# SpikeRain: Towards Energy-Efficient Single Image Deraining with Spiking Neural Networks (Supplementary Materials)

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## 1. Training Strategy

Training SNNs is challenging due to their non-differentiable spike generation mechanisms. Specifically, the binary nature of spikes in LIF neurons [6] hinders the use of standard gradient descent, prompting the use of surrogate gradients to enable backpropagation. In our framework, we employ a differentiable approximation of the spike activation function to compute effective gradients while preserving the discrete firing behavior during the forward pass.

We adopt the *Sigmoid Surrogate Gradient* [4] to approximate the Heaviside derivative, where $V_t$ is the membrane potential at time $t$. The surrogate and its gradient are:

$$\sigma(V_t) = \frac{1}{1 + e^{-\alpha V_t}}, \quad \frac{d\sigma(V_t)}{dV_t} = \alpha_s \cdot \sigma(V_t) \cdot (1 - \sigma(V_t)), \tag{1}$$

where $\alpha_s$ is a tunable steepness parameter that controls the sharpness of the gradient approximation. Higher values of $\alpha_s$ approximate the binary spike thresholding behavior more closely, but may lead to unstable gradient dynamics if not regularized.

To ensure temporal credit assignment in the spiking domain, we integrate this surrogate gradient within the LIF neuron update equations across all time steps $t = 1, \ldots, T$, enabling the training process to capture both instantaneous and accumulated membrane dynamics. This ensures robust, energy-efficient learning and smooth gradient flow through the spike sequence.

## 2. Model Optimization

To encourage the network to preserve fine-grained image structures and eliminate rain-induced degradations, we adopt the *Structural Similarity Index Measure* (SSIM) [5] as the primary objective of the SpikeRain training process. Unlike pixel-wise losses, SSIM is designed to measure perceptual similarity by comparing local patterns of luminance, contrast, and structure between two images.

Let $\mathbf{X}$ and $\mathbf{Y}$ denote the input rainy image and the corresponding clean ground-truth, respectively. The derained output is obtained as $\hat{\mathbf{Y}} = \mathbf{S}(\mathbf{X})$, where $\mathbf{S}(\cdot)$ denotes the forward pass of our proposed SpikeRain. The SSIM-based loss function is then formulated as:

$$\mathcal{L}_{\text{SSIM}} = 1 - \text{SSIM}(\hat{\mathbf{Y}}, \mathbf{Y}), \tag{2}$$

where $\text{SSIM}(\cdot, \cdot)$ computes the perceptual similarity index between the output and ground-truth. This formulation penalizes structural inconsistencies more effectively than MSE or $L_1$ losses, ensuring improved visual fidelity under severe visual degradation. During training, we optimize $\mathcal{L}_{\text{SSIM}}$ using the AdamW optimizer, incorporating learning rate scheduling and mixed precision.

## 3. Discussion on Real-World Deployment

To further assess the practicality of SpikeRain in real-world scenarios, we analyze its scalability, efficiency on edge devices, and potential for neuromorphic deployment.

### 3.1. Scalability Across Image Sizes

We evaluate the inference cost of SpikeRain on different input resolutions. Table 1 reports the latency, FLOPs, and estimated energy. Results indicate that performance scales approximately linearly with image size, while maintaining favorable energy efficiency compared to ANN counterparts. This highlights SpikeRain's suitability for edge deployment where input sizes may vary.

