

## 240FPS Stereo Vision from Monocular Mixed Spikes

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### Abstract

Stereo vision is fundamental for enabling machines to perceive and interact with the world. While monocular stereo methods offer hardware compactness, they struggle with generalization due to reliance on data-driven priors. Binocular and multi-view systems improve accuracy but incur higher hardware complexity and data inefficiency. In this paper, we introduce a monocular solution for high-frame-rate stereo vision via temporal optical modulation. The modulation directs light from two views onto a single sensor in a mixed manner, while periodically attenuating one view at 60 Hz. To capture the temporal variations introduced by this modulation, we employ a high-speed spike camera that records the mixed scene as temporally dense spikes. The high temporal resolution of these spikes enables the construction of a linear system for efficient binocular video decoupling. Consequently, we introduce a two-stage decoding methodology for achieving high-quality stereo vision: An efficient least-squares-based baseline reconstruction followed by a deep learning refinement module. Experimental results demonstrate that our approach achieves 240FPS binocular video reconstruction with superior accuracy compared to monocular systems, while maintaining the hardware compactness and data efficiency. Code is available at <https://github.com/yongqiye00/MonoSpikeStereo>.

### 1. Introduction

Stereo vision serves as a fundamental technology for enabling machine interaction with the world. In many high-level computer vision tasks, such as detection [16] and tracking [22], stereo vision provides more fine-grained scene understanding capabilities. Existing stereo vision systems can be categorized into monocular [1, 25, 31],

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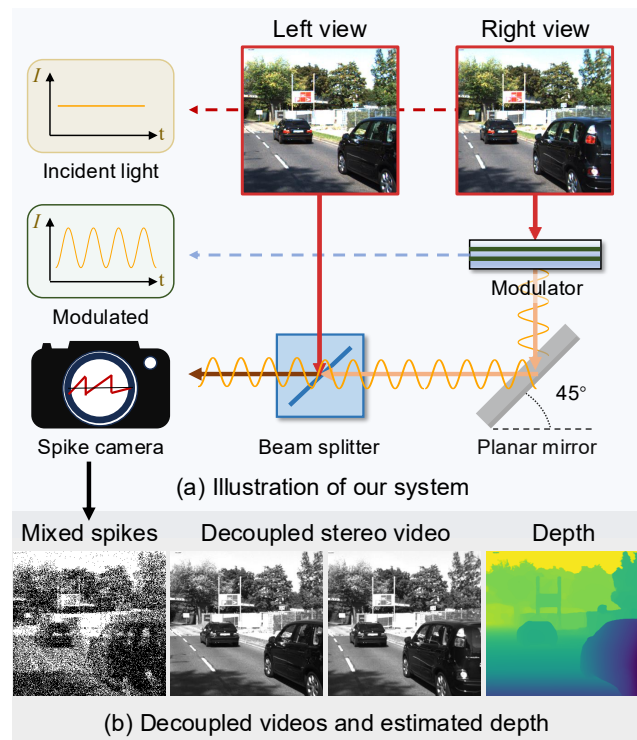


Figure 1. We propose a monocular solution capable of producing 240FPS stereo video. (a) Our optical setup mixes light from two views onto a single spike camera via a beam splitter. While one view remains unmodulated, the other view passes through an LCD modulator whose transmittance varies periodically. (b) We decouple binocular video from mixed spikes and feed the reconstructed stereo pair into an off-the-shelf stereo matcher (e.g., DEFOM-Stereo [13]) to estimate depth.

binocular [30, 36], and multi-view [21, 33] configurations. Monocular systems [1, 25, 31] offer advantages in hardware compactness. However, their generalization to unseen scenarios remains limited as they rely heavily on data-driven priors. In contrast, binocular and multi-view

systems [21, 30] typically employ two or more cameras to enhance accuracy. However, this performance advantage comes at the cost of increased hardware complexity. Moreover, in many high-speed scenarios such as competitive sports, autonomous driving, and aerospace applications [9, 11, 27], the demand for high frame rates in these systems adversely affects data efficiency.

To simultaneously achieve accuracy, hardware compactness, and data efficiency, one line of research utilizes two or more planar mirrors to project multiple views onto separate sub-regions of a single sensor [5, 10, 18]. In these *spatial optical modulations*, the captured sub-images are then geometrically corrected through epipolar rectification to obtain binocular video. However, epipolar rectification relies on planar scene assumptions, which may lead to geometric distortion and degraded accuracy. Therefore, another line of research projects incident light from two views onto the same sensor in a mixed manner [20]. Although this optical modulation avoids geometric distortions, decoupling binocular videos from the mixed signal still relies on a global consideration of limited disparity. For mixed signals from two views, if we introduce *temporal optical modulation* to one view, the variations will provide strong cues for effectively decoupling binocular videos. However, implementing temporal modulation requires the camera to operate at a sufficiently high speed. Given the limited frame rate of conventional digital cameras, a high-speed and data-efficient camera is highly desirable.

