

# AE2VID: Event-based Video Reconstruction via Aperture Modulation

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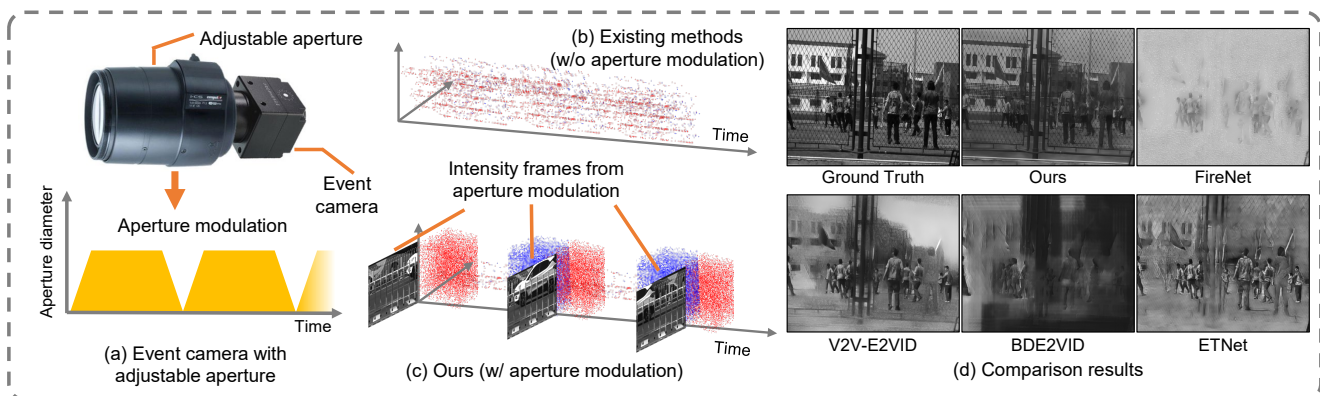


Figure 1. (a) We propose a framework that dynamically modulates the adjustable aperture of an event camera for video reconstruction. The aperture periodically opens and closes, injecting controlled illumination variations that encode scene information. (b) Existing methods operate without aperture modulation and thus rely solely on motion-triggered events, which are typically spatially sparse and provide little information about static regions. (c) Leveraging aperture modulation, our method reconstructs intermediate dense intensity frames, effectively complementing the sparse motion-triggered events to enhance fidelity. (d) The comparison results with FireNet [33], V2V-E2VID [26], BDE2VID [9], and ETNet [41]. Our method better preserves the static regions and overall scene structure than existing methods.

## Abstract

Event-based video reconstruction seeks to recover high-speed, high-dynamic-range videos from event streams. While existing approaches rely exclusively on motion-triggered events, these events are inherently sparse and primarily capture dynamic regions. Therefore, they often suffer from error accumulation and degraded quality in regions with few events. In this work, we introduce aperture-modulation-triggered events as a complementary mechanism to enrich the captured scene information. Specifically, we periodically modulate the aperture to actively generate dense event signals, thereby encoding intensity cues even in static or low-motion regions. Building upon this idea, we design an AE2VID framework that jointly leverages aperture-modulation-triggered and motion-triggered events to en-

hance the fidelity of predictions. The proposed framework consists of two subnetworks for the dedicated processing of both event types. We further collect a real dataset and validate the effectiveness of our method. Extensive experiments show our superiority over state-of-the-art methods. Code and data will be available at <https://github.com/alhenu/AE2VID/>.

## 1. Introduction

Event cameras [4] are bio-inspired sensors that capture high-speed, high-dynamic-range scene information [30, 31]. Unlike spike cameras [16, 43], another type of neuromorphic sensor that records scenes through temporal integration, event cameras directly measure intensity changes. As a practical way to bridge event cameras with off-the-shelf frame-based algorithms, event-to-video reconstruction has attracted increasing attention [9, 11, 46]. The reconstructed

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videos can benefit many downstream computer vision tasks, such as 3D reconstruction [12], object recognition [42], and instance segmentation [24].

Early methods for event-based video reconstruction attempted to use hand-crafted operations [27, 32]. With the development of deep learning, recurrent learning-based methods [30, 31, 33, 45] have become the mainstream choice. Recently, some methods have incorporated diffusion-based priors [44, 49] to enhance the perceptual quality. However, as motion-triggered events are usually sparsely distributed along the edges (Fig. 1 (b)), this task is still highly ill-posed. Despite the improvements in model capacity, problems such as prediction error accumulation and static regions could restrict their performance (the building in the background and chain-link fence in the foreground of Fig. 1 (d)).

In order to tackle the above problems, additional dense observation of the scene radiance is necessary. An intuitive approach is to incorporate an additional frame-based camera as a supplementary input to the network [20, 38]. However, this may cause spatial-temporal misalignments [7] and incur additional costs. Alternatively, active lighting could be used to modulate the intensity received by cameras [13]. Although they can provide dense information of the scene by triggering events on almost every pixel, it is infeasible in outdoor or uncontrolled environments. Besides, static background noisy events can be jointly modeled to achieve reconstruction [10], but such an approach may encounter bottlenecks in outdoor scenes due to the presence of non-discriminative noisy events. To robustly acquire dense observations of the scene with fewer additional costs, we introduce aperture shutters [1, 36] for light intensity modulation.

The aperture is a ubiquitous and easily controllable component of most imaging systems. By adjusting the aperture, we can modulate the irradiance at each pixel (Fig. 1(a)), thereby triggering events for dense predictions that complement the sparsity of motion-triggered events. These predictions facilitate static background reconstruction and mitigate error accumulation, effectively addressing the aforementioned challenges (Fig. 1 (c)). However, the aperture-modulated video reconstruction still faces two challenges: (1) Effectively integrating aperture-modulation-triggered and motion-triggered events, which differ in spatial density, necessitates the design of novel architectures and specialized training strategies. (2) Acquiring real data under our modulation strategy, which involves dynamically closing and reopening the aperture, requires a dedicated capture system.