### 3.2. Deployment on Neuromorphic Hardware

Although our experiments are conducted on GPUs with simulated energy estimates, SpikeRain is inherently compatible with neuromorphic platforms due to its event-driven,

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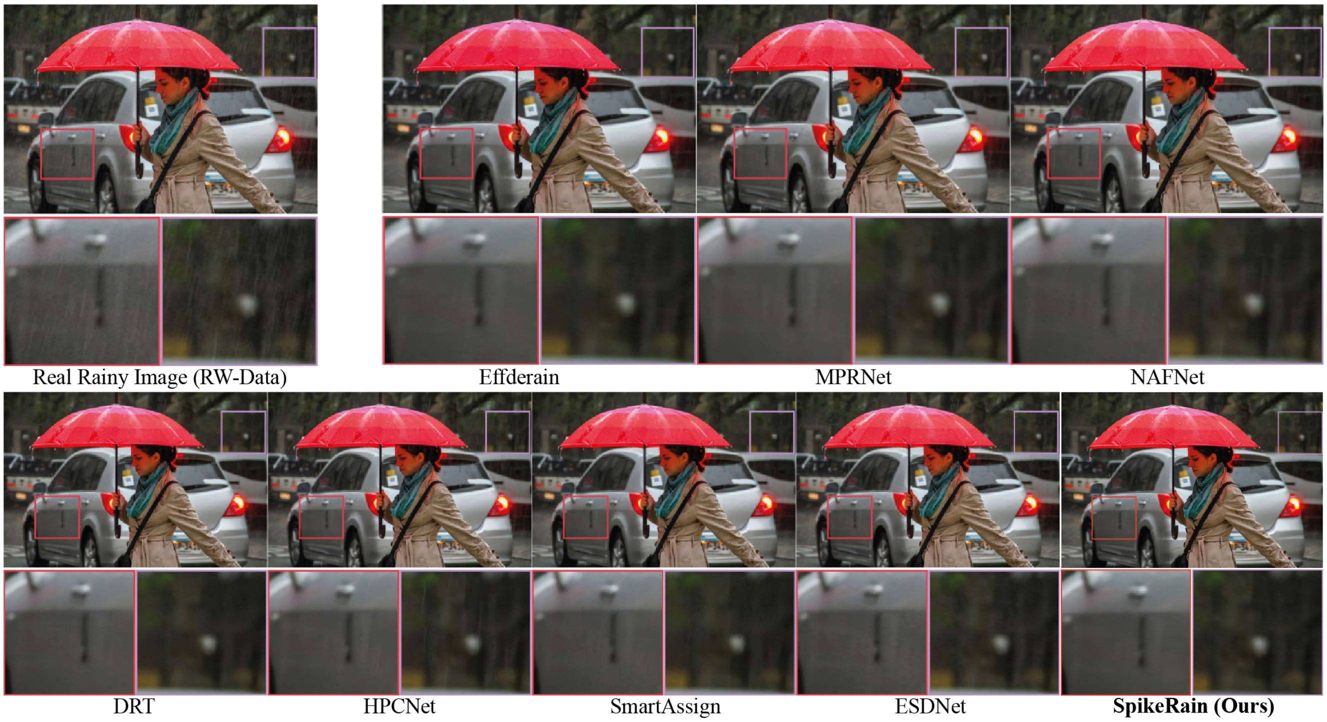


Figure 1. Qualitative comparison on a real-world image from the RW-Data benchmark. Visual results from various deraining methods are shown alongside close-up insets highlighting challenging regions.

| Input Size | FLOPs (G)↓ | Energy (mJ)↓ |
|---|---|---|
| $256 \times 256$ | 12.928 | 161.6 |
| $512 \times 512$ | 51.712 | 646.4 |
| $720 \times 720$ | 102.263 | 1278.3 |

Table 1. Scalability of SpikeRain across input resolutions (measured on RTX 3090, batch size = 1). Energy estimates follow [2].

spike-based computation. Platforms such as Intel Loihi [1] and SpiNNaker [3] support spiking neurons and can natively exploit the sparsity of MDSA and ARFE modules. Deployment primarily requires mapping LIF neurons and attention operations into supported primitives, which is feasible through toolchains like Lava and PyNN. While full hardware deployment is beyond the scope of this work, we emphasize that SpikeRain's low FLOP design and sparse computation profile make it a strong candidate for real-time inference on edge and neuromorphic devices. Extending evaluation to additional weather conditions such as fog and snow, is another important direction for improving robustness.

## References

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