Distill Drops into Data: Event-based Rain-Background Decomposition Network

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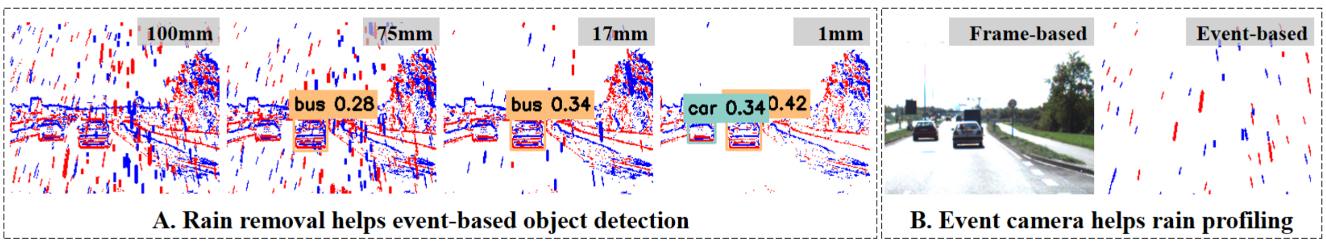

Figure 1. (A) YOLOv10[1] detections on event sequence with various rainfall rates (mm/hr). We render physically-based, realistic rain sequences on images from the KITTI[2] dataset with simulator[3, 4]. Separating rain streaks contamination from event data is beneficial for downstream tasks like object detection. (B) Event cameras, with their high temporal resolution and dynamic range, excel in capturing rain's complex spatio-temporal properties compared to frame-based cameras.

ABSTRACT

Event cameras excel in high-speed and high-dynamic-range scenarios but are highly sensitive to rain, which introduces significant noise while also revealing detailed rain features. This paper introduces a novel Event-based Rain-Background Decomposition Network that integrates Spiking Neural Networks (SNNs) and Convolutional Neural Networks (CNNs). By "Distilling Rain," we reconstruct a rain-free background for downstream tasks, and by "Collecting Rain," we extract the physical characteristics of rain. Experimental evaluations demonstrate the network's effectiveness in both background reconstruction and rain modeling. This work extends the capabilities of event cameras by mitigating the adverse effects of rain while also leveraging rain-induced noise to extract valuable environmental data, enhancing their utility in both challenging weather conditions and detailed environmental analysis.

CCS Concepts: • **Computing methodologies** → *Machine learning*; • **Hardware** → *Sensors and actuators*; • **Applied computing** → *Physical sciences and engineering*.

Keywords: Event Camera, Rain Modeling, Background Reconstruction

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1 INTRODUCTION

Event cameras, inspired by biological vision, are advanced sensors that asynchronously report intensity changes at the pixel level. Unlike traditional frame-based cameras that capture images at fixed intervals, event cameras excel in dynamic scenes with microsecond-level resolution, effectively capturing high-speed motion without blurring[5, 6].

The potential applications of event cameras are vast and varied, showing promise in drones[7], robotics[8], surveillance[9], and virtual reality[10]. For instance, although robots have proven crucial in applications such as urban sensing[11] and emergency response[12], they often encounter challenges in obstacle avoidance[13] and localization[14], especially in high dynamic range and rapid motion scenarios due to the limitations of traditional visual sensors. Introducing event cameras presents a fresh opportunity for real-time perception in such challenging environments[15].

The main challenge of deploying event cameras in outdoor environments, particularly under adverse weather conditions such as rain, lies in their high sensitivity to motion[16]. Event cameras can detect minute changes in illumination. While this characteristic is beneficial in capturing fast-moving objects and handling sudden lighting variations, **it becomes problematic in rainy conditions where raindrops generate rapid dynamic streaks in the event camera's output.** These streaks can interfere with tasks such as object detection and crowd sensing[17–19], leading to erroneous detection and degraded performance (Figure 1(A)).