In this paper, we propose an event-based video reconstruction framework, which combines aperture-modulation-triggered and motion-triggered events for more robust predictions. We observe that events triggered by aperture modulation can provide dense scene priors to assist video reconstruction. Additionally, we design a reconstruction framework capable of adaptively fusing events from both sources to

produce a continuous high-quality video. Furthermore, we design a modulation strategy consisting of periodically closing and reopening the aperture (Fig. 1(a)) to mitigate error accumulation. Finally, we employ our strategy on diverse scenes and construct a new real-world dataset for comprehensive evaluation. Overall, our contributions are:

- We are the first to introduce an aperture modulation strategy into event-based video reconstruction, which solves slow initialization and error accumulation problems in mainstream methods based on motion-triggered events.
- We design a framework named AE2VID consisting of two dedicated subnetworks AENet and MENet, which fuses the information from aperture-modulation-triggered and motion-triggered events in an efficient way, and outputs video frames with high speed and high dynamic range.
- We collect a real-world captured Aperture-modulation- and Motion-triggered Events Dataset (AMED), where we adopt our modulation strategy and specify several aperture control parameters. This dataset is utilized for evaluating the performance and inspiring future research.

Extensive experiments on both semi-real and real data show the superior background preservation ability and overall scene reconstruction quality of our approach.

## 2. Related work

### 2.1. Reconstruction with motion-triggered events

Early attempts for event-based video reconstruction employed extended Kalman filters through 2D Poisson integration [19]. Later, Bardow *et al.* [2] designed a variational energy minimization framework to simultaneously reconstruct video frames and optical flow. Scheerlinck *et al.* [32] proposed high-pass filters to process events and realized continuous video reconstruction. Recently, learning-based methods have made great breakthroughs in this task. Rebecq *et al.* [30, 31] proposed the first learning-based video reconstruction method, namely E2VID, which employs Recurrent Neural Networks (RNNs) to improve the quality of output frames. Scheerlinck *et al.* [33] replaced LSTMs with GRUs to get an efficient reconstruction network with much fewer parameters. Later, Weng *et al.* [41] introduced self-attention mechanisms and designed a Transformer for this task. Cadena *et al.* [5] employed spatially-adaptive denormalization (SPADE) layers and proposed SPADE-E2VID to improve the quality of reconstructed frames. SSL-E2VID [28] proposed a self-learning approach for this task to alleviate the dependence on labeled datasets. Zhu *et al.* [48] developed a novel framework based on spiking neural networks (SNNs) to achieve comparable performance with less energy consumption. More recently, Ercan *et al.* [8] introduced hypernetworks and dynamic convolutions to generate per-pixel adaptive filters that combine information from events and previously reconstructed images. Gao *et al.* [9]

proposed to leverage the bidirectional temporal information in event sequences for better predictions. Lou *et al.* [26] further proposed an efficient V2V training strategy to boost the performance of E2VID utilizing large training data. Zhu *et al.* [49] introduced diffusion models to leverage the prior from events. Despite great progress made by these methods, they lack the dense information of the scene due to the sparsity of motion-triggered events. In contrast, we combine aperture-modulation-triggered events to complement.

## 2.2. Reconstruction with intensity-triggered events

There are several works exploring the modulation of light intensity received by the sensor to trigger events. They can be divided into active lighting modulation and aperture modulation. Chen *et al.* [6] utilized the event streams triggered in the split second when the light is turned on for indoor lighting estimation and alleviated the problem of intensity-distance ambiguity. Han *et al.* [13] proposed the concept of transient event frequency (TEF) when the light is turned on, and achieved more accurate and stable estimations of irradiance values of the scene. Both of them need actively controlled lights, which are only practical in indoor circumstances. Bao *et al.* [1] proposed a temporal mapping photography for event cameras, where they employed Transmittance Adjustment Devices (such as aperture shutters) for brightness modulation, and employed the timestamp of the first positive event to reconstruct a dense intensity map. Later, they fused the estimated intensity map with low-light images and proposed a low-light image enhancement pipeline [36]. However, these methods only focused on static scenes and did not ensemble motion-triggered events for video reconstruction.

## 3. Method

In this section, we first formulate motion-triggered and aperture-modulation-triggered events in Sec. 3.1. Then we introduce our framework for video reconstruction with aperture modulation and its key components in Sec. 3.2. Our training details are illustrated in Sec. 3.3.

### 3.1. Formulation

**Motion-triggered events.** An event camera outputs a spatio-temporal stream of polarity changes. An event signal  $e = (t, \mathbf{r}, p)$  is triggered whenever the logarithmic irradiance changes exceed the preset threshold  $C$ :

$$\left| \log \frac{\mathbb{I}(\mathbf{r}, t) + I_{\text{dark}}}{\mathbb{I}(\mathbf{r}, t - \Delta t) + I_{\text{dark}}} \right| \geq C, \quad (1)$$

where  $\mathbb{I}(\mathbf{r}, t)$  and  $\mathbb{I}(\mathbf{r}, t - \Delta t)$  represents the pixel irradiance at pixel  $\mathbf{r}$  at time  $t$  and  $t - \Delta t$ , respectively. The polarity  $p \in \{+1, -1\}$  represents the direction of irradiance changes.  $I_{\text{dark}}$  is the dark-current term with stochastic fluctuations,

which is typically much smaller than the pixel irradiance under normal illumination.

