Event-Based Intensity Reconstruction: A Comparative Study of Filtering Techniques in High-Speed Dynamic Environments

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Abstract—Event-based vision sensors (EVS) offer high-speed, low-latency imaging, making them ideal for dynamic environments such as autonomous vehicles, robotics, and surveillance. However, their inherent susceptibility to noise and artifacts presents challenges in reconstructing high-quality intensity images. This paper evaluates the effectiveness of three noise filtering techniques - Median Filtering, Wiener Filtering, and Anisotropic Diffusion - for event-based intensity reconstruction. By leveraging event frame accumulation and systemic noise reduction strategies, we analyze their impact on visual clarity and Peak Signal to Noise Ratio (PSNR) across high-speed scenes. Our experimental results indicate that while each technique offers unique benefits, Anisotropic Diffusion achieves the best balance between noise suppression and edge preservation. This study provides practical insights into optimizing event-based imaging systems, highlighting the trade-offs between real-time performance and image quality.

Index Terms—Computational Photography

1 Introduction

Event-based sensors (EVS) are rapidly gaining traction in applications requiring high-speed, low-latency imaging, such as autonomous vehicles, robotics, and surveillance. Unlike traditional cameras, EVS capture changes in intensity asynchronously at the pixel level, providing a data-efficient representation of dynamic scenes. This capability enables continuous updates, offering significant advantages in real-time applications, particularly for tracking rapid changes in the environment. Event-based data contributes significantly to real-time intensity reconstruction by providing high temporal resolution, reduced motion blur, and efficient data processing.

One of the primary benefits of event data is its high temporal resolution, allowing for continuous updates rather than being constrained by fixed intervals, as is the case with frame-based imaging. This continuous updating provides a significant advantage in tracking rapid scene changes, ensuring that even the most dynamic elements of the scene are captured with high accuracy.

Moreover, event data helps reduce motion blur, a common issue with traditional frame-based methods that often struggle to capture fast movements without distorting the image. Since event data is not constrained by frame rates, it minimizes motion blur, resulting in sharper intensity reconstructions, particularly for fast-moving objects in dynamic scenes.

Event-based data also benefits from efficient data processing. Unlike traditional frame-based methods, event data only encodes changes in brightness, significantly reducing data bandwidth and computational overhead. This leads to faster processing and allows for real-time performance, which is crucial in applications requiring timely decision-making.

Despite its advantages, event-based data often suffers from noise and artifacts due to sensor limitations, complicating the reconstruction of clear intensity images. Traditional filtering methods often face a trade-off between noise suppression and detail preservation. This paper investigates the performance of three distinct noise filtering techniques—Median Filtering, Wiener Filtering, and Anisotropic Diffusion—to enhance the quality of event-based intensity images. By using event frame accumulation and systematic noise reduction strategies, the objective is to address the challenges of artifact suppression while maintaining edge details. Through experimental evaluation using high-speed dynamic scenes, this project provides a comparative analysis of the methods, offering practical guidance for optimizing event-based imaging in real-world scenarios.

2 Related Work

2.1 Frame-Assisted Interpolation

Frame-assisted interpolation is a widely explored approach for event-based intensity reconstruction, leveraging both sparse intensity frames and event data to generate a continuous-time representation of a scene. Unlike purely event-driven methods, this technique integrates conventional frame-based information to improve reconstruction accuracy and reduce ambiguity in intensity estimation.

Scheerlinck et al. [1] introduced a continuous-time intensity estimation framework that fuses event streams with periodic intensity frames. Their approach employs adaptive interpolation to estimate pixel intensities at arbitrary time points, effectively bridging the gaps between sparse frames. This method enhances reconstruction quality by leveraging the complementary strengths of frame-based imaging, which provides an absolute intensity reference, and event-based vision, which enables high-speed temporal updates.

However, frame-assisted interpolation faces notable limitations. One major issue is high-speed motion artifacts. When dealing with rapidly moving objects, the reliance on sparse frames can introduce motion blur and misalignment between event-based and frame-based data. Additionally, low-light sensitivity poses a challenge, as intensity frames captured under poor lighting conditions may suffer from reduced contrast and noise, thereby diminishing the accuracy of interpolated reconstructions. Another key limitation is latency constraints. Since this method depends on frame acquisition, it does not fully exploit the ultra-low-latency capabilities of event cameras, making it less suitable for real-time applications requiring instantaneous updates.

