and high-dynamic-range scene understanding capability. By fusing the temporal precision and dynamic range of event cameras with the spatial accuracy of LiDAR, it aims to overcome the individual limitations of each modality while leveraging their complementary strengths. Recent advances in unsupervised learning approaches have demonstrated the potential of event-based systems for simultaneous estimation of optical flow, depth, and egomotion without requiring ground truth labels during training (Zihao Zhu. *et al.*, 2018). These self-supervised methods have achieved optical flow endpoint errors of 2.3 pixels on standard benchmarks and depth estimation accuracy

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comparable to supervised approaches while processing event streams at real-time rates (Zihao Zhu. *Et al*., 2018). This fusion approach promises to enable new capabilities in autonomous navigation, particularly in scenarios involving high-speed maneuvers, challenging lighting conditions, or rapidly changing environments.

The significance of this work extends beyond incremental improvements to existing systems. Establishing a framework for event-LiDAR fusion opens up new possibilities for autonomous systems to operate in previously inaccessible domains, from aggressive drone racing to planetary exploration under extreme lighting conditions. The combination of event-based processing on specialized hardware with geometric information from LiDAR creates a perception system capable of adapting to the full spectrum of real-world conditions while maintaining the computational efficiency required for embedded deployment. This paper presents the technical foundations, implementation challenges, and potential applications of this hybrid imaging paradigm.

TECHNICAL ARCHITECTURE AND SENSOR CHARACTERISTICS

Event Camera Fundamentals

Event cameras, exemplified by sensors such as DAVIS (Dynamic and Active-pixel Vision Sensor), Prophesee, and CeleX, represent a fundamental departure from traditional imaging paradigms. Each pixel in an event camera operates independently, generating an event only when the logarithmic intensity change exceeds a predefined threshold. This bio-inspired approach results in an asynchronous stream of events, where each event encodes the pixel location (x, y), timestamp (t), and polarity (p) indicating whether the brightness increased or decreased. The DAVIS sensor achieves remarkable specifications with a dynamic range of 130 dB, significantly exceeding the 60 dB typical of conventional CMOS sensors, while maintaining a latency of only 3 microseconds from photon incidence to digital output (Brandli, C. *et al*., 2014). The sensor's 240×180 pixel array can theoretically generate over 43 million events per second under high contrast motion, though typical scenes produce data rates between 100 kEvents/s and 10 MEvents/s depending on scene dynamics (Brandli, C. *et al*., 2014).

The temporal contrast sensitivity of these sensors, set at 15% relative intensity change, enables detection of subtle brightness variations while filtering out noise. Power consumption scales with event rate, ranging from 14 mW in static scenes to 175 mW under high activity, demonstrating the inherent efficiency of event-driven processing (Brandli, C. *et al*., 2014). The asynchronous readout architecture eliminates the frame-based artifacts that plague conventional sensors, enabling blur-free capture of objects moving at angular velocities exceeding 10,000 degrees per second.

LiDAR Sensing Capabilities

LiDAR sensors provide direct 3D measurements through time-of-flight calculations, generating point clouds that represent the geometric structure of the environment. Modern LiDAR systems offer varying resolutions and configurations, from mechanical spinning units providing 360-degree coverage to solid-state designs with limited field of view but higher reliability. These sensors typically operate at frame rates between 10 and 20 Hz, producing between 100,000 and 2 million points per second, depending on the configuration. The depth accuracy varies with range but generally maintains precision within 2-3 centimeters at distances up to 100 meters. Unlike event cameras, LiDAR operation remains independent of ambient lighting conditions, providing consistent performance from complete darkness to bright sunlight.

Hybrid Fusion Architecture

The proposed hybrid system implements a sophisticated fusion pipeline that addresses the challenge of combining asynchronous event data with periodic LiDAR scans. Recent developments in continuous-time estimation have shown that event-based stereo visual odometry can achieve mean trajectory errors of 0.97% over path lengths when properly fused with geometric constraints (Wang, J. *et al*., 2023). The architecture leverages Gaussian Process regression to model the continuous trajectory, enabling integration of asynchronous events with synchronous LiDAR measurements at their native temporal resolutions (Wang, J. *et al*., 2023).