Assume that the light conditions remain unchanged,  $\mathbb{I}(\mathbf{r}, t_0)$  is the irradiance at a reference timestamp  $t_0$ , and there are  $N_e$  events triggered at pixel  $\mathbf{r}$  between  $t_0$  and  $t$ . Then the irradiance at anytimestamp  $t$  can be derived as:

$$\mathbb{I}(\mathbf{r}, t) = \mathbb{I}(\mathbf{r}, t_0) \cdot \exp(\mathbf{S}(t_0, t)), \quad (2)$$

where

$$\mathbf{S}(t_0, t) = \begin{cases} C \cdot \sum_{n=1}^{N_e} p_n, & t > t_0, \\ \frac{1}{C \cdot \sum_{n=1}^{N_e} p_n}, & t < t_0. \end{cases} \quad (3)$$

Video reconstruction from pure motion-triggered events is an ill-posed problem as none of the reference irradiance  $\mathbb{I}(\mathbf{r}, t_0)$  is known throughout the capture process. Because the models can only infer relative irradiance changes, *i.e.*,  $\mathbf{S}(t_0, t)$  from the event stream, the static regions with no events triggered are hard to reconstruct.

**Aperture-modulation-triggered events.** When we open the aperture from zero, the contribution of the dark current in Eq. (1) will become non-negligible [1, 15]. We assume that the transmittance rate function of our aperture shutter is  $\text{TR}(t)$  whose value range is  $[0, 1]$ . Then the irradiance at pixel  $\mathbf{r}$  can be calculated as:

$$\mathbb{I}(\mathbf{r}, t) = \mathbb{I}_{\text{max}}(\mathbf{r}) \cdot \text{TR}(t), \quad (4)$$

where  $\mathbb{I}_{\text{max}}(\mathbf{r})$  is the irradiance when the transmittance is 1.

Based on Eq. (1), if we increase the transmittance from 0, *i.e.*,  $\text{TR}(0) = 0$ , the first positive event (FPE) triggered at pixel  $\mathbf{r}$  will occur at time  $t^*(\mathbf{r})$ , which satisfies:

$$\log \frac{\mathbb{I}_{\text{max}}(\mathbf{r}) \text{TR}(t^*(\mathbf{r})) + I_{\text{dark}}}{I_{\text{dark}}} = C. \quad (5)$$

Therefore, an inverse proportion relation between  $\mathbb{I}_{\text{max}}(\mathbf{r})$  and  $\text{TR}(t^*(\mathbf{r}))$  holds:

$$\mathbb{I}_{\text{max}}(\mathbf{r}) = \frac{(e^C - 1) \cdot I_{\text{dark}}}{\text{TR}(t^*(\mathbf{r}))} \propto \frac{1}{\text{TR}(t^*(\mathbf{r}))}. \quad (6)$$

Equation (6) indicates that we can use the aperture-modulation-triggered events to calculate the FPE timestamp  $t^*(\mathbf{r})$ , and then estimate the dense intensity map  $\mathbb{I}_{\text{max}}(\mathbf{r})$  for each pixel  $\mathbf{r}$  in the scene. These intermediate dense intensity maps can complement the motion-triggered events, serving as the reference  $\mathbb{I}(\mathbf{r}, t_0)$  in Eq. (2). Note that the above derivations are invalid for events triggered by aperture closure, as the initial pixel voltage is unknown [1, 36]. Therefore, the ‘‘aperture-modulation-triggered events’’ exclusively refer to events triggered by aperture opening and do not include those triggered by closing throughout this paper.

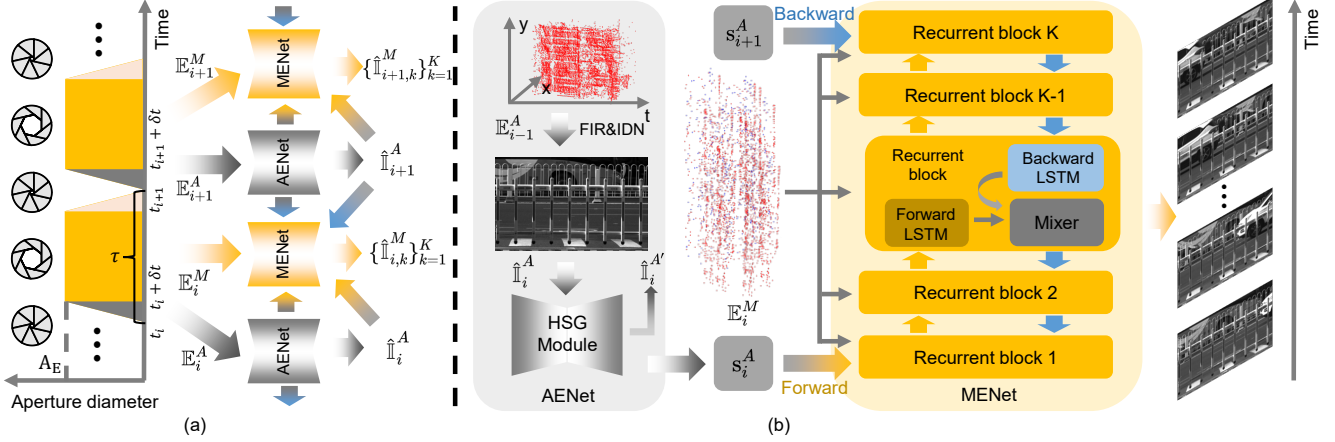


Figure 2. The overview of our AE2VID framework. (a) We periodically open the aperture to  $A_E$  with an interval  $\tau$ . Note that the proportion of  $\delta t$  and  $\tau$  does not reflect the actual values, as in practice we use a relatively small  $\delta t$  compared with  $\tau$  (Sec. 4.1).  $\mathbb{E}_i^A$  and  $\mathbb{E}_i^M$  are extracted from each time window  $[t_i, t_{i+1}]$ , and fed into AENet and MENet, respectively. AENet predicts dense references  $\hat{\mathbb{I}}_i^A$ , which are also fed into MENet for the frame sequence  $\{\hat{\mathbb{I}}_{i,k}^M\}_{k=1}^K$ . (b) The detailed architecture of AENet and MENet. AENet contains an FIR module for initial intensity prediction, an IDN module for denoising, and an HSG module that predicts a hidden state  $s_i^A$  using features extracted from the frame. MENet is a bidirectional network consisting of the recurrent block with bidirectional LSTMs and a pixel-wise mixer. It reconstructs frames from dense references, hidden states, and event streams.