Recently developed spike cameras [3, 4, 12] offer readout frequencies of up to 40,000 Hz and output 1-bit data. Such characteristics make them ideally suited for our application requirements. Therefore, as shown in Fig. 1(a), we construct a temporally modulated stereo system using a monocular spike camera. In our system, incident light from one view is reflected by the mirror and optically mixed with the other view through the beam splitter. To facilitate binocular video decoupling, we maintain one view without modulation while periodically attenuating the other view at 60 Hz using an LCD modulator. Compared to existing stereo systems employing two spike cameras [14, 29], our monocular setup offers more compact hardware and efficient data.

Benefiting from the temporal optical modulation applied to one view, binocular video decoupling from mixed spikes becomes more tractable. To enable an efficient and fast solution, we initially consider that motions across consecutive frames are negligible for the high-speed spike camera. This consideration allows us to construct a linear system where the decoupling problem can be efficiently solved through least-squares optimization. For each modulation period, we decouple 4 pairs of binocular frames, thereby achieving a baseline binocular video at 240FPS<sup>1</sup>. These baseline results

<sup>1</sup>We drive the LCD modulator at 60 Hz in our current prototype; higher frame rates are possible with faster modulators.

can be further refined through a learning-based module to eliminate residual artifacts induced by motions. We refer to this learning-based refinement module as SMS-Net, as our goal is Stereo vision from Mixed Spikes. SMS-Net is a fully end-to-end deep learning framework that refines the results through multi-scale feature fusion and temporal integration. Furthermore, we introduce a cross-view attention mechanism [6] to effectively exploit complementary information between the two views at multiple feature scales, enabling accurate and high-quality reconstruction. To validate the quality of the decoupled binocular videos, we apply them to depth estimation (Fig. 1(b)). Experimental results show that our method outperforms monocular approaches in accuracy, while maintaining the data efficiency and hardware compactness. The main contributions of this work are summarized as follows:

- a monocular solution for 240FPS binocular video reconstruction through mixed-spike decoupling;
- an SMS-Net that enables robust binocular video decoupling, which is validated on depth estimation; and
- a corresponding hardware platform that enables real-world data for testing, along with a data simulator for training.

## 2. Related work

**Monocular stereo with mirrors.** Monocular stereo vision systems commonly rely on optical modulation to capture light from multiple viewpoints [5, 10, 18]. Over the past decades, numerous such systems have been proposed. Early approaches, such as the motor-driven mirror assembly by Teoh and Zhang [24] and the rotating glass plate by Nishimoto and Shirai [19], exploit mechanical movement to acquire stereo image pairs. However, these pioneering methods are primarily suitable for static scenes due to their inherent mechanical constraints. Another line of research utilizes two or more planar mirrors to project multiple viewpoints onto separate sub-regions of a single sensor. Nene and Nayar [18] propose four stereo systems that use a single camera, establishing the practical viability of this approach. Their work is formalized by Gluckman and Nayar [10], who detail the epipolar geometry and calibration for catadioptric stereo with planar mirrors. A common requirement for these mirror-based systems is geometric correction. In contrast, Pachidis and Lygouras [20] introduce a method that projects light from two viewpoints onto the sensor in a mixed manner, thereby avoiding geometric distortions at the cost of requiring subsequent separation. Compared with existing monocular stereo vision with mirrors, the LCD modulator in our approach introduces more temporal information for binocular video reconstruction.

**Stereo vision from spikes.** Spike cameras have been widely used in many computer vision tasks [3, 34, 35] including stereo vision. Zhang *et al.* [32] demonstrate the fea-