On the one hand, though **rain streak removal** is crucial for the outdoor applications of event cameras, research on event-based derain models remains relatively limited. Existing rain removal techniques predominantly focus on **frame-based cameras** or utilize event cameras to assist frame cameras in mitigating rain effects[20, 21]. Apart from these, methods with direct use of **event cameras** generally convert event data into images with frame-based algorithms[22] or use predefined rules[23] based on raindrop characteristics like direction and correlation. However, rainy conditions are highly variable, these methods often lack adaptability to varying rainy intensities and weather conditions.

On the other hand, **understanding raindrop characteristics**—like size, shape, velocity, kinetic energy, and distribution—is crucial for various applications such as remote sensing, meteorology (weather prediction), telecommunications (signal distortion), agriculture, and horticulture (crop yield)[24]. The moving rain streaks generate noticeable intensity changes that match the dynamic perception of event cameras (Figure1(B)), making them well-suited for modeling the complex spatio-temporal properties of rain. Existing studies primarily use visible light video for daytime rainfall estimation[25]. To address the need for rainfall estimation in low visibility scenarios[26] (e.g., at night), some research has proposed using near-infrared (NIR) cameras [27]. In this study, event cameras' high dynamic range and detailed edge detection[28] are crucial for accurate rain profiling, especially in low-light conditions. Additionally, by deploying event cameras on platforms such as unmanned aerial vehicles[29, 30] and unmanned ground vehicles[31–33], this technology can serve as a mobile rain gauge or weather station. Thus, exploring the application of event cameras in rainy weather is a promising new direction that deserves more attention from researchers.

The problem this paper tries to address is: how to effectively decompose the rain and background events from a rainy event sequence, thereby leveraging both components to enhance event camera performance and broaden their applications. Three technical challenges have to be solved:
C1: Noise in Event Data. Noise from the physical properties of event cameras and brightness variations during movement significantly impact data reconstruction quality.
C2: Variations in Rain Intensity. Different rain intensities complicate the separation of rain from the background, requiring model to generalize well across varying conditions.
C3: Reconstruction of Overlapping Rain and Background Events. Overlapping rain streaks at various positions makes high-fidelity restoration challenging.

In this paper, we propose an Event-based Rain-Background Decomposition Network using a hybrid neural network of SNNs and CNNs. SNNs model spatio-temporal information by updating neuron membrane potentials and encoding data through spike position and timing, effectively mitigating noise and capturing event dynamics[34]. To avoid the vanishing spike phenomenon in deep spiking layers[35], we instead implement the rain attention block and decoders with deep CNNs, ensuring accurate decomposition across varying rain intensities. For reconstructing overlapping rain and background, we incorporate GAN-based learning mechanisms and contrastive loss functions. This hybrid approach ensures robust performance across complex scenarios.

We created an event-based rainy synthetic dataset to validate our approach and assessed the model's performance in two areas: background reconstruction and rain modeling. The main contributions are summarized as follows:

- We leverage the unique properties of event cameras to separate rain from the background, and to the best of our knowledge, this work is the first to extend their capabilities by mitigating rain effects while also extracting valuable data from rain-induced noise.
- We propose an Event-based Rain Decomposition Hybrid Network that integrates SNNs and CNNs to enhance rain separation and background recovery efficiency and accuracy in diverse rainy conditions.
- We created an event-based rainy synthetic dataset and conducted systematic experiments to validate our approach, demonstrating its effectiveness and reliability in rain modeling and background reconstruction.

2 PROBLEM DEFINITION

The purpose of this paper is twofold: first, to **distill** rain from rainy events, and second, to **collect** and analyze the separated rain data. By separating rain from the background, our approach enhances the capabilities of event cameras in outdoor rainy conditions. Furthermore, the extracted rain data contributes to a more precise understanding and modeling of raindrop characteristics.