### 3.2. AE2VID framework

According to Eq. (2), we may only need to open the aperture once at  $t_0$  to get a reference intensity map, and predict all the other frames with the motion-triggered events. However, we observe that as the temporal span increases, the predictions tend to exhibit larger errors at timestamps farther away from  $t_0$ . As shown in Fig. 2 (a), to alleviate the accumulation of prediction errors, we propose a periodic aperture closing and reopening mechanism that intermittently resets the observation window, thereby providing additional supervisory signals for more stable predictions.

Suppose that we open the aperture from zero at timestamps  $t_i, i = 0, \dots, N$ , with a globally equivalent interval  $\tau = t_{i+1} - t_i$ . Then we get  $N$  observation windows, each corresponding to time  $[t_i, t_{i+1}]$ . If each opening process takes time  $\delta t$ , the events triggered during one temporal window can be further split into aperture-modulation-triggered events  $\mathbb{E}_i^A$  for  $[t_i, t_i + \delta t]$ , motion-triggered events  $\mathbb{E}_i^M$  for  $[t_i + \delta t, t_{i+1} - \delta t]$ , and aperture-closing-triggered events  $\mathbb{E}_i^C$  for  $[t_{i+1} - \delta t, t_{i+1}]$ . Through our experiments, we find that  $\mathbb{E}_i^C$  are usually noisy and provide negligible information about the scene, neither conveying dense intensity details nor motion cues. Moreover, interpolation between frames can effectively compensate for the information missing during this interval. Therefore, we simply discard these events and concentrate on the first two categories.

As illustrated in Fig. 2 (b), to facilitate more effective use of dedicated modules for handling the two types of events, our whole pipeline includes two key components: Aperture-triggered Event Network (AENet) and Motion-

triggered Event Network (MENet). Based on Eq. (6), AENet takes  $\mathbb{E}_i^A$  as inputs, and outputs intermediate dense intensity predictions  $\hat{\mathbb{I}}_i^A$ . Additionally, to provide dense reference for MENet, AENet also outputs hidden states  $s_i^A$ . According to Eq. (2), MENet takes motion-triggered events  $\mathbb{E}_i^M$ , intensity predictions  $\hat{\mathbb{I}}_i^A$ , and hidden states  $s_i^A$  from AENet, and outputs a sequence of images  $\{\hat{\mathbb{I}}_{i,k}^M\}_{k=1}^K$  where  $K$  is the frame number of each sequence. They can be formulated as:

$$\begin{aligned} \hat{\mathbb{I}}_i^A, s_i^A &= \text{AENet}(\mathbb{E}_i^A), \\ \{\hat{\mathbb{I}}_{i,k}^M\}_{k=1}^K &= \text{MENet}(\mathbb{E}_i^M, s_i^A, s_{i+1}^A, \hat{\mathbb{I}}_i^A, \hat{\mathbb{I}}_{i+1}^A). \end{aligned} \quad (7)$$

**AENet.** The goal of AENet is to predict intermediate dense intensity maps and hidden states from aperture-modulation-triggered events. In order to fully exploit the information encoded in  $\mathbb{E}_i^A$ , our AENet consists of three modules: (1) FPE-based Intensity Reconstruction (FIR), (2) Image Denoising (IDN), and (3) Hidden State Generation (HSG).

In the FIR module, we first build a temporal matrix from the FPE of each pixel in  $\mathbb{E}_i^A$ . Subsequently, we reconstruct initial intensity images  $\hat{\mathbb{I}}_i^{FIR}$  based on Eq. (6). As the temporal matrix may contain much noise, we further employ a network to denoise the initial image into  $\hat{\mathbb{I}}_i^A$ .

We adopt SwinIR [22] as our denoising network, and employ the checkpoint pretrained by [1]. Since this checkpoint introduces an additional super-resolution effect, we further downsample the output to restore the original resolution.

To provide robust initialization and reference for MENet from  $\mathbb{E}_i^A$ , we further introduce the HSG module. For better feature alignments, we adopt the same structure as the for-

ward LSTM of MENet’s recurrent block for HSG module. Given the denoised frame  $\hat{\mathbb{I}}_i^A \in \mathbb{R}^{H \times W}$ , where  $(H, W)$  is the sensor resolution, we replicate it in channel axis for  $b$  times to form a frame voxel  $V_i^A \in \mathbb{R}^{b \times H \times W}$  where  $b$  in the number of bins for event voxels. The HSG module then produces the hidden state  $s_i^A$  from  $V_i^A$ . Besides, to better supervise the training of HSG, an additional pseudo-frame  $\hat{\mathbb{I}}_i^{A'}$  is also predicted, which can be formulated as:

$$\hat{\mathbb{I}}_i^{A'}, s_i^A = \text{HSG}(V_i^A). \quad (8)$$

**MENet.** For reconstructing temporally consistent frames from motion-triggered events and dense references provided by AENet, we propose a recurrent network MENet. The backbone of MENet is based on E2VID [30, 31], which employs convolutional LSTM [34] as the recurrent unit. While the majority of existing video reconstruction frameworks operate in a unidirectional fashion, we observe that the absence of backward temporal information notably impairs the fidelity of static background reconstruction under long-term temporal dependencies. To mitigate this issue, we propose a bidirectional pipeline that more effectively leverages temporal correlations in the event streams as well as guidance from AENet. Note that strictly speaking, the reference frames fed into MENet should be at timestamps  $t_i + \delta t$  and  $t_{i+1} - \delta t$  since  $\delta t > 0$ . However, as  $\delta t$  is relatively small compared with  $\tau$  (refer to Sec. 4.1), here we approximate  $\hat{\mathbb{I}}_i^A$  as the intensity at  $t_i + \delta t$  and  $\hat{\mathbb{I}}_{i+1}^A$  as the intensity at  $t_{i+1} - \delta t$ .

