

Learning to Robustly Reconstruct Dynamic Scenes from Low-light Spike Streams

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Abstract

As a neuromorphic sensor with high temporal resolution, spike camera can generate continuous binary spike streams to capture per-pixel light intensity. We can use reconstruction methods to restore scene details in high-speed scenarios. However, due to limited information in spike streams, low-light scenes are difficult to effectively reconstruct. In this paper, we propose a bidirectional recurrent-based reconstruction framework, including a Light-Robust Representation (LR-Rep) and a fusion module, to better handle such extreme conditions. LR-Rep is designed to aggregate temporal information in spike streams, and a fusion module is utilized to extract temporal features. Additionally, we have developed a reconstruction benchmark for high-speed low-light scenes. Light sources in the scenes are carefully aligned to real-world conditions. Experimental results demonstrate the superiority of our method, which also generalizes well to real spike streams. Related codes and proposed datasets will be released after publication.

1. Introduction

As a neuromorphic sensor with high temporal resolution (40000 Hz), spike camera [8, 31] has shown enormous potential for high-speed visual tasks, such as reconstruction [2, 26, 27, 30, 32, 33], optical flow estimation [7, 23, 29], and depth estimation [14, 16, 25]. Different from event cameras [1, 3, 15], it can record per-pixel light intensity by accumulating photons and firing continuous binary spike streams. Correspondingly, high-speed dynamic scenes can be reconstructed from spike streams. Recently, many deep learning methods have advanced this field and shown great success in reconstructing more detailed scenes. However, existing methods struggle to perform well in low-light environments due to insufficient information in spike streams.

A dilemma arises for visual sensors, that is, the quality

of sampled data can greatly decrease in a low-light environment [5, 6, 11, 12, 29]. Low-quality data creates many difficulties for all kinds of vision tasks. Similarly, the reconstruction for the spike camera also suffers from this problem. To improve the performance of reconstruction in low-light high-speed scenes, two non-trivial matters should be carefully considered. First, Constructing a low-light high-speed scene benchmark for spike camera is crucial to evaluating different methods. However, due to the frame rate limitations of traditional cameras, it is difficult to capture images clearly in real high-speed scenes as supervised signals. Instead of it, a reasonable way is to synthesize datasets for spike camera [7, 25, 27, 33]. To ensure the reliability of the reconstruction benchmark, synthetic low-light high-speed scenes should be as consistent as possible with the real world, e.g., light source. Second, as shown in Fig. 1, with the decrease of illuminance in the environment, the total number of spikes in spike streams decreases greatly which means the valid information in spike streams can greatly decrease. Fig. 1(a) shows that previous methods often fail under low-light conditions since they have no choice but to rely on inadequate information.

In this work, we aim to address all two issues above-mentioned. In more detail, a reconstruction benchmark for high-speed low-light scenes is proposed. We carefully design the scene by controlling the type and power of the light source and generating noisy spike streams based on [28]. Besides, we propose a light-robust reconstruction method as shown in Fig. 1(b). Specifically, to compensate for information deficiencies in low-light spike streams, we propose a **light-robust representation** (LR-Rep). In LR-Rep, the release time of forward and backward spikes is used to update a **global inter-spike interval** (GISI). Then, to further excavate temporal information in spike streams, LR-Rep is fused with forward (backward) temporal features. During the feature fusion process, we add alignment information to avoid the misalignment of motion from different timestamps. Finally, the scene is clearly reconstructed from fused features.

Empirically, we show the superiority of our reconstruction

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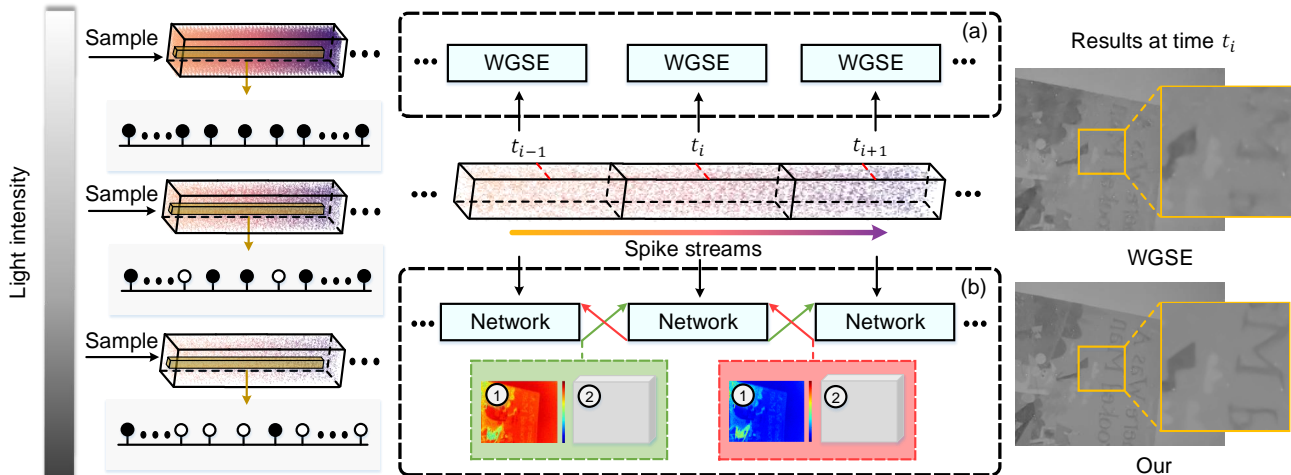


Figure 1. Overview of reconstruction for high-speed spike streams. Left: with decreasing light intensity, more sparse spike streams are difficult to extract features. A black circle is a spike. Middle: (a) The state-of-the-art method, WGSE [24]. The arrow with a gradient color is the timeline. (b) Our reconstruction method. Green (red) lines denote the forward (backward) data flow. ① (②) is the release time of spikes (temporal features). ① (②) in forward and backward data flow is independent. Right: reconstructed results from WGSE and our method.

method. Importantly, our method also generalizes well to real spike streams. In addition, extensive ablation studies demonstrate the effectiveness of each component. The main contributions of this paper can be summarized as follows:

- A reconstruction benchmark for high-speed low-light scenes is proposed. We carefully construct varied low-light scenes that are close to reality.
- We propose a bidirectional recurrent-based reconstruction framework where a light-robust representation, LR-Rep, and fusion module can effectively compensate for information deficiencies in low-light spike streams.
- Experimental results on real and synthetic datasets have shown our method can more effectively handle spike streams under different light conditions than previous methods.