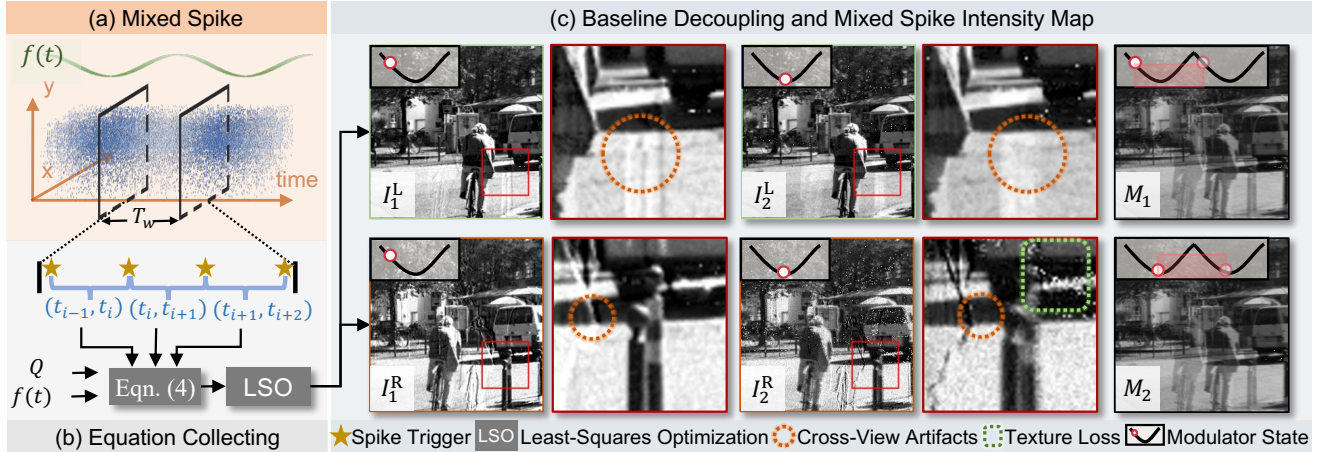


Figure 2. (a) Mixed spikes are sliced by a sliding window of length  $T_w$ . (b) We collect all spikes triggered within  $T_w$  to construct a linear system (Eqn. (4)), which is then solved using the least-squares optimization (LSO). (c) Baseline decoupling results reveal brightness inconsistency, residual cross-view artifacts, and texture loss in the right view. The mixed spike intensity maps  $M_t$  ( $t = 1, 2$ ) reconstructed by accumulating all spikes during a modulation period can serve as brightness-consistency guidance.

sibility of estimating depth directly from continuous spikes captured with a monocular camera. However, in regions with low texture or repeated patterns, monocular cues such as shading or perspective are insufficient to disambiguate depth. For spike-based stereo vision, constructing a binocular system is a straightforward solution [14, 29]. Li *et al.* [14] propose a dual-task depth estimation framework with joint training and uncertainty-guided fusion to combine monocular and stereo cues. Wang *et al.* [29] develop a hybrid stereo camera platform and introduce a corresponding dataset, along with a transformer-based network for dense depth prediction. Gao *et al.* [8] employ raw dual-view spike streams and iteratively refine depth estimation using a recurrent spiking neural network. However, these approaches rely on multiple cameras, which inevitably increase hardware complexity and system cost. In contrast, our monocular spike camera integrated with a temporal modulator achieves competitive performance while significantly reducing system integration complexity.

### 3. Method

**Overview.** We present a two-stage framework for achieving stereo vision using a monocular spike camera equipped with temporal optical modulation. This modulation introduces temporal inconsistency in one view within the captured mixed spikes, which serves as strong guidance for decoupling binocular videos. In the first stage (Sec. 3.1), we find that the spikes are temporally dense, which permits the consideration that motion within several adjacent frames is negligible. This consideration allows us to formulate a linear system and perform fast baseline decoupling by using least-squares optimization. In Sec. 3.2, to remove residual artifacts in the baseline decoupling results and compensate for texture loss caused by optical modulation, we design a

learning-based refinement module, *i.e.*, SMS-Net, to effectively remove these artifacts and restore fine details. Finally, in Sec. 3.3, we describe details of our dataset.

#### 3.1. Baseline decoupling

**Imaging model of mixed spikes.** The pixels in a spike sensor operate asynchronously. Each pixel continuously integrates photo-generated electrons and triggers a spike of 1 when the accumulated electrons reach a threshold  $Q$ , after which the electrons are cleared. Due to the discrete sampling strategy, a discrepancy ( $\Delta Q$ ) may exist between the true number of accumulated electrons and the computed value. Therefore, the accumulated electrons are

$$Q(x, y) + \Delta Q(x, y) = \int_{t_{i-1}}^{t_i} \alpha(x, y) I(t, x, y) dt, \quad (1)$$

where  $t_i$  denotes the timestamp of the  $i$ -th detected spike,  $\alpha$  is the photoelectric conversion coefficient,  $I$  is the light intensity, and  $(x, y)$  is spatial coordinates. When we add temporal optical modulation, the incident light intensity is a mixture of two views. Omitting spatial coordinates  $(x, y)$  for brevity, the imaging model becomes:

$$Q + \Delta Q = \int_{t_{i-1}}^{t_i} \alpha [I^L(t) + I^R(t) f(t)] dt, \quad (2)$$

where  $I^L(t)$  and  $I^R(t)$  denote the light from two views, and  $f(t)$  (see Fig. 2(a)) is the temporal modulation.