For each time window  $[t_i + \delta t, t_{i+1} - \delta t]$ , we run a forward process from the initial hidden state  $s_i^A$  and a backward process from the terminal hidden state  $s_{i+1}^A$ . Specifically, we first convert event stream  $\mathbb{E}_i^M$  into  $K + 1$  voxel grids  $\{V_{i,k}^M\}_{k=1}^{K+1}$ . In the forward run, we sequentially feed voxel grids  $V_{i,k}^M$  and hidden states from the previous iteration  $s_{i,k-1}^{M,\text{fwd}}$  into the recurrent block  $\mathcal{R}$ , which outputs forward predictions  $\hat{\mathbb{I}}_{i,k}^{M,\text{fwd}}$ . This can be formulated as:

$$\hat{\mathbb{I}}_{i,k}^{M,\text{fwd}}, s_{i,k}^{M,\text{fwd}} = \mathcal{R}(V_{i,k}^M, s_{i,k-1}^{M,\text{fwd}}), \quad (9)$$

where  $s_{i,0}^{M,\text{fwd}} = s_i^A, k = 1, 2, \dots, K$ .

In the backward run, we first reverse the events with the approach similar to [37]. Then we feed the reversed voxel grids in a backward manner, which is:

$$\hat{\mathbb{I}}_{i,k}^{M,\text{bwd}}, s_{i,k}^{M,\text{bwd}} = \mathcal{R}(\text{rev}(V_{i,k+1}^M), s_{i,k+1}^{M,\text{bwd}}), \quad (10)$$

where  $\text{rev}(\cdot)$  denotes the reverse operator for each voxel, and  $s_{i,K+1}^{M,\text{bwd}} = s_{i+1}^A$ .

To effectively utilize complementary information from both directions, we fuse forward and backward candidates  $\hat{\mathbb{I}}_{i,k}^{M,\text{fwd}}, \hat{\mathbb{I}}_{i,k}^{M,\text{bwd}}$ , and the reference frames  $\hat{\mathbb{I}}_i^A$  and  $\hat{\mathbb{I}}_{i+1}^A$  for each intermediate frame  $k$  with a lightweight pixel-wise

mixer  $\mathcal{M}$ . The mixer predicts a weight  $\alpha_{i,k} \in [0, 1]^{4 \times H \times W}$ :

$$\alpha_{i,k} = \text{softmax}(\mathcal{M}(\hat{\mathbb{I}}_{i,k}^{M,\text{fwd}}, \hat{\mathbb{I}}_{i,k}^{M,\text{bwd}}, \hat{\mathbb{I}}_i^A, \hat{\mathbb{I}}_{i+1}^A, V_{i,k}^M)). \quad (11)$$

Finally, we obtain the prediction by mixing the four items:

$$\begin{aligned} \hat{\mathbb{I}}_{i,k}^M &= \alpha_{i,k}^{(0)} \odot \hat{\mathbb{I}}_{i,k}^{M,\text{fwd}} + \alpha_{i,k}^{(1)} \odot \hat{\mathbb{I}}_{i,k}^{M,\text{bwd}} \\ &+ \alpha_{i,k}^{(2)} \odot \hat{\mathbb{I}}_i^A + \alpha_{i,k}^{(3)} \odot \hat{\mathbb{I}}_{i+1}^A, \end{aligned} \quad (12)$$

### 3.3. Training details

**Loss functions.** Because all observation windows share an identical processing pipeline, it suffices to apply the constraint to a single window. Accordingly, we omit subscripts  $i$  in loss functions. To supervise the HSG module to output feature-aligned hidden states, we first constrain the similarity between the pseudo frame  $\hat{\mathbb{I}}^{A'}$  output by HSG and the reconstructed frame  $\hat{\mathbb{I}}^A$  from events with an  $\ell_1$  loss  $\|\hat{\mathbb{I}}^{A'} - \hat{\mathbb{I}}^A\|_1$ . Additionally, for the quality of predicted image sequence  $\hat{\mathbb{I}}_k^M$ , we utilize a combination of  $\ell_1$  loss, VGG perceptual loss [18], and temporal consistency loss [21]. The first two loss functions are used for regularizing the fidelity between predicted frames  $\hat{\mathbb{I}}_k^M$  and ground truth  $\mathbb{I}_k^M$ :

$$\mathcal{L}_{\text{rec}}^k = \|\hat{\mathbb{I}}_k^M - \mathbb{I}_k^M\|_1 + d(\hat{\mathbb{I}}_k^M, \mathbb{I}_k^M), \quad (13)$$

where  $d(\cdot)$  denotes the LPIPS distance. The temporal consistency loss is for reducing the temporal artifacts. However, as we observe that this term may introduce dirty-window artifacts [26], only the latter half frames are applied. Thus, the final loss over  $K$  frames per window is:

$$\mathcal{L} = \|\hat{\mathbb{I}}^{A'} - \hat{\mathbb{I}}^A\|_1 + \sum_{k=0}^K \mathcal{L}_{\text{rec}}^k + \lambda_{\text{TC}} \sum_{k=L_0}^K \mathcal{L}_{\text{TC}}^k, \quad (14)$$

where we set  $K = 20, L_0 = 10$ , and  $\lambda_{\text{TC}} = 1$ .