2. Related Work

2.1. Low-light Vision

Low-light environment has always been a challenge not only for human perception but also for computer vision methods. For traditional cameras, some works concern the enhancement of low-light images. [20] propose the LOL dataset containing low/normal-light image pairs and propose a deep Retinex-Net including a Decom-Net for decomposition and an Enhance-Net for illumination adjustment. [9] proposes the EnlightenGAN which is first trained on unpaired data to low-light image enhancement. [6] proposes Zero-DCE which formulates light enhancement as a task of image-specific curve estimation with a deep network. Besides, some work focuses on the robustness of vision task to low-light, e.g., object detection. [17] proposes a method

of domain adaptation for merging multiple models to handle objects in a low-light situation. [13] integrates a new non-local feature aggregation method and a knowledge distillation technique to with the detector networks. [18] combines with the image enhancement algorithm to improves the accuracy of object detection. For spike camera, it are also affected by low-light environments. [4] propose a real low-light high-speed dataset for reconstruction. However, it lacks corresponding image sequences as ground truth. To solve the challenge in the reconstruction of low-light spike streams, We have fully developed the task including a reconstruction benchmark for high-speed low-light scenes and a light-robust reconstruction method.

2.2. Reconstruction for Spike Camera

The reconstruction of high-speed dynamic scenes has been a popular topic for spike camera. Based on the statistical characteristics of spike stream, [31] first reconstruct high-speed scenes. [26] improved the smoothness of reconstructed scenes by introducing motion aligned filter. [32] construct a dynamic neuron extraction model to distinguish the dynamic and static scenes. For enhancing reconstruction results, [30] uses short-term plasticity mechanism to exact motion area. [27] first proposes a deep learning-based reconstruction framework, Spk2ImgNet (S2I), to handle the challenges brought by both noise and high-speed motion. [2] build a self-supervised reconstruction framework by introducing blind-spot networks. It achieves desirable results compared with S2I. The reconstruction method [24] presents a novel Wavelet Guided Spike Enhancing (WGSE) paradigm. By using multi level wavelet transform, the noise in the re-

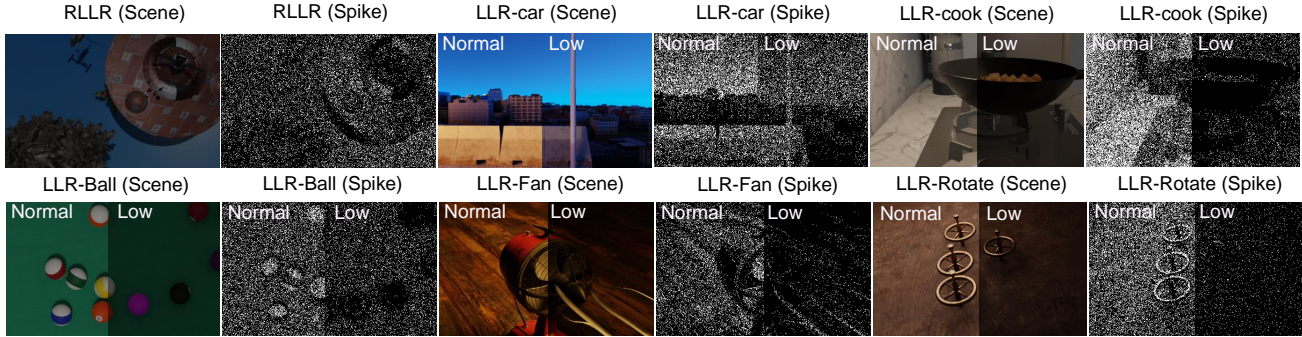


Figure 2. Proposed datasets, RLLR and LLR. RLLR includes the random scenes and LLR includes carefully designed scenes.

constructed results can be effectively suppressed.

2.3. Spike Camera Simulation

Spike camera simulation is a popular way to generate spike streams and accurate labels. [27] first convert interpolated image sequences with high frame rate into spike stream. Based on [27], [10, 28, 33] add some random noise to generate spike streams more accurately. To avoid motion artifacts caused by interpolation, [7] presents the spike camera simulator (SPCS) combining simulation function and rendering engine tightly. Then, based on SPCS, optical flow datasets for spike camera are first proposed. [25] generate the first spike-based depth dataset by the spike camera simulation.

3. Reconstruction Datasets

In order to train and evaluate the performance of reconstruction methods in low-light high-speed scenes, we propose two low-light spike stream datasets, **Rand Low-Light Reconstruction (RLLR)** and **Low-Light Reconstruction (LLR)** based on spike camera model. RLLR is used as our train dataset and LLR is carefully designed to evaluate the performance of different reconstruction methods as test dataset. We first introduce the spike camera model, and then introduce our datasets where noisy spike streams are generated by the spike camera model.

Spike camera model Each pixel on the spike camera model converts light signal into current signal and accumulate the input current. For pixel $\mathbf{x} = (x, y)$, if the accumulation of input current reaches a fixed threshold ϕ , a spike is fired and then the accumulation can be reset as,

$$A(\mathbf{x}, t) = A_{\mathbf{x}}(t) \bmod \phi = \int_0^t I_{tot}(\mathbf{x}, \tau) d\tau \bmod \phi, \quad (1)$$

$$I_{tot}(\mathbf{x}, \tau) = I_{in}(\mathbf{x}, \tau) + I_{dark}(\mathbf{x}, \tau), \quad (2)$$

where $A(\mathbf{x}, t)$ is the accumulation at time t , $A_{\mathbf{x}}(t)$ is the accumulation without reset before time t , $I_{in}(\mathbf{x}, \tau)$ is the input current at time τ (proportional to light intensity) and

$I_{dark}(\mathbf{x}, \tau)$ is the main fixed pattern noise in spike camera, *i.e.*, dark current [28, 33]. Further, due to limitations of circuits, each spike is read out at discrete time nT , $n \in \mathbb{N}$ (T is a micro-second level). Thus, the output of the spike camera is a spatial-temporal binary stream S with $H \times W \times N$ size. The H and W are the height and width of the sensor, respectively, and N is the temporal window size of the spike stream. According to the spike camera model, it is natural that the spikes (or information) in low-light spike streams are sparse because reaching the threshold is lengthy. More details about low-light spike streams are in appendix.

RLLR As shown in Fig. 2, RLLR includes 100 random low-light high-speed scenes where high-speed scenes are first generated by SPCS [7] and then the light intensity of all pixels in each scene is darkened by multiplying a random constant (0-1). Each scene in RLLR continuously records a spike stream with $400 \times 250 \times 1000$ size and corresponding image sequence. Then, for each image, we clip a spike stream with $400 \times 250 \times 41$ size from the spike stream as input.