Despite these challenges, frame-assisted interpolation remains a valuable technique for improving event-based intensity reconstruction, particularly in scenarios where frame data is available and conditions permit stable interpolation. Future research aims to address its shortcomings by enhancing alignment techniques, improving low-light robustness, and optimizing real-time performance.

2.2 Variational Optimization

Variational optimization is a powerful technique for event-based intensity reconstruction, as it simultaneously estimates optical flow and intensity information, thereby improving the accuracy of the reconstruction. Unlike frame-assisted interpolation, which relies on sparse intensity frames, variational approaches solve an optimization problem that models both scene dynamics and event-based changes. Bardow et al. [2] introduced a simultaneous optical flow and intensity estimation framework, formulating intensity reconstruction as a variational optimization problem. This approach jointly recovers intensity values and motion information by minimizing an energy function that incorporates event consistency, spatial regularization, and optical flow constraints. Event consistency ensures that the reconstructed intensity changes align with the observed event data, spatial regularization enforces smoothness in intensity estimates to reduce artifacts, and optical flow constraints refine intensity reconstruction over time by estimating motion.

By leveraging optical flow estimation, this method enhances intensity reconstruction in dynamic scenes where motion plays a significant role. However, variational optimization has notable limitations. One of the key drawbacks is its high computational cost, as solving the optimization problem is computationally expensive and requires iterative solvers, which may be impractical for real-time applications. Additionally, the method is sensitive to noise, assuming well-structured motion, and can struggle with noisy or ambiguous event data, leading to instability in the reconstructed intensity map. Another challenge is parameter tuning, as the effectiveness of variational methods depends on the careful selection of regularization parameters, making it difficult to generalize across different scenes. Despite these challenges, variational optimization remains a promising approach for high-accuracy intensity reconstruction, particularly in applications where motion estimation is crucial. Future research aims to reduce computational complexity, improve robustness to noise, and integrate deep learning techniques to enhance real-time performance.

2.3 Contrast-Based Methods

Contrast-based methods provide an effective approach to event-based intensity reconstruction by leveraging the principle of contrast maximization. Unlike interpolation or variational techniques, these methods focus on optimizing the reconstructed image to maximize the alignment of event data with high-contrast edges, which enhances sharpness and scene details. Stoffregen et al. [3] proposed an event-based contrast maximization framework that refines intensity reconstruction by formulating it as an optimization problem. Their approach aims to reconstruct images that best align with the observed event stream by maximizing image contrast, ensuring that the reconstructed intensity map emphasizes the most event-dense regions, thereby improving edge clarity. It also incorporates temporal consistency, using event timestamps to guide intensity updates over time, and adaptive refinement, which iteratively adjusts the reconstruction to reduce inconsistencies.

This approach offers advantages in preserving fine details and achieving high temporal resolution. However, contrast-based methods come with inherent trade-offs. One key challenge is the balance between noise and detail preservation—while contrast maximization sharpens details, it can also amplify sensor noise, making intensity estimates less stable in low-quality event data. Additionally, the method's effectiveness heavily relies on tuning contrast thresholds and regularization parameters, which may need to be adjusted for different scenes. Another challenge is the computational overhead, as iterative optimization increases processing time, making real-time deployment challenging without hardware acceleration. Despite these limitations, contrast-based methods remain a promising approach for enhancing edge definition in event-based reconstruction. Future research is focused on improving noise suppression techniques, adaptive contrast weighting, and achieving real-time implementation for high-speed applications.

3 Methodology

3.1 Dynamic Active-Pixel Vision Sensor (DAVIS)

The Dynamic Active-Pixel Vision Sensor (DAVIS) is a hybrid imaging device that integrates both frame-based and event-based sensing, making it an effective solution for intensity reconstruction in high-speed and high-dynamic-range scenarios. Unlike conventional cameras, which capture images at fixed frame rates, DAVIS sensors asynchronously detect changes in brightness at the pixel level. This event-driven approach significantly reduces motion blur, lowers latency, and ensures more efficient data processing, especially in environments with rapid scene variations.