**Decoupling with least-squares optimization.** When observing the accumulated electrons (*i.e.*, spikes) within a temporal window  $T_w$ , from Eqn. (2) we note that both  $I^L(t)$  and  $I^R(t)$  are unknown quantities. Under the assumption that motion is negligible between adjacent time windows for temporally dense spikes, we can construct a linear

system. The temporal variation of  $f(t)$  guarantees that the observations across different intervals are linearly independent, rendering the system well-posed for decoupling. The linear system can be expressed as

$$Q + \Delta Q_i = \int_{t_{i-1}}^{t_i} \mathcal{G}(t) dt, \quad i = 1, \dots, n, \quad (3)$$

where  $\mathcal{G}(t) = \alpha[I^L(t) + I^R(t)f(t)]$ . Since motions are negligible, light intensities across adjacent time windows can be approximated as constants, *i.e.*,  $I^L(t) \approx I^L$ ,  $I^R(t) \approx I^R$ . Let  $\eta_i = \Delta Q_i + \epsilon_i$  denote a composite error term, where  $\epsilon_i$  arises from residual intensity inconsistency. Substituting these into the preceding formulation leads to:

$$Q + \eta_i = \alpha(I^L \Delta t_i + I^R F_i), \quad i = 1, \dots, n, \quad (4)$$

where  $\Delta t_i = t_i - t_{i-1}$  and  $F_i = \int_{t_{i-1}}^{t_i} f(t) dt$ . Thus, for each pixel in each window, we construct a linear system where  $Q, f(t), \alpha$  and  $\{t_i | i \in [0, n]\}$  are known, and the unknown quantities are  $I^L$  and  $I^R$ . The unknowns  $I^L$  and  $I^R$  are estimated via least-squares optimization:

$$\min_{I^L, I^R} \sum_{i=1}^n (Q - \alpha [I^L \Delta t_i + I^R F_i])^2. \quad (5)$$

To ensure numerical stability, we augment the objective with an  $\ell_2$  regularization term  $\lambda((I^L)^2 + (I^R)^2)$ , with  $\lambda = 1 \times 10^{-3}$  fixed across all experiments. The above process is shown in Fig. 2(b).

**Strengths and potential refinements.** The baseline decoupling method offers low computational complexity and achieves fast execution speed. When tested on a device equipped with an Intel® Core™ i9-13900KF, the average time for constructing the linear system is 0.093s, and the time for solving the least-squares optimization is only 0.0151s. This demonstrates that although our baseline method may not yet achieve real-time performance at hundreds of frames per second, it is fully capable of supporting real-time video decoupling in daily scenarios. However, as shown in Fig. 2(c), under the assumption that motions are negligible, the baseline solution may suffer from: (1) inconsistent brightness distributions across consecutive frames; (2) cross-view residual artifacts remaining in the two-view results; (3) and texture loss for the modulated view. To address these issues, we further utilize a learning-based method to refine the decoupling results and obtain high-quality binocular videos.

### 3.2. Refinement with SMS-Net

Since deep learning has shown strong capabilities in computer vision, we adopt a learning-based refinement network to improve the baseline and recover high-quality stereo videos. Since our network refines binocular videos from

Mixed Spikes, we name the proposed architecture SMS-Net. As shown in Fig. 3, the SMS-Net consists of three modules: (1) an Adaptive Brightness Consistency (ABC) module that utilizes the intensity map reconstructed from mixed spikes over one modulation period  $T_f$  to remove temporal inconsistency; (2) a Collaborative Binocular Augment (CBA) module that employs cross-attention on two views to remove residual artifacts; (3) and a Recurrent Stereo Fusion (RSF) module that fuses the temporal information of historical frames to compensate for texture loss.