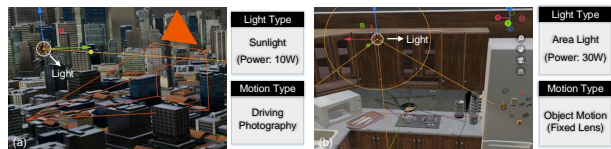


Figure 3. The Car_N (left) and $Cook_L$ (right) in LLR. N (L) means normal (low) light.

LLR As shown in Fig. 2, LLR includes 5×2 carefully designed high-speed scenes where we use the scenes with five kinds of motion (named Ball, Car, Cook, Fan and Rotate) and each scene corresponds to two light sources (normal and low). To ensure the reliability of our scenes, different light sources are used, and the power of light source is consistent with the real world. Specially, we set the lighting parameters in the advanced 3D graphics software, Blender, to make the lighting conditions as consistent as possible with the real world. The following are the configuration details in

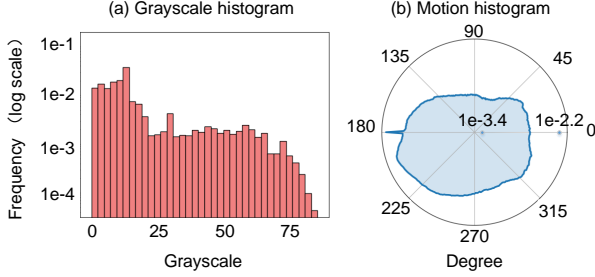


Figure 4. (a) Grayscale histograms of images in low-light scenes, i.e., Ball, Car, Cook, Fan and Rotate with low-light light source. Each bar represents 5 grayscale levels (b) Motion direction histogram of optical flow in LLR.

Blender. In Blender, various types of lighting simulation functions, including sunlight, point lights, and area lights, have been integrated into the graphical interface. We can adjust lighting parameters to control brightness and darkness. For sunlight in Blender, the watts per square meter can be modified. Typically, 100 watts per square meter corresponds to a cloudy lighting environment. For the Car_L scene, as shown in Fig. 3(a), we have set sunlight to 10 watts per square meter, which is deemed sufficiently low. For point lights and area lights, Blender allows modification of radiant Power, measured in watts. This is not the electrical power of consumer light bulbs. A light tube with the electrical power of 30W approximately corresponds to a radiant power of 1W. In the $Cook_L$ scene, as shown in Fig. 3(b), we have set an area light with the radiant Power to 1W (the electrical power of 30W). It already represents a very dim indoor light source. Each scene in LLR continuously records 21 spike streams with $400 \times 250 \times 41$ size and 21 corresponding images.

In fact, LLR has diverse grayscale and motion information. To illustrate this fact, we calculate the grayscale distribution and optical flow distribution in LLR. As shown in Fig. 4(a), we can see that the grayscale is diverse and in a lower range. The motion in LLR is also diverse. We generate a optical flow every 40 frames for LLR. The degree distribution of the optical flow is in Fig. 4(b). We can find that the motion in LLR covers all kinds of directions.

4. Method

4.1. Problem Statement

For simplicity, we write $\mathbf{S}_t \in \{0, 1\}^{H \times W \times (2\Delta t + 1)}$ to denote a spike stream from time $t - \Delta t$ to $t + \Delta t$ ($2\Delta t + 1$ is the fixed temporal window) and write $\mathbf{Y}_t \in \mathbb{R}^{H \times W}$ to denote the instantaneous light intensity received in spike camera at time t . Reconstruction is to use continuous spike streams, $\{\mathbf{S}_{t_i}, t_i = i * (2\Delta t + 1) | i = 1, 2, 3 \dots K\}$ to restore the light intensity information at different time, $\{\mathbf{Y}_{t_i}, t_i = i * (2\Delta t + 1) | i = 1, 2, 3 \dots K\}$. Generally, the

temporal window $2\Delta t + 1$ is set as 41 which is the same with [2, 24, 27].

4.2. Overview

To overcome the challenge of low-light spike streams, i.e., the recorded information is sparse (see Fig. 1), we propose a light-robust reconstruction method which can fully utilize temporal information of spike streams. It is beneficial from two modules: 1. A light-robust representation, LR-Rep. 2. A fusion module. As shown in Fig. 5, to recover the light intensity information at time t_i , \mathbf{Y}_{t_i} , we first calculate the light-robust representation at time t_i , written as \mathbf{Rep}_{t_i} . Then, we use a ResNet module to extract deep features, \mathbf{F}_{t_i} , from \mathbf{Rep}_{t_i} . \mathbf{F}_{t_i} is fused with forward (backward) temporal features as $\mathbf{F}_{t_i}^f$ ($\mathbf{F}_{t_i}^b$). Finally, we reconstruct the image at time t_i , $\hat{\mathbf{Y}}_{t_i}$ with $\mathbf{F}_{t_i}^f$ and $\mathbf{F}_{t_i}^b$.

4.3. Light-robust Representation

As shown in Fig. 6, a light-robust representation, LR-Rep, is proposed to aggregate the information in low-light spike streams. LR-Rep mainly consists of two parts, GISI transform and feature extraction.

GISI transform Calculating the local inter-spike interval from the input spike stream is a common operation [2, 29] and we call it as LISI transform. Different from LISI transform, we propose a GISI transform which can utilize the release time of forward and backward spikes to obtain the global inter-spike interval \mathbf{GISI}_{t_i} . It need to be performed twice, i.e. once forward and once backward respectively. Taking GISI transform for backward as an example, it can be summarized as three steps as shown in Fig. 7. Our GISI transform can extract more temporal information from spike streams than LISI transform as shown in Fig. 8.

Feature extraction After GISI transform, we separately extract shallow features of \mathbf{GISI}_{t_i} and input spike stream, \mathbf{F}_G and \mathbf{F}_S through convolution block. Finally, \mathbf{Rep}_{t_i} is obtained by an attention module where \mathbf{F}_G and \mathbf{F}_S are integrated, i.e.,

$$[\beta_{t_i}, \alpha_{t_i}] = Att([\mathbf{F}_G, \mathbf{F}_S]), \quad (3)$$

$$\mathbf{Rep}_{t_i} = \beta_{t_i} \mathbf{F}_G + \alpha_{t_i} \mathbf{F}_S, \quad (4)$$

where $Att(\cdot)$ denotes an attention block including 3-layer convolution with 3-layer activation function and \mathbf{Rep}_{t_i} is our LR-Rep at time t_i . Related details are in our appendix.