In the context of intensity reconstruction, the DAVIS sensor provides a continuous stream of both grayscale intensity frames and event-based data. The grayscale frames serve as absolute reference images, while the event data encodes fine-grained temporal information about brightness changes. By combining these two sources, intensity reconstruction algorithms can recover high-fidelity images even under challenging lighting conditions and rapid motion scenarios. The key advantage of this approach is that it allows the system to track and reconstruct pixel intensities in near real-time, offering a more responsive and efficient alternative to traditional frame-based imaging.

To validate this concept, a computational model of the DAVIS sensor was implemented in code. This model ex-

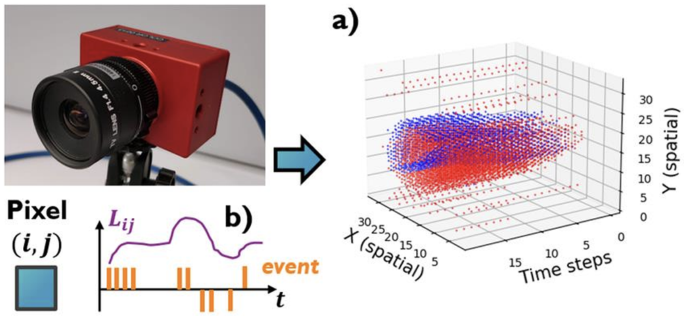

Fig. 1. DAVIS Camera

tracts event-based data by computing the absolute difference between consecutive grayscale frames and applying a dynamic threshold to filter out insignificant changes. The event data is then used to simulate the asynchronous behavior of the sensor, ensuring that intensity updates occur in response to detected brightness variations. This implementation enables a realistic simulation of DAVIS functionality, allowing for detailed analysis and evaluation of intensity reconstruction methods in a controlled environment.

3.2 Intensity Reconstruction Process

3.2.1 Data Acquisition

The intensity reconstruction process begins with data acquisition from video frames, which serve as an approximation of DAVIS sensor data. The input video provides two key sources of information: frame-based intensity images and event-based data extracted from frame differences. The frame-based images offer absolute grayscale values but suffer from motion blur and limited temporal resolution. In contrast, event-based data is derived from the absolute difference between consecutive frames, simulating the event-driven nature of real DAVIS sensors. This event data captures fine-grained temporal variations in intensity, enabling a more dynamic reconstruction process. To enhance intensity reconstruction, both sources are integrated: frame-based images provide a reference intensity structure, while event-based information refines temporal variations. This combination ensures a more accurate reconstruction by compensating for the limitations of frame-only data.

3.2.2 Preprocessing and Noise Reduction

Once data is acquired, preprocessing is performed to enhance the quality of the intensity reconstruction. The primary goal is to mitigate noise while preserving critical scene details. The first step is the generation of an event image, computed as the absolute difference between consecutive grayscale frames. A dynamic thresholding operation is applied to filter out insignificant intensity changes, ensuring that only meaningful variations contribute to reconstruction. To refine event data, multiple noise filtering techniques are applied. Median filtering is used to remove impulse noise, particularly salt-and-pepper noise, which can distort intensity reconstruction. Wiener filtering enhances the signal-to-noise ratio (SNR) by reducing random fluctuations in intensity values, thereby smoothing noise while preserving key scene structures. Anisotropic diffusion further reduces noise while maintaining edge integrity, ensuring sharp features remain visible in the final reconstruction. Each of these filters is applied separately to evaluate their effectiveness, and the best-performing technique is chosen based on the noise characteristics and reconstruction fidelity.

3.2.3 Event-Based Intensity Update Mechanism

The intensity reconstruction follows an iterative update model that continuously refines pixel intensities using both frame-based and event-based data. The process begins with the decay of previous intensities to maintain temporal consistency. Prior intensity estimates gradually decay over time, simulating the natural fading of intensity values and making room for new updates based on incoming event data. Next, the model accumulates event-based adjustments, where event data modifies pixel intensities by adding or subtracting brightness increments. Since event-based data captures rapid intensity changes, this step enhances the reconstruction's temporal accuracy. Finally, the updated intensity values are normalized and clipped to a valid grayscale range (0–255) to prevent visual artifacts and ensure a realistic reconstruction output. By iteratively applying this update mechanism, the system achieves high temporal precision, effectively capturing fast-changing brightness variations.