**Training datasets.** Aligning with the previous method [30, 31], we employ the **synthetic dataset** generated by the event simulator ESIM [14], which contains 1,000 2-second sequences for training our framework. However, as their datasets only contain globally homographic motion, we find that solely training on these data leads to a lack of generality and unsatisfactory performance. In order to add to the motion diversity, we further synthesize our own training dataset with Blender [3], where we randomly select objects to move in the foreground, and wrap their surfaces with images sampled from the MS-COCO dataset [23]. The generated videos are further fed into ESIM to simulate events. Our newly synthesized dataset is composed of 500 1-second sequences, resulting in more than 40 minutes of training data in total.

**Implementation details.** Our framework is implemented using Pytorch [29] and runs on a single NVIDIA GeForce

RTX 4090 GPU. We choose AdamW [25] as the optimizer. We augment our training data using random 2D rotations ( $\pm 20^\circ$ ), horizontal and vertical flips, and random cropping ( $128 \times 128$ ). The input events for MENet are transformed into voxel grids with  $b = 5$  bins. We initialize the weights of both the HSG module and the recurrent block of MENet with the pretrained checkpoint of V2V-E2VID [26]. The training is conducted in two stages. In the first stage, we freeze MENet and finetune the HSG module for 10 epochs with a batch size of 4 to enforce the hidden states output by HSG to align with MENet. In the second stage, we finetune the whole framework for 10 epochs with a batch size of 4. For each training stage, we adopt a cosine learning rate decay strategy with an initial learning rate of  $10^{-5}$  and a minimum learning rate of  $10^{-7}$ . An additional gamma correction with parameter 1.2 is further applied for each predicted frame.

## 4. Experiments

In this section, we first introduce our real data capture process in Sec. 4.1. The experimental settings, including datasets, compared methods, and metrics, are elaborated in Sec. 4.2. Then we provide quantitative comparison results in Sec. 4.3, and illustrate qualitative comparisons in Sec. 4.4. Ablation studies including the advantage of bidirectional pipeline, two-stage training scheme, and the structure of AENet can be found in the supplementary material.

### 4.1. Aperture modulation real data capture

We capture a real Aperture-modulation-triggered and Motion-triggered Events Dataset (AMED) with the aperture modulation system shown in Fig. 1 (a). The system contains a Prophesee EVK4 event camera with resolution  $1280 \times 720$  and a Computar LensConnect BH Series Variable Focal Length Lens<sup>1</sup> as the aperture shutter. The aperture of this lens can be modulated with a motorized module according to the predefined curves in the software.

To obtain higher-quality videos through aperture modulation in the real world, several critical aperture control parameters must be configured. Firstly, the time of the aperture opening process  $\delta t$  is determined jointly by the final aperture position  $A_E$  and the aperture speed  $v_A$ . Our experiments reveal that an excessively large  $A_E$  or a slow  $v_A$  prolongs the opening process, causing motion cue degradation and temporal discontinuities across frames. Conversely, when  $A_E$  is too small, some pixels fail to trigger FPE, while an overly fast  $v_A$  may produce an excessive event rate beyond the sensor’s handling capacity, impairing the fidelity of predicted  $\hat{I}_i^A$ . Secondly, the interval between two consecutive opening processes  $\tau$  also plays a crucial role. A large  $\tau$  may lead to prediction errors accumulating in  $\hat{I}_{i,k}^M$ ,

<sup>1</sup><https://www.edmundoptics.cn/p/9---50mm-lensconnect-bh-series-variable-focal-length-lens/53086/>

Table 1. Quantitative comparisons of event-based video reconstruction on EvAid [7].  $\uparrow$  ( $\downarrow$ ) indicates the higher (lower), the better performance. The best performances are highlighted in **bold**, and the second best in underline.

Method	MSE $\downarrow$	SSIM $\uparrow$	MS-SSIM $\uparrow$	LPIPS $\downarrow$
E2VID [30, 31]	0.227	0.471	0.345	0.639
FireNet [33]	0.160	0.493	0.350	0.608
ETNet [41]	<u>0.051</u>	0.602	0.457	0.486
SPADE-E2VID [5]	0.126	0.508	0.335	0.623
PAEVSNN [48]	0.123	0.511	0.301	0.624
BDE2VID [9]	0.079	0.571	0.321	0.583
V2V-E2VID [26]	0.052	<u>0.642</u>	<u>0.524</u>	<b>0.409</b>
Ours	<b>0.037</b>	<b>0.707</b>	<b>0.544</b>	<u>0.411</u>

whereas an overly small  $\tau$  may destabilize the system and cause excessive information loss during aperture transitions.

After extensive experiments, we find a set of empirical parameters in our data capture process, where we set  $A_E$  as  $1/4$  of the largest aperture,  $\delta t$  as an average of 0.13 seconds,  $\tau - 2\delta t$  as 5 seconds. Besides, data with other parameter values are also collected to add diversity. Detailed discussions on these parameters can be found in supplementary material.