4.4. Fusion and Reconstruction

We first extract the deep feature \mathbf{F}_{t_i} of \mathbf{Rep}_{t_i} through a ResNet with 16 layers. Then, as shown in Fig. 9(a), for forward, temporal features $\mathbf{F}_{t_{i-1}}^f$ and \mathbf{F}_{t_i} are fused as temporal features of the input spike stream $\mathbf{F}_{t_i}^f$. For backward, temporal features $\mathbf{F}_{t_{i+1}}^b$ and \mathbf{F}_{t_i} are fused as temporal features of

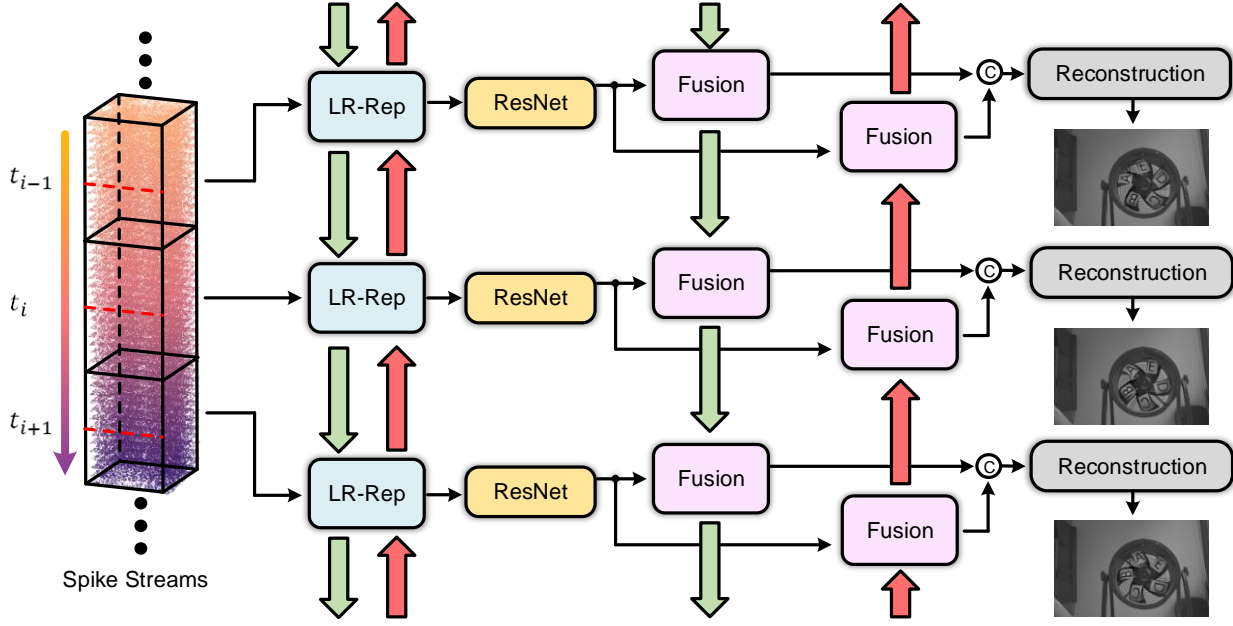


Figure 5. Illustration of the proposed bidirectional recurrent-based reconstruction framework. It includes a light-robust representation, feature extractor (ResNet), fusion and reconstruction. The green and red lines represent the forward and backward data flow. The two kinds of data flow are independent.

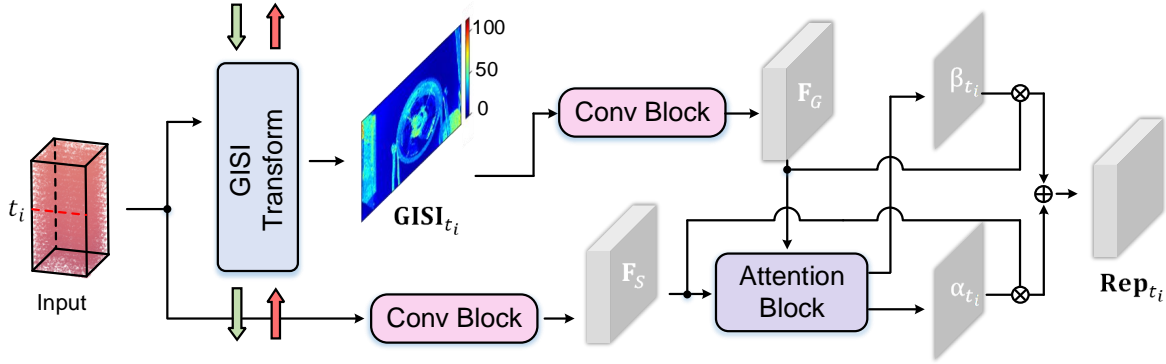


Figure 6. Illustration of the proposed light-robust representation. We use convolution blocks to extract shallow features from input spike stream and GISI, respectively. Then they are fused by an attention block.

the input spike stream $\mathbf{F}_{t_i}^b$. To avoid the misalignment of motion from different timestamps, we use a Pyramid Cascading and Deformable convolution (PCD) [19] to add alignment information to \mathbf{F}_{t_i} . The above process can be written as,

$$\mathbf{F}_{t_i} = f(\text{Rep}_{t_i}), \quad (5)$$

$$\mathbf{F}_{t_i}^f = f([\mathbf{F}_{t_i} + a(\mathbf{F}_{t_{i-1}}^f, \mathbf{F}_{t_i}), \mathbf{F}_{t_{i-1}}^f]), \quad (6)$$

$$\mathbf{F}_{t_i}^b = f([\mathbf{F}_{t_i} + a(\mathbf{F}_{t_{i+1}}^b, \mathbf{F}_{t_i}), \mathbf{F}_{t_{i+1}}^b]), \quad (7)$$

where $f(\cdot)$ denotes the feature extraction and $a(\cdot, \cdot)$ denotes the PCD module. Finally, as shown in Fig. 9(b), we use

forward and backward temporal features ($\mathbf{F}_{t_i}^b$ and $\mathbf{F}_{t_i}^f$) to reconstruct the current scene at time t_i , i.e.,

$$\hat{\mathbf{Y}}_{t_i} = c([\mathbf{F}_{t_i}^b, \mathbf{F}_{t_i}^f]), \quad (8)$$

$$\mathcal{L} = \sum_{i=1}^K \|\hat{\mathbf{Y}}_{t_i} - \mathbf{Y}_{t_i}\|_1 \quad (9)$$

where $c(\cdot)$ denotes 3-layer convolution with 2-layer ReLU, \mathcal{L} is loss function, $\|\cdot\|_1$ denotes 1-norm and K is the number of continuous spike streams.