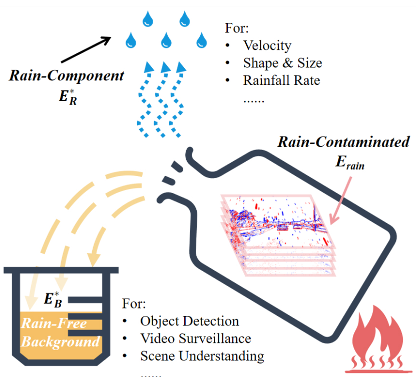

Figure 2. Rain distillation and collection for downstream visual processing and rain analysis.

Given an observed rainy event sequence E_{Rain}, it can be mathematically expressed as the superposition of a rain component E_R and the clean background event E_B:

$$E_{\text{Rain}} = E_R + E_B. \tag{1}$$

Thus, the objective of "Distill Rain" is to generate a rain-free output E_B^* from the rain-contaminated event E_{Rain}, approaching the clean background event E_B. Simultaneously, our research indicates that event cameras are well-suited for modeling the complex spatio-temporal properties of rain. Collecting these "distilled" rain events can obtain certain physical characteristics of the rain. Therefore, the objective of the event-based "Collect Rain" process is to extract features from the separated rain component E_R^*, thereby obtaining information such as the velocity, size, and rainfall rate.

3 METHODOLOGY

The key to the rain-background decomposition network is to project the rain layer and background layer into distinguishable subspaces[21]. Figure 3 illustrates the pipeline of the decomposition network, which aims at reconstructing the high-quality event sequence of the rain-free background and learning rain physical properties from rain features.

3.1 Event Representation

Compared with conventional frame data, event data is essentially a sparse spatio-temporal stream. Previous methods sum events per pixel in event images[36], sacrificing temporal detail and prone to motion blur. Our method converts it into a fixed-size representation by discretizing the time domain into B bins, sharing a similar idea with[15]. Events $\{(x_i, y_i, t_i, p_i)\}_{i=1}^N$ are discretized across B bins to scale their timestamps into the range $[0, B-1]$:

$$\begin{aligned} t_i^* &= (B-1)\frac{t_i - t_1}{t_N - t_1}, \\ V(x,y,t) &= \sum_i p_i k_b(x-x_i) k_b(y-y_i) k_b(t-t_i^*), \end{aligned} \tag{2}$$

where $k_b(a) = \max(0, 1-|a|)$, which is equivalent to the bilinear sampling kernel defined in [37]. Through this method, we convert an event sequence into a fixed-size representation $E \in \mathbb{R}^{B\times H\times W}$. In this paper, we consider two consecutive event volumes E as the input.

3.2 Hybrid Network with SNNs and CNNs

We illustrate the hybrid network in Figure 3. Initially, event voxel grids are processed by an SNN encoder[34] that extracts spatio-temporal features using three layers of Leaky Integrate-and-Fire (LIF)[38] neurons. These neurons, combined with convolutional operations, effectively encode temporal dynamics while filtering out noise through their inherent leaky properties. The SNN encoder processes data within a predefined temporal window across multiple simulation steps. This methodology helps preserve critical signal events while minimizing the impact of irrelevant noise.

To avoid the vanishing spike phenomenon in deep spiking layers[35], we integrate a Motion Encoder[39] with CNN blocks. This encoder extracts higher-level motion features, focusing on multi-scale and multi-level motion information, ensuring robust feature extraction throughout the network. These features are then fed into a rain attention block[21], allowing the network to extract rain features due to their lower density compared to the background. Background features are obtained by subtracting the rain features, facilitating efficient rain-background separation. Finally, reconstruction blocks[39] restore the background and rain layers, which can be used to analyze raindrop size and fall speed distributions.

3.3 Network Training

To guide the training, we mainly explore three kinds of loss for rain-background decomposition.