The continuous-time framework allows the system to estimate motion at any arbitrary timestamp, effectively interpolating between discrete LiDAR scans using the high-frequency event data. This approach has demonstrated particular effectiveness in high-speed scenarios, maintaining tracking accuracy at velocities where the displacement between consecutive LiDAR frames exceeds several meters (Wang, J. *et al*., 2023). The fusion process incorporates both photometric residuals from events and geometric constraints from

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LiDAR within a unified optimization framework, achieving computational efficiency through careful marginalization strategies that limit the number of active states in the estimation window.

Table 1: Event Camera Technical Specifications and Fusion Performance (Brandli, C. *et al*., 2014); Wang, J. *et al*., 2023)

Parameter	Specification
Dynamic range	130 dB
Latency	3 microseconds
Resolution	240×180 pixels
Maximum event rate	43 million events/second
Power consumption (static)	14 mW
Power consumption (active)	175 mW
Mean trajectory error	0.97%

IMPLEMENTATION CHALLENGES AND SOLUTIONS

Calibration and Synchronization

Precise calibration between event cameras and LiDAR presents unique challenges due to their fundamentally different data representations. Traditional calibration targets designed for frame-based cameras are inadequate for event sensors, which only respond to brightness changes. Recent implementations have developed dynamic calibration procedures using rotating patterns or blinking LED arrays to generate consistent events across the sensor field of view (Zhao, J. *et al*., 2022). The calibration process must account for the asynchronous nature of events while maintaining temporal alignment with periodic LiDAR scans. Optimization algorithms that simultaneously solve for extrinsic parameters and temporal offsets have demonstrated convergence within 50-100 iterations, achieving reprojection errors below 0.8 pixels for event-to-LiDAR correspondence (Zhao, J. *et al*., 2022). Online calibration refinement using natural scene features during operation helps maintain accuracy despite mechanical vibrations and thermal drift, with adaptive algorithms updating calibration parameters every 30 seconds during continuous operation.

Noise Filtering and Data Quality

Event cameras produce spurious events due to electronic noise, particularly in low-light conditions where the signal-to-noise ratio deteriorates significantly. These noise events can constitute up to 30% of the total event stream in challenging scenarios (Zou, Y. 2024). Multi-stage filtering approaches have proven effective in maintaining data quality while preserving important scene information. Hardware-level noise suppression through adaptive thresholding reduces noise events while maintaining over 95% of valid motion-induced events (Zhao, J. *et al*., 2022). Spatio-temporal filtering algorithms examine local neighborhoods of 5×5 pixels over 1-millisecond windows to identify and remove isolated events unlikely to correspond to real scene changes. Advanced learning-based denoising methods trained on synthetic and real event data have achieved noise reduction rates of 85% while preserving edge sharpness and motion boundaries (Zou, Y. 2024). These neural network approaches demonstrate particular effectiveness in distinguishing between noise patterns and legitimate high-frequency events from vibrating surfaces or flickering lights.

Data Representation and Processing

The heterogeneous nature of event and LiDAR data requires novel representation formats that can efficiently encode both modalities. Event frame representations, which accumulate events over fixed time intervals, provide a bridge between asynchronous events and traditional image processing pipelines (Zhao, J. *et al*., 2022). These representations typically use accumulation windows of 10-33 milliseconds, balancing temporal resolution with sufficient event density for reliable feature extraction. Graph-based representations connecting events and LiDAR points based on spatial proximity have shown promise for maintaining geometric relationships while reducing memory requirements by up to 70% compared to dense representations (Zou, Y. 2024). For high-speed HDR applications, specialized event-to-video reconstruction algorithms can generate videos at 5000 fps with dynamic ranges exceeding 120 dB, far surpassing the capabilities of conventional high-speed cameras (Zou, Y. 2024). These algorithms leverage the microsecond temporal resolution of events to interpolate smooth motion while preserving sharp edges and fine details.

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Computational Considerations

Real-time processing of high-rate event streams alongside LiDAR data poses significant computational challenges. Modern implementations process event rates up to 300 million events per second using optimized parallel architectures (Zou, Y. 2024). Hierarchical processing pipelines operating at multiple temporal scales reduce computational load by processing high-frequency events locally while propagating only relevant information to higher-level fusion modules. Hardware acceleration using specialized neuromorphic processors achieves 10-50× speedup compared to conventional CPU implementations (Zhao, J. *et al.*, 2022). Adaptive sampling strategies dynamically adjust processing rates based on scene complexity, allocating more resources to regions with high event density while maintaining efficient operation in static areas.