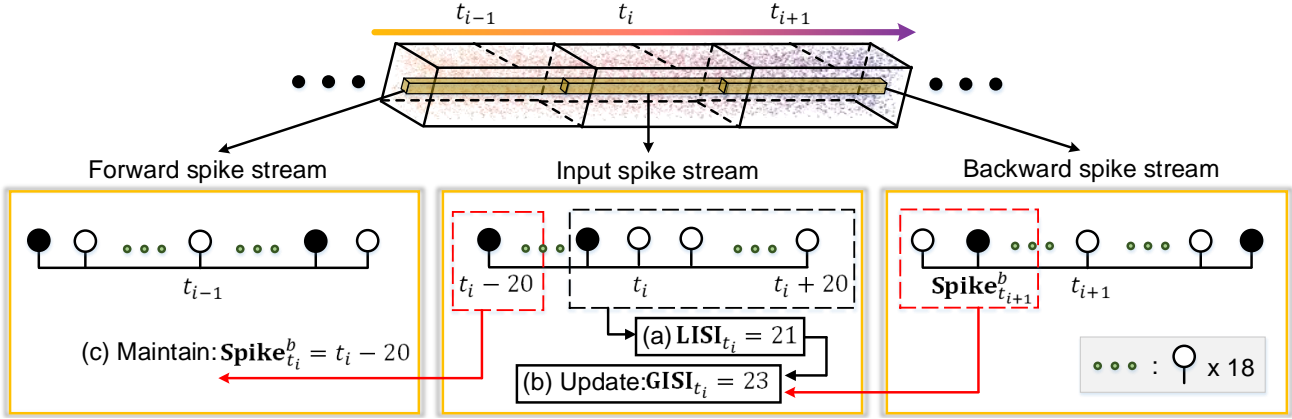


Figure 7. Illustration of GISI transform for backward in a pixel. (a). Calculate the local inter-spike interval, LISI_{t_i} from the input spike stream [2, 29]. (b). Update global inter-spike interval, GISI_{t_i} based on the release time of backward spike, $\text{Spike}_{t_{i+1}}^b$ and LISI_{t_i} . (c). Maintain and transmit the release time of backward spike, $\text{Spike}_{t_i}^b$. Black (white) circle is a (no) spike and the red line is backward data flow. More details are shown in algorithm. 1.

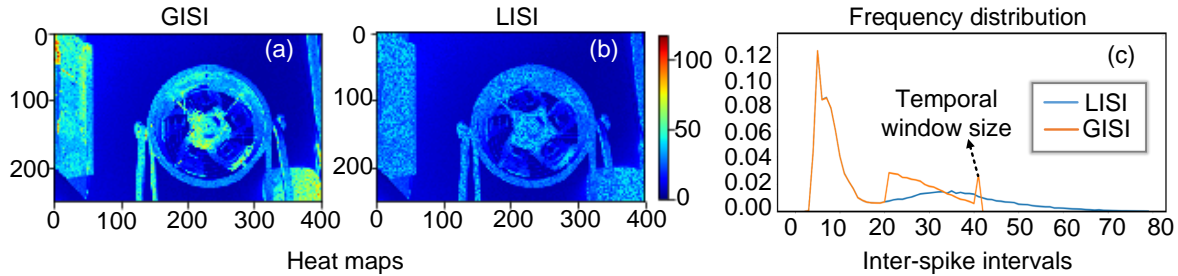


Figure 8. (a) and (b) show the visualizations of GISI_{t_i} and LISI_{t_i} in a real spike stream. (c) shows the distribution of pixel-wise values in GISI_{t_i} and LISI_{t_i} .

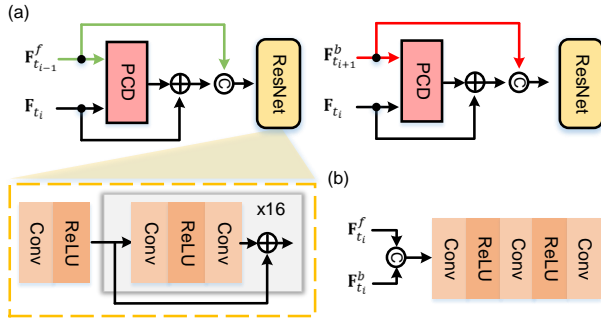


Figure 9. Illustration of fusion module and reconstruction module. (a) denotes forward (green line) and backward (red line) fusion modules. (b) denotes reconstruction module.

5. Experiment

5.1. Implementation Details

We train our method in the proposed dataset, RLLR. Consistent with previous work [2, 24, 27], the temporal window

of each input spike stream is 41. The spatial resolution of input spike streams is randomly cropped the spike stream to 64×64 during the training procedure and the batch size is set as 8. Besides, forward (backward) temporal features and the release time of spikes in our method are maintained from 21 continuous spike streams. We use Adam optimizer with $\beta_1 = 0.9$ and $\beta_2 = 0.99$. The learning rate is initially set as $1e-4$ and scaled by 0.1 after 70 epochs. The model is trained for 100 epochs on 1 NVIDIA A100-SXM4-80GB GPU.

5.2. Results

We compare our method with traditional reconstruction methods, *i.e.*, TFI [31], STP [33], SNM [32] and deep learning-based reconstruction methods, *i.e.*, SSML [2], Spk2ImgNet (S2I) [27], WGSE [24]. The supervised learning methods, S2I and WGSE, are retrained on RLLR and the parameter configuration is the same as their respective papers. We evaluate methods on two kinds of data: (1) The carefully designed **synthetic** dataset, LLR. (2) The **real** spike streams dataset, PKU-Spike-High-Speed [27] and low-light high-speed spike streams dataset [4].

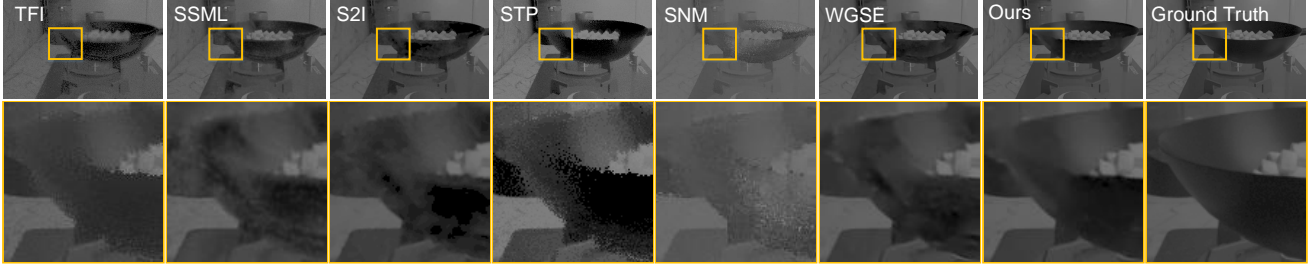


Figure 10. Results from different reconstruction methods on our LLR. More results are in appendix.