Event Contrast Loss We exploit the idea of contrastive loss for the decomposition process, which brings positive pairs closer and separates negative pairs. Rain events are typically sparse and directional, whereas background events display more complex spatiotemporal features. In our context, we aim to pull estimated background events E_B^* closer to the target events E_B, while increasing the difference between E_B^* and estimated rainy events E_R^* by push them far away. The contrastive loss $\mathcal{L}_{Contrastive}$ function is defined as:

$$\begin{aligned} \mathcal{L}_{Contrastive}^{\text{pos}} &= -\,\text{sim}(f_{E_{B_k}^*}, f_{E_{B_k}})/\tau, \\ \mathcal{L}_{Contrastive}^{\text{neg}} &= \log\left(\sum_k \exp\left(\text{sim}(f_{E_{B_k}^*}, f_{E_{R_k}^*})/\tau\right)\right), \\ \mathcal{L}_{Contrastive} &= \mathcal{L}_{Contrastive}^{\text{pos}} + \mathcal{L}_{Contrastive}^{\text{neg}}. \end{aligned} \tag{3}$$

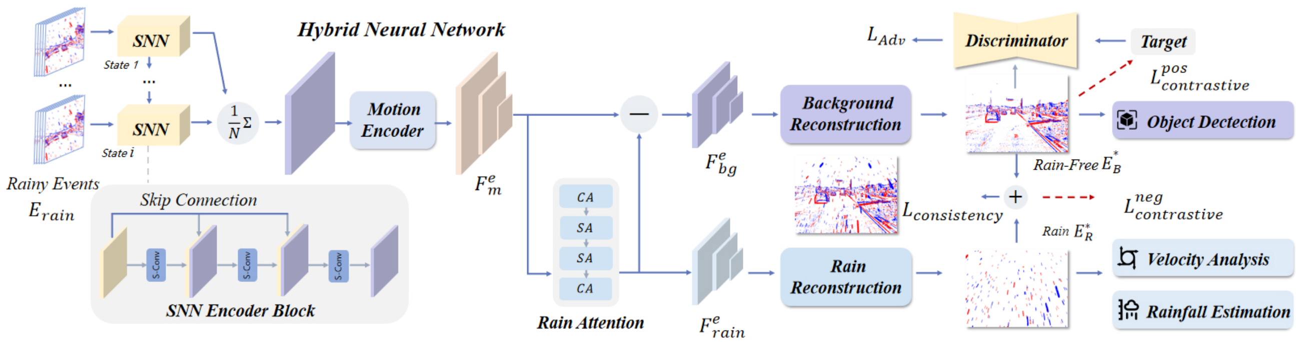

Figure 3. Pipeline of Our Proposed Rain-Background Decomposition Network. The network reconstructs high-quality event sequences of the rain-free background and learns rain physical properties by separating rain features from the background.

where k indexes the events voxel in the dataset. The symbols $f_{E^*_{B_k}}$, $f_{E_{B_k}}$, and $f_{E^*_{R_k}}$ represent the downsampling features of the estimated rain-free background event $E^*_{B_k}$, the target clean event E_{B_k}, and the estimated rainy event $E^*_{R_k}$, respectively. The function $\text{sim}(f, f')$ computes the similarity between feature representations, and τ is a temperature parameter that scales the similarity scores.

Consistency Loss. To maintain the integrity of the image content in the estimated background layer E^*_B, we employ a self-consistency loss[21] by reconstructing the original rainy frame E_{Rain} from the estimated background and rain layers. The self-consistency loss is formulated as follows:

$$\mathcal{L}_{\text{Consistency}} = \|E^*_B + E^*_R - E_{Rain}\|_1, \tag{4}$$

where $\|\cdot\|_1$ denotes the $L1$ norm. This approach ensures that the combination of the estimated background and rain layers closely matches the observed rainy event data, thereby preserving the content of the background layer.