3.2.4 Quality Evaluation and Output Generation

To assess reconstruction quality, two primary evaluation techniques are employed. The first is Peak Signal-to-Noise Ratio (PSNR) calculation, which quantifies reconstruction accuracy by comparing the reconstructed intensity map with ground-truth grayscale frames. Higher PSNR values indicate better reconstruction fidelity. The second method involves snapshot-based visualization, where periodic snapshots of the reconstructed intensity maps are saved and compared against original frames. Additionally, a PSNR-over-time plot is generated to visualize reconstruction performance throughout the video. By incorporating both quantitative (PSNR) and qualitative (snapshot visualization) evaluation methods, the reconstruction approach is systematically validated, ensuring both numerical accuracy and visual coherence.

4 Experimental Results

4.1 Median Filtering

Median Filtering demonstrated moderate noise suppression, achieving a PSNR of 27.85 dB for Frame 150. This technique effectively reduced impulse noise and preserved edges to a certain degree. However, its visual evaluation revealed minor artifacts, especially in regions with intricate details, indicating a slight compromise in maintaining fine textures. The PSNR-over-time analysis showed fluctuations, suggesting that the filter's performance varied depending on the scene dynamics. Despite its simplicity and computational efficiency, Median Filtering's effectiveness was limited in highly complex or noisy environments.

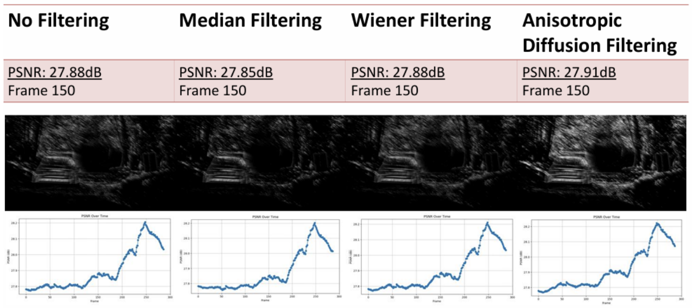

Fig. 2. Intensity Reconstruction Comparison

4.2 Wiener Filtering

The Wiener Filtering approach produced a PSNR of 27.88 dB for Frame 150, comparable to the unfiltered frame. Its strength lay in smoothing random noise while maintaining the general structure of the scene. The visual representation of the filtered frames displayed minimal perceptible differences when compared to the unfiltered data. Moreover, the PSNR-over-time graph highlighted consistent performance across the test frames, indicating stability and reliability in diverse conditions. Nevertheless, this technique's performance was less pronounced in noise-intensive scenarios, where it struggled to preserve finer image details.

4.3 Anisotropic Diffusion

Among the evaluated methods, Anisotropic Diffusion Filtering achieved the highest PSNR of 27.91 dB for Frame 150. This approach effectively reduced noise while preserving edge details, as evident in the qualitative and quantitative assessments. The reconstructed frames exhibited sharpness and clarity, highlighting its ability to maintain fine textures. The PSNR-over-time graph demonstrated an overall improvement in reconstruction quality, reflecting its adaptability and robustness across dynamic scenes. Anisotropic Diffusion emerged as the most effective technique for balancing noise suppression and detail preservation, outperforming the other methods in challenging environments.

5 Conclusion

This study evaluated the effectiveness of three noise filtering techniques—Median Filtering, Wiener Filtering, and Anisotropic Diffusion—for event-based intensity reconstruction. By leveraging event frame accumulation and systematic noise reduction strategies, we analyzed their impact on visual clarity and Peak Signal-to-Noise Ratio (PSNR) across high-speed dynamic scenes. Our findings indicate that while all three methods contribute to noise suppression, Anisotropic Diffusion achieves the best balance between noise reduction and edge preservation, making it the most suitable choice for enhancing event-based intensity reconstruction.

Additionally, this research demonstrated the feasibility of modeling a Dynamic Active-Pixel Vision Sensor (DAVIS) in software, enabling controlled evaluation of event-based sensing algorithms. The computational model effectively simulated the asynchronous nature of event-driven vision, providing a framework for testing and optimizing intensity reconstruction techniques.

Future work will focus on enhancing real-time performance through hardware acceleration and adaptive filtering techniques that dynamically adjust to scene conditions. Integrating deep learning-based denoising models and exploring hybrid approaches that combine multiple filtering methods may further improve reconstruction quality. Ultimately, this study provides valuable insights for optimizing event-based imaging systems, particularly in applications requiring high-speed, low-latency vision processing.

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