Algorithm 1: GISI Transform.

Require: The spike streams at different time $\{S_{t_i} \mid i = 1, 2, \dots, K\}$, K is the number of Continuous spike streams.

- 1: Initialize forward state $\text{Spike}_{t_1}^f = 0$.
 - 2: Initialize backward state $\text{Spike}_{t_K}^b = 2K\Delta t$.
 - 3: **for** i from 1 to K **do**
 - 4: Calculate LISI_{t_i} based on S_{t_i} .
 - 5: **end for**
 - 6: **for** i from 2 to K **do**
 - 7: Forward search the recent release time of spike to t_{i+1} , $\text{Spike}_{t_i}^f$ based on S_{t_i} .
 - 8: **if** $\text{Spike}_{t_i}^f$ is None **then**
 - 9: Set $\text{Spike}_{t_i}^f = \text{Spike}_{t_{i-1}}^f$.
 - 10: **end if**
 - 11: Update GISI_{t_i} based on S_{t_i} and $\text{Spike}_{t_{i-1}}^f$.
 - 12: **end for**
 - 13: **for** i from $K - 1$ to 1 **do**
 - 14: Backward search the recent release time of spike to t_{i-1} , $\text{Spike}_{t_i}^b$ based on S_{t_i} .
 - 15: **if** $\text{Spike}_{t_i}^b$ is None **then**
 - 16: Set $\text{Spike}_{t_i}^b = \text{Spike}_{t_{i+1}}^b$.
 - 17: **end if**
 - 18: Update GISI_{t_i} based on S_{t_i} and $\text{Spike}_{t_{i+1}}^b$.
 - 19: **end for**
 - 20: Return $\{\text{GISI}_{t_i} \mid i = 1, 2, \dots, K\}$
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Table 1. PSNR, PSNR_S , and SSIM of reconstruction results on synthetic dataset, LLR. PSNR_S : PSNR is calculated after scaling both the ground truth and reconstructed images to 0-255 (More details are in appendix).

| Metric | TFI | SSML | S2I | STP | SNM | WGSE | Ours |
|-----------------|--------|--------|--------|--------|--------|---------|---------------|
| PSNR | 31.409 | 38.432 | 40.883 | 24.882 | 25.741 | 42.959 | 45.075 |
| PSNR_S | 21.665 | 30.176 | 31.202 | 14.894 | 18.527 | 32.439 | 38.131 |
| SSIM | 0.7231 | 0.8994 | 0.9592 | 0.5554 | 0.8028 | 0.97067 | 0.9868 |

Results on our synthetic dataset As shown in Table. 1, we use the two reference image quality assessment (IQA) metrics, *i.e.*, PSNR, PSNR_S and SSIM to evaluate the per-

formance of different methods on LLR. We can find that our method achieves the best reconstruction performance and has a PSNR gain over 4dB than the reconstruction method, S2I, which demonstrates its effectiveness. Fig. 10 shows the visualization results from different reconstruction methods. We can find that our method can better restore motion details in dark regions than other methods.

Results on real datasets For real data, we test different methods on two spike stream datasets, PKU-Spike-High-Speed [27] and low-light spike streams [4]. PKU-Spike-High-Speed includes 4 high-speed scenes under normal-light conditions and [4] includes 5 high-speed scenes under low-light conditions. Fig. 11 shows the reconstruction results. Note that we apply the traditional HDR method [22] to reconstruction results on [4] because scenes are too dark. Our method can more effectively restore the information in scenes *i.e.*, clear texture and less noise.

We perform a user study written as US [9, 21] to quantify the visual quality of different methods. For each scene in datasets, we randomly select reconstructed images at the same time from different methods and display them on the screen (the image order is randomly shuffled). 30 human subjects (university degree or above) are invited to independently score the visual quality of the reconstructed image. The scores of visual quality range from 1 to 7 (worst to best quality). The average subjective scores for each spike stream dataset are shown in Fig. 12 and our method reaches the highest US score in all methods.

Table 2. Comparison between Spk2ImgNet (S2I), WGSE and our method. The input spike stream size is $21 \times 41 \times 250 \times 400$. We test the average of 50 rounds for Inference time.

| Method | Para. | Train time | Inference time |
|--------|--------------|------------|-----------------|
| S2I | 3.91m | 2h | 1458.45ms |
| WGSE | 3.63m | 1h | 1344.06ms |
| Our | 5.32m | 17h | 818.03ms |

Stability of continuously reconstructing Our reconstruction method is stable to spike stream at different moments. Fig. 13 shows the continuous motion of an object in a real

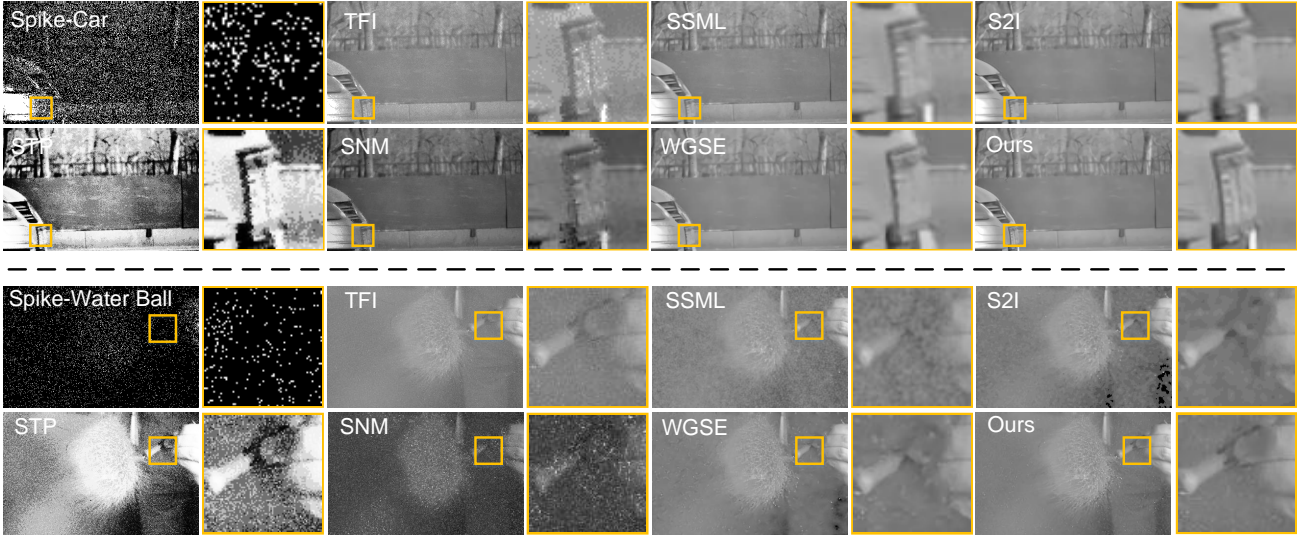


Figure 11. Results from different reconstruction methods on the real datasets, PKU-Spike-High-Speed (Top) and low-light high-speed spike streams dataset (Bottom). More results are in our appendix.