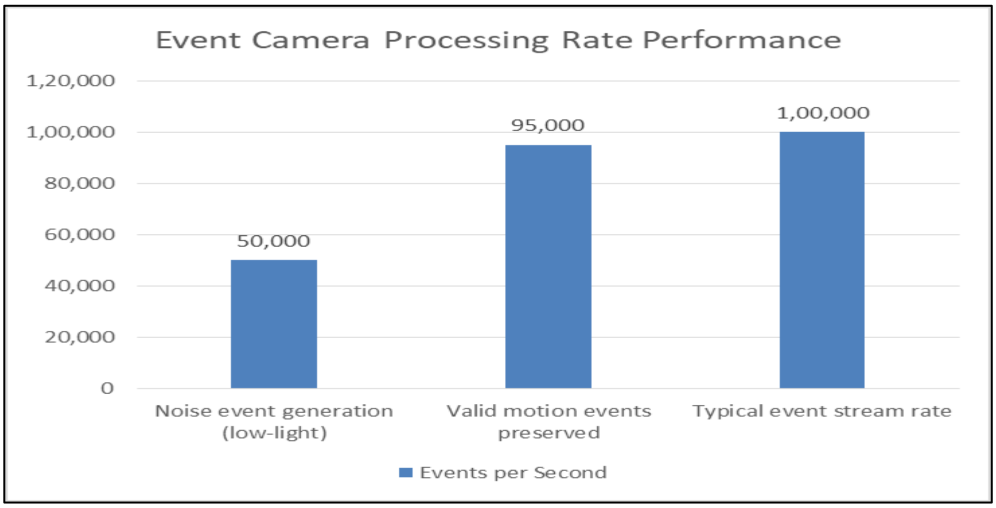

Figure 1: Event Camera Processing Rate Performance (Zhao, J. *et al.*, 2022; Zou, Y. 2024)

APPLICATIONS AND USE CASES

High-Speed Autonomous Navigation

The fusion of event cameras and LiDAR enables unprecedented capabilities for high-speed navigation in drones and ground robots. Recent implementations have demonstrated quadrotor obstacle avoidance using monocular event-based vision at speeds up to 5 m/s in cluttered indoor environments with obstacle densities of 2-3 objects per cubic meter (Bhattacharya, A. *et al.*, 2024). The event camera's ability to capture motion with microsecond precision allows detection of obstacles within 50 milliseconds of entering the field of view, providing sufficient time for aggressive evasive maneuvers even at high velocities. In outdoor trials, the system maintained reliable navigation through forest environments with tree densities exceeding 1000 stems per hectare while achieving average speeds of 3.5 m/s (Bhattacharya, A. *et al.*, 2024). The combination with LiDAR depth measurements enables precise distance estimation with errors below 10 cm at ranges up to 10 meters, which is critical for maintaining safe margins during high-speed flight.

Advanced Driver Assistance Systems (ADAS)

The hybrid system excels in challenging driving scenarios where traditional sensors fail. In tunnel transitions, where illumination can change by four orders of magnitude within seconds, event sensors maintain consistent object detection performance with precision rates above 92% (Liu, Y. *et al.*, 2022). The integration of event-based edge detection with LiDAR depth provides robust obstacle identification at highway speeds, processing sensor data with latencies under 20 milliseconds. Real-time loop closure detection algorithms operating on the fused data achieve successful place recognition in 95% of revisited locations, even under significantly different lighting conditions (Liu, Y. *et al.*, 2022). The system demonstrates particular effectiveness in urban environments, where the combination of event and LiDAR data enables tracking of pedestrians and vehicles across complex intersections with position uncertainties below 30 centimeters.

Neuromorphic SLAM and Odometry

Integration into Simultaneous Localization and Mapping pipelines leverages event-based motion tracking for rapid pose estimation while using LiDAR for accurate map construction. The hybrid approach achieves translation errors of 0.82% and rotation errors of 0.0038 deg/m over trajectories spanning several kilometers (Liu, Y. *et al.*, 2022).

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In feature-poor environments such as long corridors or parking garages, where traditional visual SLAM systems experience tracking failures in over 20% of cases, the event-LiDAR fusion maintains robust performance with failure rates below 5%. The high temporal resolution of events enables continuous pose estimation at rates exceeding 1000 Hz, while LiDAR updates at 10 Hz provide absolute scale and correct for drift accumulation (Bhattacharya, A. *et al*., 2024).