Adversarial Loss. We integrate an adversarial loss into our model to improve the realism of the generated clean background event while maintaining data fidelity.

$$\mathcal{L}_{\text{Adv}} = \mathbb{E}_{E^*_B}\left[\log D(E^*_B)\right] + \mathbb{E}_{E_{\text{rain}}}\left[\log\left(1 - D\left(G_{E^*_B}(E_{\text{rain}})\right)\right)\right], \tag{5}$$

where D is the discriminator network that distinguishes between target clean event E_B and generated events $G_{E^*_B}(E_{\text{rain}})$, which are generated from rainy weather events using $G_{E^*_B}$.

The basic overall loss function is formulated as follows:

$$\mathcal{L}_{\text{Overall}} = \mathcal{L}_{Contrastive} + \mathcal{L}_{\text{Consistency}} + \mathcal{L}_{\text{Adv}}. \tag{6}$$

4 EVALUATION

In this section, we evaluate the proposed model in two ways. First, we assess the method's accuracy in background recovery using self-generated synthetic rainy event datasets. Second, we demonstrate the effectiveness of our approach in rain physical modeling through two case studies.

4.1 Dataset Preparation

To date, we have not found any large-scale datasets focused on rainy event scenarios. For training and quantitative evaluation, we generated a synthetic dataset using an event simulation framework[3]. Initially, we utilized a rain rendering simulator to generate rainy videos based on the KITTI dataset[2]. These videos encompassed varying camera motion speeds and rain intensities, encompassing 12 distinct levels of rainfall rates, ranging from 1 mm/hr to 200 mm/hr. Then we utilized these rainy videos to simulate event sequences[3]. This dataset consists of 4776 paired sequences of rainy and corresponding clean event sequences. Each sequence is standardized to a duration of 100 milliseconds.

4.2 Training Details

We use PatchGAN[40] as the discriminator and the Adam optimizer with learning rates of 2×10^{-4} and 4×10^{-4} for the discriminator and generator, respectively, reduced via cosine annealing. The event sequence is discretized into 10 bins, with each bin treated as a voxel; the model processes two voxels at a time. The entire network is trained for 450 epochs on four NVIDIA RTX3080Ti GPUs.

4.3 Rain-free Background Reconstruction

Current deraining methods are mostly frame-based, leading to suboptimal performance with event data due to mismatches in texture and structure[41]. Frame-based models, designed for spatially coherent images, do not align well with the sparse, asynchronous nature of event data. Event-based approaches like[42] treat event data as images, remaining within the frame domain, while [23] focus on raindrop detection. However, removing detected raindrops can cause loss of overlapping information, making direct comparisons difficult. Additionally, probability-based raindrop detection is less effective in dense rainfall and noisy conditions.

Table 1. Deraining Performance and Estimated Rainfall Rates at Various Intensities (mm/hr).

Rainfall	PSNR	SSIM	Estimated Rainfall
1	26.56	0.89	0.98
20	23.76	0.92	20.3
50	24.43	0.85	49.2
100	23.87	0.82	99.1
125	24.29	0.80	125.5
150	23.56	0.78	149.3
175	23.44	0.75	175.2
200	23.29	0.73	197.7