**ABC module.** Although brightness inconsistency is introduced by the optical modulation, its periodic nature ensures that these artifacts cancel out when the reconstruction window spans an integer multiple of the modulation period  $T_f$ . Therefore, as shown in the last column of Fig. 2(c), we construct a brightness consistency guidance by integrating spikes over one full modulation cycle:

$$M_t = \frac{Q}{T_f} \sum_{k: t_k \in (t - T_f, t]} 1. \quad (6)$$

The ABC module first extracts multi-scale features from the baseline decoupled video frames and  $M_t$ , denoted as  $\mathbf{F}_t^L, \mathbf{F}_t^R$ , and  $\mathbf{F}_t^M$ , respectively. Specifically, for each scale, we align the features of the left and right views independently using  $\mathbf{F}_t^M$  as a shared reference. To align the left-view features  $\mathbf{F}_t^L$ , we first compute the global channel-wise mean and standard deviation from both  $\mathbf{F}_t^L$  and  $\mathbf{F}_t^M$ . These concatenated statistics are fed into a lightweight prediction network of two  $1 \times 1$  convolutional layers to generate a scaling factor  $\gamma_t^L$  and  $\beta_t^L$ . The alignment is then formulated as  $\bar{\mathbf{F}}_t^L = \gamma_t^L \cdot \mathbf{F}_t^L + \beta_t^L$ . The same procedure is applied to the right-view features  $\mathbf{F}_t^R$  to obtain  $\bar{\mathbf{F}}_t^R$ .

**CBA module.** As shown in the regions marked by red circles in Fig. 2(c), residual artifacts manifest differently across views. In  $I_1^L$  the residual edges of the guardrail appear to the right of the pedestrian, whereas in  $I_1^R$  the residual edges appear to his left. This spatial inconsistency of residual artifacts provides crucial guidance for the refinement. Building on this observation, we design the CBA module that leverages a cross-attention mechanism to enable information interaction between the two views, thereby removing residual artifacts. At each feature scale, we adopt the Stereo Cross-Attention Module (SCAM) [6], which computes attention along corresponding epipolar lines to obtain complementary information between two views. Integrating SCAM into the CBA allows the network to leverage cross-view consistency and suppress residual artifacts. The output features are denoted as  $\bar{\mathbf{F}}_t^L, \bar{\mathbf{F}}_t^R$ .

**RSF module.** The RSF module (details in Fig. 4) is designed to compensate for texture degradation caused by low-transmittance phases of the LCD modulator through temporal fusion. Since we use a recurrent architecture, RSF takes  $\bar{\mathbf{F}}_t^L, \bar{\mathbf{F}}_t^R$ , and the hidden states from previous time