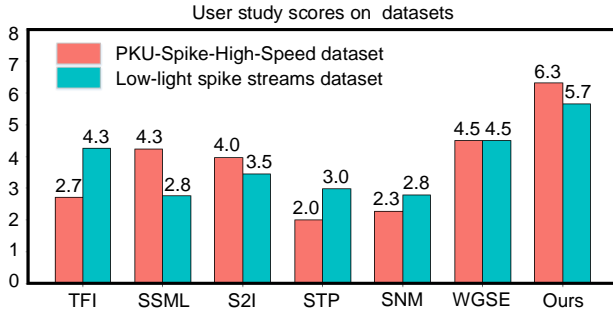


Figure 12. User study scores (\uparrow) of reconstructed images from different methods. The max (min) score is 7 (1).

high-speed low-light scene. We find that our method can clearly recover motion details at different moments, while the loss introduced by the state-of-the-art WGSE is varied at different time. Besides, we also provide a reconstruction video in our supplementary material.

Network Efficiency Analysis Table. 2 demonstrates the training time and inference time of the supervised methods, i.e., Spk2ImgNet, WGSE and our method. Although our method requires more training time compared to Spk2ImgNet and WGSE (bidirectional recurrent-based networks typically consume more time during training due to Backpropagation Through Time (BPTT)), our method outperforms Spk2ImgNet and WGSE in terms of inference speed. Besides, due to the need to fuse both forward and backward temporal features, our method is offline, i.e., After spike camera collects spike stream for a long period of time, the data can be reconstructed. In future work, we would

extend our method so to online reconstruct.

5.3. Ablation

Proposed modules To investigate the effect of the proposed light-robust representation LR-Rep, the adjacent (forward and backward) deep temporal features (ADF), i.e., $\mathbf{F}_{t_i}^b$ and $\mathbf{F}_{t_i}^f$ in our fusion module, the alignment information in our fusion module (AIF) and GISI transform in LR-Rep, we compare 5 baseline methods with our final method. (A) is the basic baseline without LR-Rep, ADF and AIF. Table. 3 shows ablation results on proposed dataset, LLR. The comparison between (A) and (C) ((B) and (D)) proves the effectiveness of LR-Rep. The comparison between (A) and (B) ((C) and (D)) proves the effectiveness of ADF. Further, by adding the alignment information in the fusion module i.e., AIF, our final method (F) appropriately reduces the misalignment of motion from different timestamps and can reconstruct high-speed scenes more accurately than (D). Besides, the comparison between (E) and (F) shows GISI has better performance than LISI. It is because GISI can extract more temporal information than LISI (see Fig. 8). As shown in Fig. 14, GISI (our final method) not only outperform LISI (Baseline (E) in Table 3) in both PSNR and SSIM on LLR but also have better generalization on real data. More importantly, the cost of using GISI instead of LISI is negligible (we only need to use two 400×250 matrices to store the time of the forward spike and the backward spike, respectively), which does not affect the parameter and efficiency of the network.

Comparison with other representation We compare the performance of different representation in our frame-

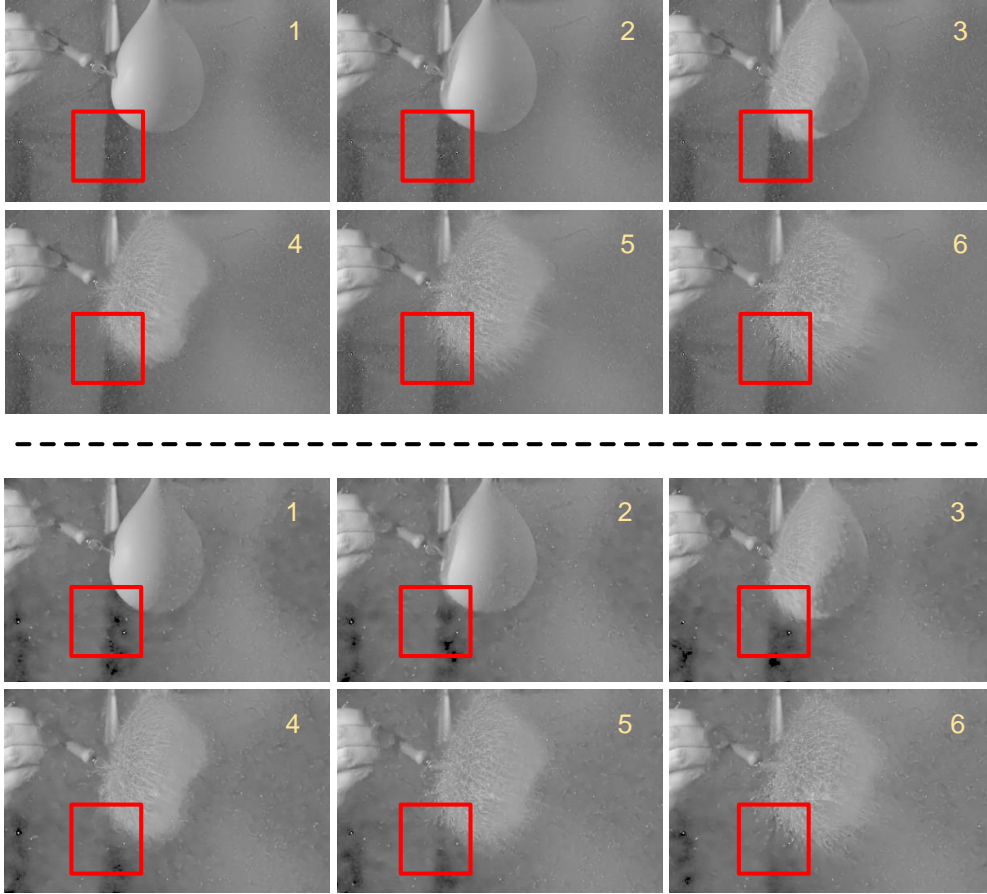


Figure 13. A water polo bursting at high speed in a low-light indoor. We selected the reconstruction results under 6 sampling moments, and the interval between two adjacent sampling moments is 41/40000 s. The above is our method and the bottom is the state-of-the-art reconstruction method [24]. We apply the traditional HDR method [22] to reconstruction results because the scene is too dark.