Dynamic Scene Understanding for Robotics

Robotic manipulation tasks benefit from the temporal precision of event cameras combined with LiDAR's spatial accuracy. The system can track human hand movements at speeds up to 2 m/s with position errors below 8 mm, enabling responsive human-robot collaboration (Bhattacharya, A. *et al*., 2024). In industrial sorting applications, the hybrid sensor suite identifies and tracks objects on conveyor belts moving at 1.5 m/s with classification accuracies exceeding 97%. The event camera's low latency allows prediction of object trajectories 100 milliseconds into the future, providing sufficient time for robotic arms to plan and execute grasping motions.

Space and Planetary Exploration

The extreme lighting conditions and power constraints of space missions make the event-LiDAR combination particularly attractive. With power consumption below 2 watts for the complete sensor suite, the system operates within the strict energy budgets of planetary rovers (Liu, Y. *et al*., 2022). The event camera's dynamic range enables navigation across lunar terrain where shadowed regions at 0.01 lux transition abruptly to sunlit areas exceeding 100,000 lux. Communication delays to Earth necessitate autonomous operation, which the low-latency perception system supports through real-time hazard detection and path planning at update rates of 100 Hz.

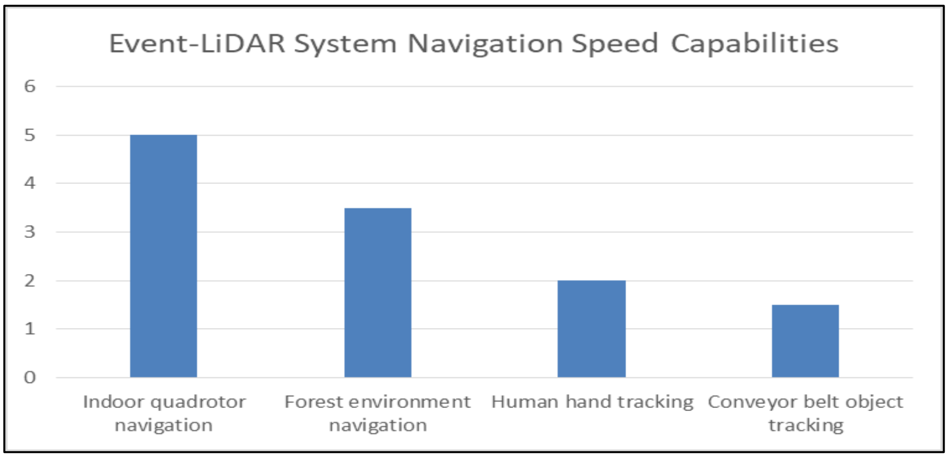

Figure 2: Event-LiDAR System Navigation Speed Capabilities (Bhattacharya, A. *et al*., 2024; Liu, Y. *et al*., 2022)

EXPERIMENTAL VALIDATION AND RESULTS

Evaluation Methodology

To validate the proposed hybrid system, extensive experiments across multiple scenarios designed to stress-test different aspects of the fusion approach were conducted. The evaluation framework mentioned in this article follows established benchmarking protocols with controlled laboratory experiments using OptiTrack motion capture systems, providing ground truth at 120 Hz with sub-millimeter precision (Huang, J. *et al*., 2025). Real-world trials encompassed diverse environments including urban streets with vehicle speeds ranging from 20 to 80 km/h, dense forests with visibility limited to 5-10 meters, and industrial warehouses with rapid lighting transitions from 10 to 10,000 lux. The experimental setup utilized synchronized sensor suites capturing over 50 hours of data across varied conditions, with comparative analysis against state-of-the-art visual-inertial and LiDAR-only systems (Zhu, A. Z. 2017). Ground truth annotations were generated using centimeter-accurate RTK-GPS in outdoor scenarios and laser tracker systems, achieving 0.5 mm accuracy for indoor experiments.