### 4.2. Experimental settings

**Evaluation datasets.** Our evaluation experiments are conducted in two parts. Firstly, we construct **semi-real datasets** based on a recent event-based vision benchmark EvAid [7] with diverse motion patterns and a commonly used dataset HQF [35] for quantitative and qualitative comparisons. To keep consistency with real data, we select each 5 seconds of a sequence as a time window. Within each window, the first frame is seen as captured by aperture opening, while the last corresponds to aperture closing. As both datasets only contain motion-triggered events, we synthesize each  $\hat{I}_i^{FIR}$  obtained by aperture opening based on the degradation model proposed by [1]. Note that the simulation process replaces only the FIR module, and the synthesized frame will be further fed into the IDN module for denoising. The last frame is discarded following the procedure described in Sec. 3.2. After processing each sequence, we interpolate the missing frames with neighboring ones using RIFE [17]. In contrast, the compared methods directly use motion-triggered events from the datasets as their inputs. Secondly, we evaluate the performance on our **real-captured AMED dataset**. As we do not capture ground truth images, only qualitative comparisons are conducted in the paper.

**Compared methods.** To prove the effectiveness of our method, we compare our framework with seven state-of-the-art event-based video reconstruction methods, consisting of E2VID [30, 31], FireNet [33], ETNet [41], SPADE-E2VID [5], PAEVSNN [48], BDE2VID [9], and V2V-E2VID [26]. For all the compared methods, we use their officially released codes and pretrained checkpoints.

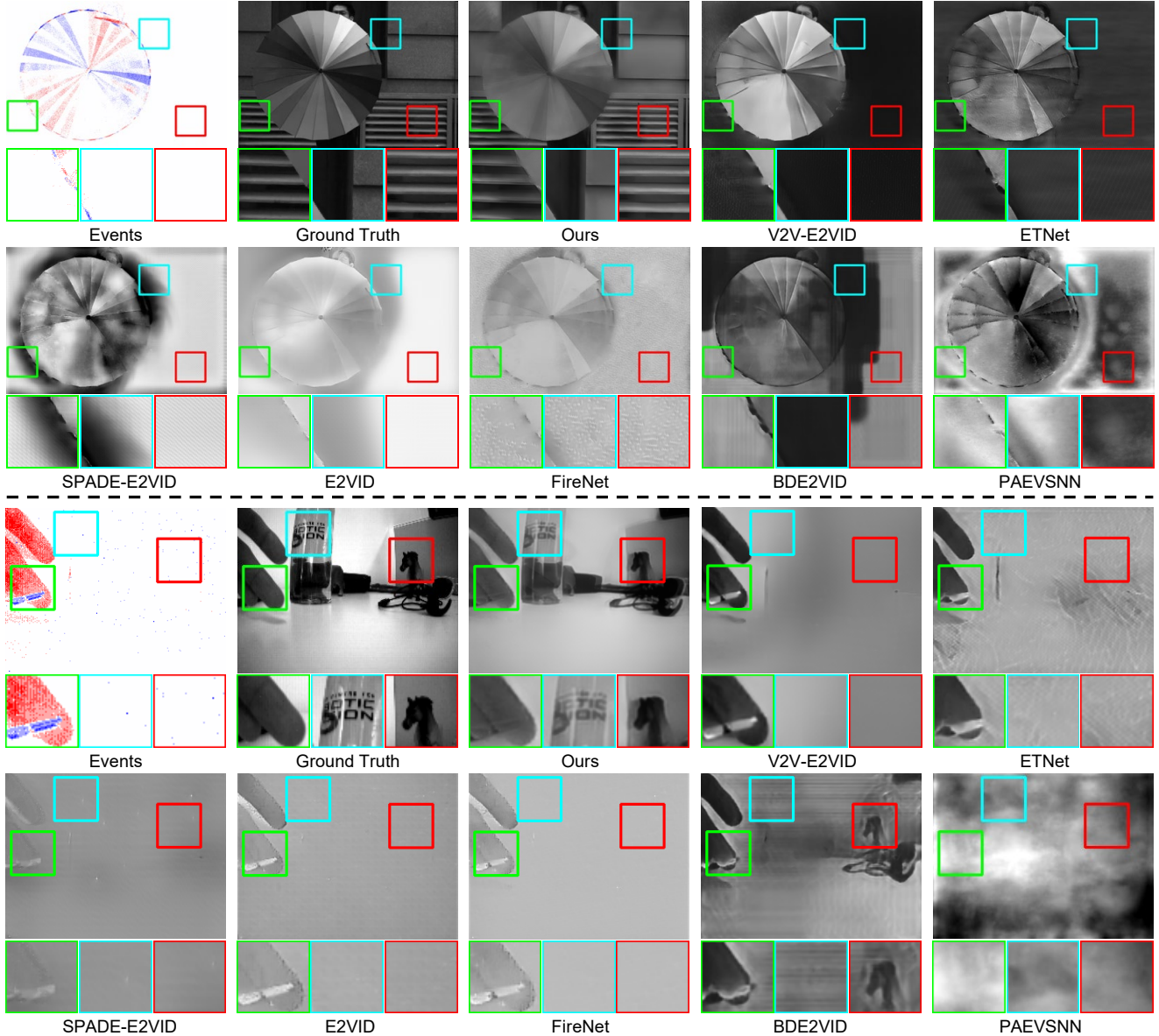


Figure 3. Qualitative experiment results on EvAid [7] and HQF [35]. The top two rows correspond to EvAid and the bottom are HQF. We compare with V2V-E2VID [26], ETNet [41], SPADE-E2VID [5], E2VID [30, 31], FireNet [33], BDE2VID [9], and PAEVSNN [48].

**Metrics.** To assess the quality of predictions, 4 commonly used metrics are adopted, including Mean Squared

Error (MSE), Structural Similarity (SSIM) [40], Multi-Scale Structural Similarity (MS-SSIM) [39], and Perceptual Loss (LPIPS) [47]. For consistency, the calculation strategy is the same as the previous methods [26].

Table 2. Quantitative comparisons on HQF [35].