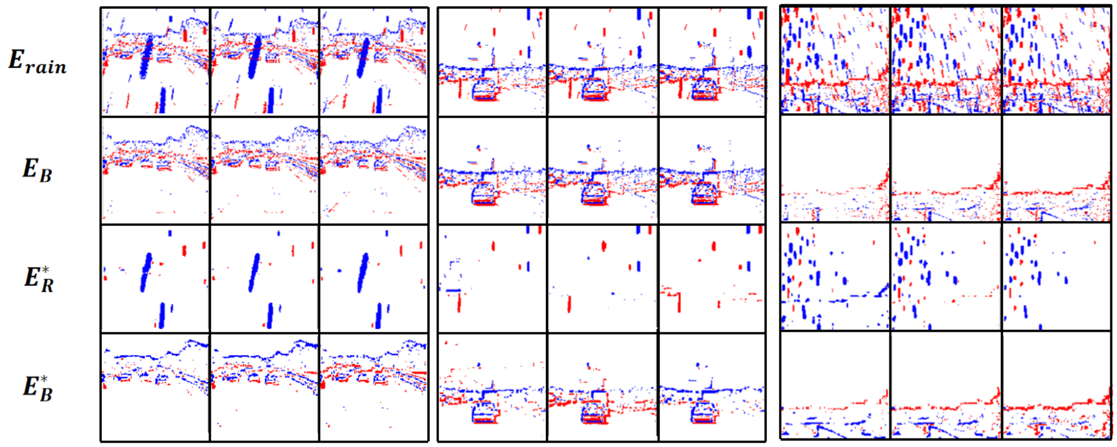

Figure 4. Results of Decomposing event camera data into rain and background layers at different rainfall intensities. We selected the top three bins of the voxel grid for visualization. The top row shows the original rainy event input (E_{rain}). The second row presents the ground truth rain-free background (E_B). The third row illustrates the extracted rain layer (E_R^*), and the bottom row shows the extracted background layer (E_B^*). Our method retains the polarity information of the events.

In contrast, our model leverages the unique characteristics of event data by employing SNNs to filter noise and encode features, and CNNs for decoding and reconstruction. This approach preserves both spatial and temporal information, including the polarity of events (with red representing positive events and blue representing negative events in Figure4). As demonstrated in Table 1, our model achieves superior background recovery across varying rainfall intensities. We use Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) as evaluation metrics to assess the performance of these methods. The average PSNR and SSIM results are 24.15 and 0.8175, respectively.

4.4 Rain Physical Modeling Validation

Rainfall Rate Prediction. Since our synthetic rainy event datasets include labels for rainfall rate, we can add a network downstream of the decomposed rain features to learn the rainfall rate. The prediction results for rainfall rate on the test dataset are presented in the last column of Table 1. The mean absolute error (MAE) in rainfall rate estimation is 0.71 mm/hr. It can be observed that the decomposed rain features accurately capture the characteristics of rainfall rate.

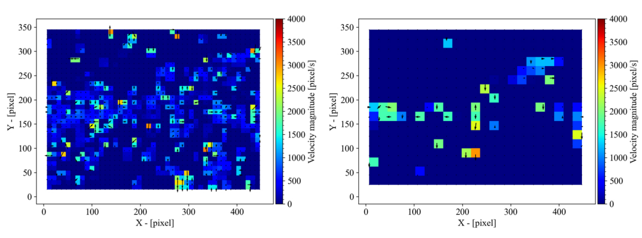

Figure 5. Comparison of velocity maps before and after rain-background decomposition. The left shows a velocity map with combined background and noise, leading to high complexity and low accuracy. The right displays the rain velocity map post-decomposition, significantly improving both efficiency and accuracy.

Rain Velocity Estimation. The combination of drop velocity and drop size distribution enables the estimation of kinetic energy. The rain layer reconstructed from rain features can be directly utilized for velocity estimation. In this case study, we employ particle-based flow measurement techniques[43] to compute a velocity map. From Figure 5, it is evident that by effectively filtering out background noise and extracting the rain layer, this method enhances the efficiency and reliability of velocity estimation. This approach significantly reduces computational load, laying a solid foundation for further analysis of rain dynamics and their impacts.

5 CONCLUSION

This paper presents an event-based Rain-Background Decomposition method utilizing a hybrid network, demonstrating robust and effective performance across various rainfall conditions. By implementing a "distill rain" approach, the paper addresses the challenges faced by event cameras in outdoor rainy environments. Furthermore, it introduces an innovative method for using event cameras to "collect rain" for rain modeling. This development enhances the performance of event cameras and expands their applicability in meteorological research. Future work will focus on developing unsupervised learning techniques for decomposition, employing more systematic approaches to capture the physical characteristics of rain with event cameras, and incorporating real-world data collection and deployment.

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