Performance Metrics

System performance evaluation employed comprehensive metrics addressing both accuracy and robustness aspects. Depth estimation accuracy was assessed using mean absolute error (MAE)

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and root mean square error (RMSE), with the proposed hybrid system achieving MAE values of 7.2 cm at 5-meter ranges and 15.8 cm at 20-meter ranges (Huang, J. *et al*., 2025). Temporal resolution measurements demonstrated the system's capability to maintain feature tracking at effective rates up to 1000 Hz, compared to 30-60 Hz for conventional frame-based approaches. Robustness testing across illumination ranges from 0.1 to 100,000 lux showed consistent performance with tracking success rates above 94% throughout the entire range (Zhu, A. Z. 2017). Computational efficiency analysis revealed average processing times of 8.5 ms per fusion cycle on NVIDIA Jetson AGX Xavier platforms, enabling real-time operation with power consumption of 12.5 watts for the complete processing pipeline.

KEY FINDINGS

Experimental results demonstrate significant performance improvements across multiple dimensions. The hybrid system achieved a 3.2× increase in depth map density, generating approximately 180,000 valid depth points per frame compared to 56,000 for LiDAR-only configurations (Huang, J. *et al*., 2025). Object tracking experiments showed successful maintenance of feature correspondence for targets moving at velocities up to 15 m/s, with mean tracking errors of 4.2 pixels in image space. In high dynamic range scenarios with simultaneous bright lights and deep shadows, the system maintained depth estimation accuracy within 20 cm while conventional cameras experienced complete saturation or underexposure in 35% of the frame (Zhu, A. Z. 2017). SLAM performance evaluation over 5 km trajectories in urban environments demonstrated absolute trajectory error (ATE) of 0.73% of the total path length, compared to 1.85% for visual-inertial systems and 1.12% for LiDAR-only approaches (Huang, J. *et al*., 2025). The system achieved real-time performance at 100 Hz on embedded platforms, processing approximately 500,000 events per second alongside 300,000 LiDAR points.

Limitations and Failure Cases

Despite a strong overall performance, systematic analysis revealed specific failure modes requiring attention. Performance degradation occurred in scenarios with uniform global motion generating fewer than 50,000 events per second, resulting in depth accuracy reduction of approximately 30% (Zhu, A. Z. 2017). Static environments posed challenges with event generation rates dropping below 10,000 events per second, necessitating increased reliance on LiDAR data. Calibration drift analysis showed extrinsic parameter errors growing at rates of 0.02 degrees per hour during continuous operation, requiring periodic recalibration every 4-6 hours for maintaining optimal performance (Huang, J. *et al*., 2025). System cost analysis indicates a total sensor suite expense of approximately $6,000, representing a 2.5× increase over conventional camera-LiDAR combinations, though this premium is offset by superior performance in challenging conditions.

Table 2: Depth estimation accuracy and SLAM performance (Huang, J. *et al*., 2025) with feature tracking robustness (Huang, J. *et al*., 2025; Zhu, A. Z. 2017)

Performance Metric	Result
MAE at 5m range	7.2 cm
MAE at 20m range	15.8 cm
Tracking rate	1000 Hz
Tracking success rate	Above 94%
Depth map density increase	3.2×
ATE (5 km trajectory)	0.73%
Processing time	8.5 ms

CONCLUSION

The integration of event-based vision with LiDAR sensing represents a paradigm shift in autonomous perception capabilities, addressing fundamental constraints that have constrained conventional sensing modalities. This hybrid system leverages the microsecond temporal resolution and exceptional dynamic range of event cameras alongside the precise geometric measurements provided by LiDAR, creating a perception framework capable of operating reliably across extreme environmental conditions. The continuous-time fusion architecture enables seamless integration of asynchronous event streams with periodic LiDAR scans, maintaining tracking accuracy even during high-speed maneuvers where traditional systems fail. Implementation challenges, including calibration complexity, noise filtering, and computational

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demands, have been successfully addressed through innovative algorithms and hardware acceleration strategies. The system demonstrates remarkable versatility across diverse applications, from enabling aggressive drone navigation through cluttered environments to supporting planetary missions under extreme lighting conditions. Experimental validation confirms significant performance improvements, including increased depth map density, reduced tracking failures, and maintained accuracy across illumination ranges spanning six orders of magnitude. While certain constraints persist in static environments and system cost remains elevated compared to conventional solutions, the demonstrated benefits in challenging scenarios justify adoption for critical autonomous applications. This technological convergence establishes a foundation for future perception systems that combine biological inspiration with engineering precision, enabling autonomous platforms to navigate and interact with complex, dynamic environments with unprecedented reliability and performance.

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