Method	MSE↓	SSIM↑	MS-SSIM↑	LPIPS↓
E2VID [30, 31]	0.187	0.475	0.325	0.511
FireNet [33]	0.096	0.520	0.387	0.456
ETNet [41]	0.043	<u>0.529</u>	0.458	<u>0.294</u>
SPADE-E2VID [5]	0.072	0.480	0.289	0.487
PAEVSNN [48]	0.098	0.496	0.371	0.484
BDE2VID [9]	0.041	0.523	<u>0.477</u>	<b>0.272</b>
Ours	<b>0.039</b>	<b>0.585</b>	<b>0.503</b>	0.352

### 4.3. Quantitative results

Quantitative results on EvAid [7] and HQF [35] datasets are shown in Table 1 and Table 2, respectively. It can be observed that our method achieves almost the best in all metrics. Specifically, we achieve more than 27.4% improvements in MSE on EvAid compared with state-of-the-art methods, demonstrating the robustness of our method across diverse

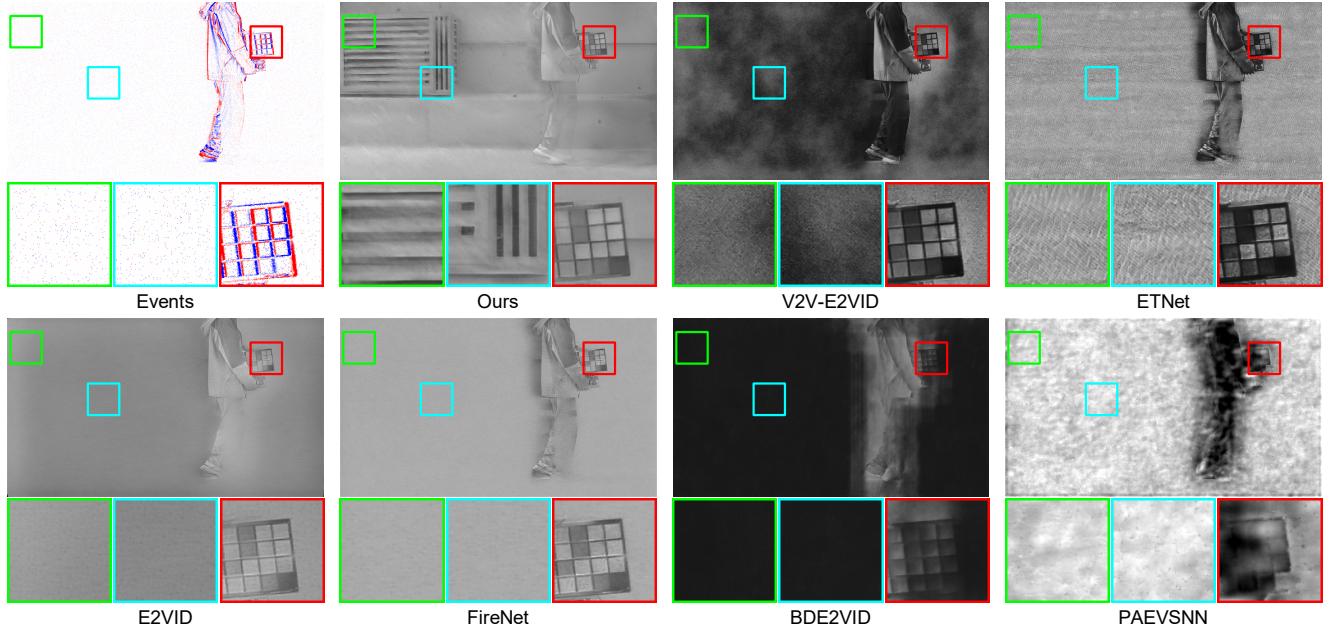


Figure 4. Qualitative experiment results on our AMED dataset with corresponding input motion-triggered events. We compare with V2V-E2VID [26], ETNet [41], E2VID [30, 31], FireNet [33], BDE2VID [9], and PAEVSNN [48].

scenarios. Although the performance increase on HQF is relatively smaller as it mainly contains global motion scenes, it also shows the effectiveness of the proposed strategy.

#### 4.4. Qualitative results

Qualitative comparisons on EvAid [7] and HQF [35] are shown in Fig. 3. Our method consistently yields superior reconstructions of backgrounds compared with others, particularly in scenes with dominant local motion. For instance, the wall in the first group and the bottle in the second group are faithfully reconstructed by our method, whereas compared methods fail due to sparsity of motion-triggered events.

Furthermore, we validate the effectiveness of our method in real-world scenarios using our AMED dataset. The qualitative comparison results on AMED are presented in Fig. 4. Our method preserves the most detailed background structures while simultaneously maintaining accurate intensity information in the foreground. For example, the wall and objects in the background are best preserved by our method compared with others. Besides, we also reconstruct the details of the colorchecker with high fidelity. More qualitative results can be found in the supplementary material.

### 5. Conclusion

In this paper, we propose to leverage aperture-modulation-triggered events to assist event-based video reconstruction. Since motion-triggered events are usually spatially sparse, we observe that aperture modulation can provide complementary dense information about the scene. Building on

this insight, we design an AE2VID framework composed of AENet and MENet for the dedicated processing of events triggered by these two sources. Furthermore, we capture a real-world AMED dataset using our modulation strategy for evaluation. Both quantitative and qualitative results demonstrate the effectiveness and superiority of our method.

**Limitations.** Due to our current hardware implementation limitations, we can only specify one fixed set of parameters, including  $A_E$ ,  $v_A$  and  $\tau$ , for each capturing process, which constrains the flexibility of the current prototype. However, when dealing with complex intensity variations and high-speed scenarios in real world, dynamically adjusting these parameters according to changes in lighting conditions and motion speeds may lead to better performance. Besides, challenging scenarios such as high-speed motion and extremely low illumination could degrade the reconstruction quality of our method. We will work on improving the adaptivity and robustness of our system in the future.

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