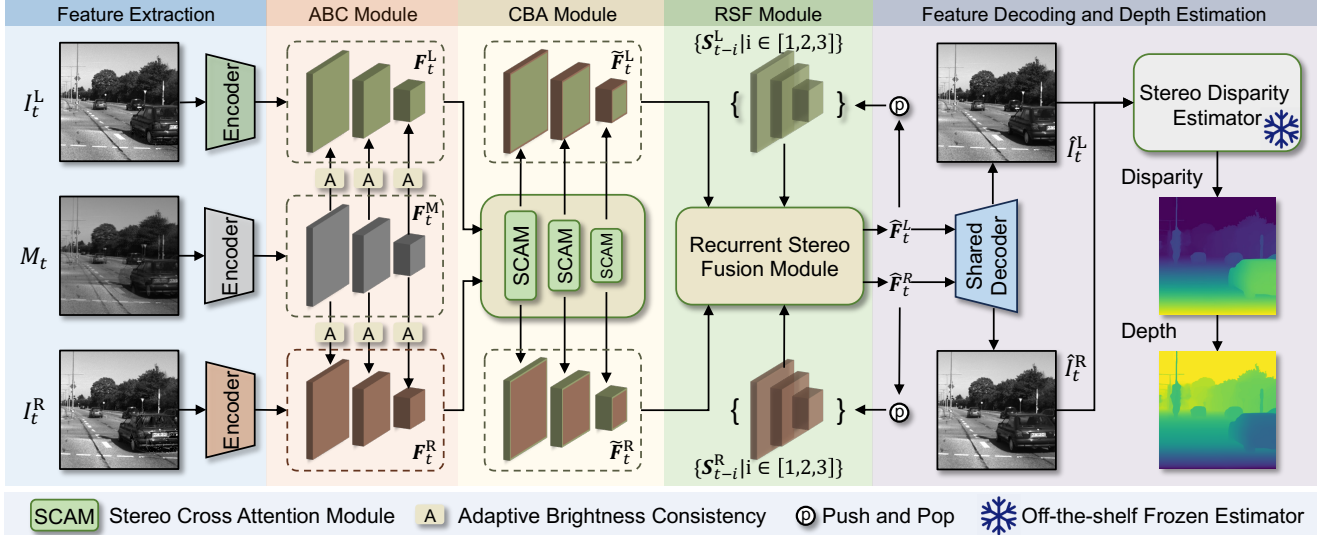


Figure 3. Overview of SMS-Net. At time  $t$ , the two-view images  $\{I_t^L, I_t^R\}$  and brightness consistency guidance  $M_t$  are encoded into multi-scale features. We design an Adaptive Brightness Consistency (ABC) module to remove temporal inconsistency, a Collaborative Binocular Augment (CBA) module to suppress cross-view residual artifacts, and a Recurrent Stereo Fusion (RSF) module that aggregates temporal and cross-view cues and maintains a state queue. The outputs follow two paths: Push and Pop update the queue, a shared decoder produces refined stereo pair  $\hat{I}_t^L$  and  $\hat{I}_t^R$ . We evaluate the reconstructed stereo video via downstream depth estimation using off-the-shelf stereo matchers (e.g., DEFOM-Stereo [13] or CREStereo [15]).

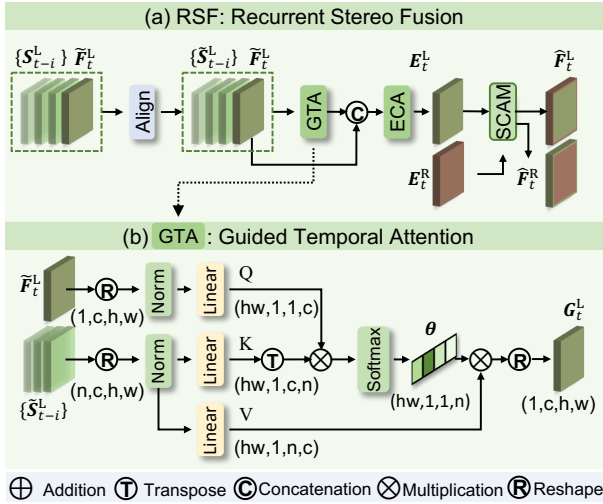


Figure 4. Architectures of (a) the Recurrent Stereo Fusion (RSF) module and (b) the Guided Temporal Attention (GTA) block.

steps  $\{S_{t-i}^L, S_{t-i}^R\}$  as inputs. To achieve spatial alignment between current and historical states, the RSF module first learns spatial offsets  $\Delta$  and modulation masks  $m$ . These learned parameters are then fed to deformable convolution to align historical features with the current timestep:

$$\tilde{S}_{t-i}^L = \text{DeformConv}(S_{t-i}^L, \Delta, m). \quad (7)$$

Subsequently, we fuse the aligned historical states  $\{\tilde{S}_{\tau}^L\}_{\tau=t-\ell}^{t-1}$  with the current feature  $\tilde{F}_t^L$  via Guided Temporal Attention (GTA). Specifically, for each spatial location  $p$ , after layer normalization  $\mathcal{N}(\cdot)$  and  $1 \times 1$  projections

$W_q, W_k, W_v$ , we can obtain the query  $\mathbf{Q}_p$ , key  $\mathbf{K}_p$  and the value  $\mathbf{V}_p$ . Next, we obtain the attention weights:

$$\theta_p = \text{softmax}\left(\frac{\mathbf{Q}_p \mathbf{K}_p^\top}{\sqrt{\dim}}\right), \quad \hat{\mathbf{y}}_p = \sum_{i=1}^{\ell} \theta_{p,i} \mathbf{V}_{p,i}, \quad (8)$$

where  $\dim$  is the dimension of  $\mathbf{Q}_p$ , and the output of GTA is  $\mathbf{G}_t^L(p) = W_o \hat{\mathbf{y}}_p \in \mathbb{R}^C$ , where  $W_o$  is a learnable output projection matrix. We then concatenate  $\tilde{F}_t^L$  and  $\mathbf{G}_t^L$  along the channel dimension, and apply an Efficient Channel Attention (ECA) block [26] to obtain the enhanced feature  $E_t^L$ . We apply the identical procedure to the right branch to obtain  $E_t^R$ . The SCAM module fuses  $E_t^L$  and  $E_t^R$  into refined features  $\hat{F}_t^L$  and  $\hat{F}_t^R$ . These are then passed to a shared decoder to reconstruct the refined stereo pair  $\hat{I}_t^L$  and  $\hat{I}_t^R$ .

**Loss and training.** The network is trained end-to-end using  $\ell_1$  loss:  $\mathcal{L} = \|\hat{I}_t^L - I_{\text{gt}}^L\|_1 + \|\hat{I}_t^R - I_{\text{gt}}^R\|_1$ . We train for 300 epochs using the AdamW optimizer with an initial learning rate of  $1 \times 10^{-4}$  and the learning rate is scheduled via cosine annealing. The batch size is set to 12, and training is conducted on a single NVIDIA RTX 4090.