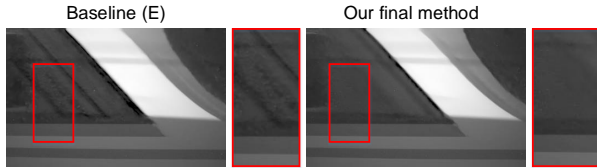


Figure 14. Reconstruction results on a real spike stream. The scene is a high-speed train that exceeds 200 km/h. The glass in the former result (left) shows obvious artifacts, and our result (right) is very smooth and natural.

work, i.e., (1) General representation of spike stream: TFI and TFP [31] (2) Tailored representation for reconstruction networks: AMIM [2] in SSML, SALI [27] in S2I and WGSE-1d [24] in WGSE. We replace LR-Rep in our method as above representation. They are retrained on the dataset, RLLR and implementation details are the same with our method. As shown in Table 4, our LR-Rep achieves the best performance which means LR-Rep can better adapt to our

framework.

Table 3. Abltion results on synthetic dataset, LLR.

| Index | Effect of different network structures | PSNR | SSIM |
|-------|--|---------------|----------------|
| (A) | Removing LR-Rep & AIF & ADF | 42.743 | 0.97403 |
| (B) | Removing LR-Rep & AIF | 44.151 | 0.98514 |
| (C) | Removing AIF & ADF | 44.739 | 0.98636 |
| (D) | Removing AIF | 44.956 | 0.98678 |
| (E) | Replace GISI with LISI | 44.997 | 0.98676 |
| (F) | Our final method | 45.075 | 0.98681 |

Table 4. Performance of different representation methods in our framework. All methods are trained on RLLR and are tested on LLR.

| Rep. | TFP | TFI | AMIM | SALI | WGSE-1d | LR-Rep |
|------|---------|---------|---------|---------|---------|----------------|
| PSNR | 38.615 | 37.617 | 41.95 | 43.314 | 42.302 | 45.075 |
| SSIM | 0.96641 | 0.93632 | 0.97493 | 0.98304 | 0.97438 | 0.98681 |

The number of continuous spike streams For solving the reconstruction difficulty caused by inadequate information in low-light scenes, the release time of spike in LR-Rep and temporal features in fusion module are maintained forward and backward in a recurrent manner. The number of continuous spike streams has an impact on our method performance. Fig. 15 shows its effect on the performance. We can find that, as the number increases, the performance of our method can greatly increase until convergence. This is because, as the number increases, our method can utilize more temporal information until sufficient. The reconstructed image from 21 continuous spike streams has more details in a shaded area.

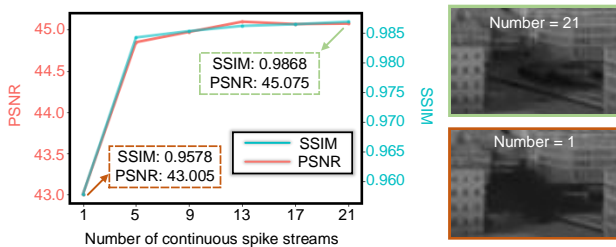


Figure 15. Effect of the number of continuous spike streams on the performance. We test on the dataset, LLR.

Table 5. Reconstruction results on synthetic dataset, LLR. Retrain_{idea}: our method is retrained on the noise-free version of RLLR.

| Metric | Our | Retrain _{idea} |
|--------|----------------|-------------------------|
| PSNR | 45.075 | 37.679 |
| SSIM | 0.98681 | 0.85374 |

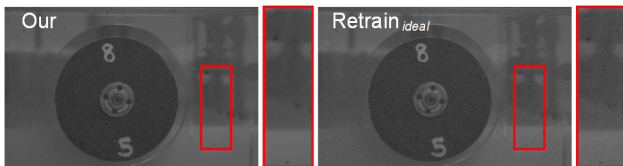


Figure 16. Reconstruction results on a real spike stream. Please enlarge the figure for more details.

Impact of spike camera noise on performance In proposed datasets, we have considered noise of spike camera refer to [28]. We further discuss the impact of noisy and noise-free spike streams on the performance of our method as shown in Table. 5. We use an ideal spike camera model in SPCS [7] to synthesize a noise-free version of RLLR and retrain our method using the dataset (written as Retrain_{idea}). We can find that our method has better performance than

Retrain_{idea}. Besides, Fig. 16 shows our method can handle noise in real spike streams better than Retrain_{idea}.

Table 6. Evaluation results on LLR. We retrain our network where 20%, 40%, 60%, and 80% of RLLR data are used as training set respectively.

| Metric | 20% | 40% | 60% | 80% | 100% |
|--------|---------|---------|---------|---------|----------------|
| PSNR | 35.001 | 38.618 | 44.415 | 44.753 | 45.075 |
| SSIM | 0.93411 | 0.97113 | 0.98459 | 0.98581 | 0.98681 |

Train dataset size The size of train datasets has an impact on the performance of our network. A larger train dataset typically provides more samples and a wider range of variations. In fact, proposed RLLR is enough for the reconstruction task of low-light spike streams. As shown in Table. 6, we find that as the dataset size increase, the performance of the model also improve. However, it is observed that the improvement in performance becomes less significant after the dataset size reaches 60% of RLLR. It shows that the proposed RLLR is sufficient for training our network.

6. Conclusion

We propose a bidirectional recurrent-based reconstruction framework for spike camera to better handle different light conditions. In our framework, a light-robust representation (LR-Rep) is designed to aggregate temporal information in spike streams. Moreover, a fusion module is used to extract temporal features. To evaluate the performance of different methods in low-light high-speed scenes, we synthesize a reconstruction benchmark where light sources are carefully designed to be consistent with reality. The experiment on both synthetic data and real data shows the superiority of our method.

Limitation Due to the need to fuse both forward and backward temporal features, our method is offline, i.e., After spike camera collects spike streams for a long period of time, the data can be reconstructed. However, real-time applications may require spike stream reconstruction to be performed while the spike camera is capturing the scene. In future work, we plan to extend our method so to online reconstruct.

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