### 3.3. Dataset

Given the specialized design of our experimental setup, no publicly available dataset exists for training the proposed SMS-Net. To address this limitation, we create a synthetic dataset as illustrated in Fig. 5(a). Furthermore, to validate the practical efficacy of our approach, we developed a dedicated camera system and collected corresponding real-world test data, shown in Fig. 5(b). The details of our data

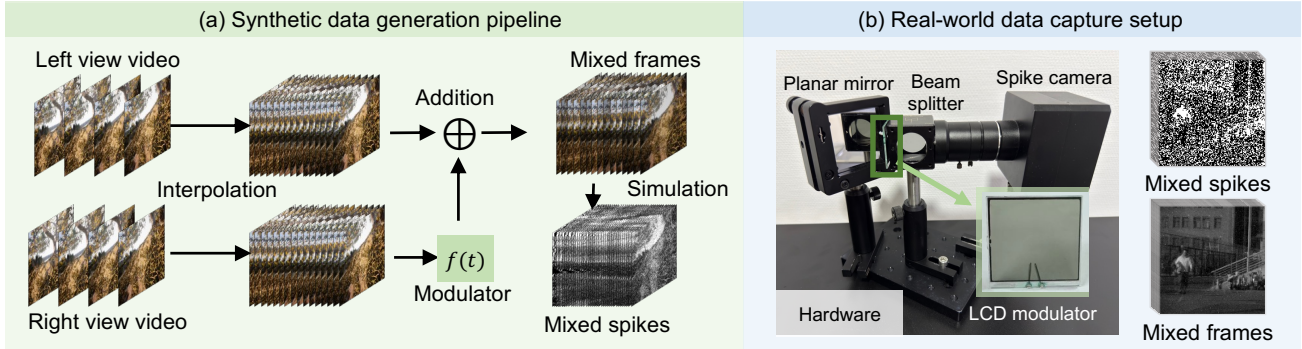


Figure 5. (a) We interpolate the binocular video, modulate the right-view video, and then mix it with the left-view video; the mixed video is subsequently simulated to generate mixed spikes. (b) The dedicated monocular camera system. A planar mirror and beam splitter optically mix two views, enabling the acquisition of mixed spikes and mixed video frames.

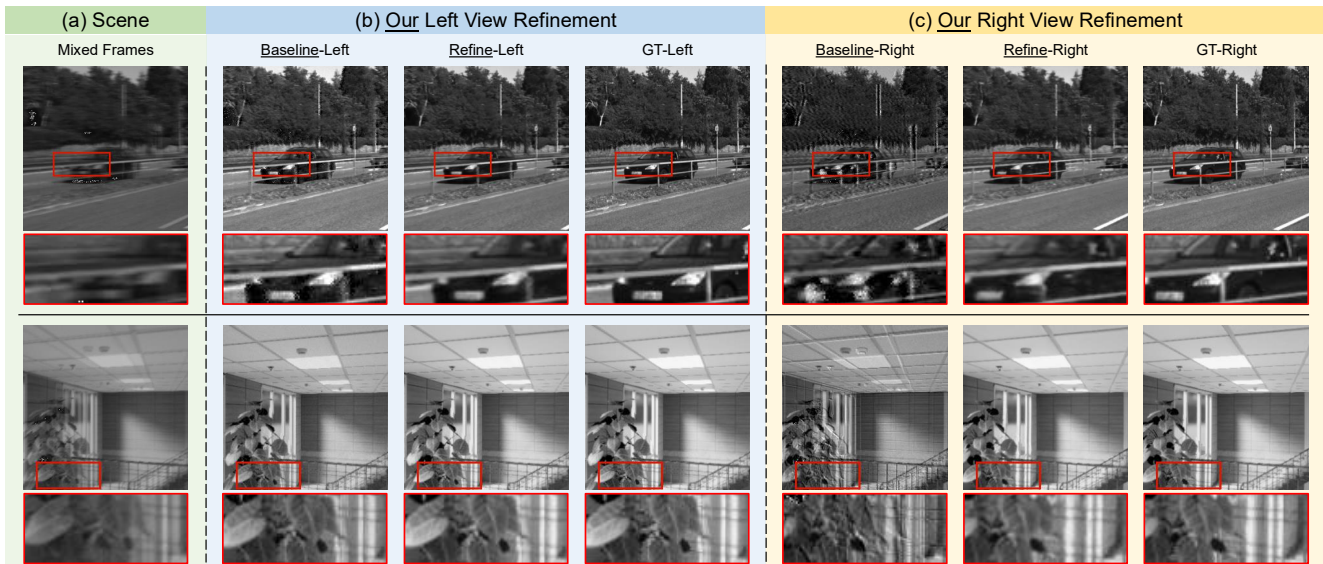


Figure 6. Decoupling binocular videos from synthetic test data. (a) The input scenes with mixed frames. (b) and (c) show the ground truth, along with the baseline and refined results. See the supplementary video for additional results.

collection methodology are described below.

**Synthetic data.** We generate synthetic training and testing data using TartanAir dataset [28], a large-scale photo-realistic simulation benchmark for robotic navigation, providing long-horizon binocular video sequences with precise ground-truth depth. We also generate a subset of synthetic data for testing using KITTI [17]. We first apply optical flow-based frame interpolation [23] to both views of the stereo image pair. The interpolated right view is then modulated by function  $f(t)$ , producing the mixed image sequence  $I_{\text{mix}}(t) = I_{\text{gt}}^L(t) + I_{\text{gt}}^R(t)f(t)$ . This mixed sequence is subsequently processed through spike camera simulation to generate mixed spike streams.

**Real-world data.** As shown in Fig. 5(b), our hardware setup employs a  $45^\circ$  planar mirror to redirect one view toward a beam splitter, which optically blends it with the direct view. Due to the depth displacement introduced by the planar mirror configuration, a specific calibration technique

is required to establish accurate geometric correspondence. Further implementation details are provided in the supplementary material. An LCD modulator placed between the mirror and the beam splitter introduces periodic intensity variations to the reflected path. This system enables the capture of real-world test data across diverse scenes, ensuring broad scenario coverage for comprehensive evaluation.

## 4. Experiments

In this section, we first demonstrate the effectiveness of our method for binocular video decoupling on synthetic data. We then show that the decoupled videos serve as high-quality inputs for depth estimation across both synthetic and real-world datasets, highlighting the superior characteristics of our reconstructed binocular videos. For depth estimation, we compare against monocular methods by adapting their input to single-view frames while maintaining our two-view input configuration. We explicitly acknowl-

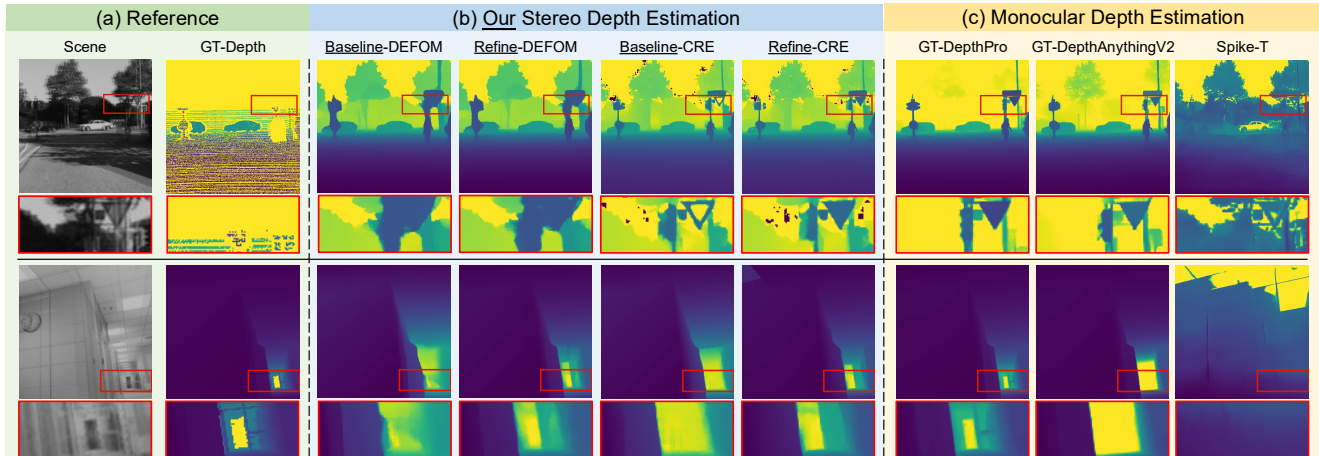


Figure 7. Depth estimation on synthetic data. We compare stereo depth maps from baseline-decoupled inputs and our refined stereo videos, and contrast them with monocular depth methods. Additional video results are provided in the supplementary material.

Table 1. Depth estimation performance on TartanAir [28] and KITTI [17] (AbsRel $\downarrow$ , RMSE $\downarrow$ ,  $\delta_1\uparrow$ ).  $\uparrow$ : higher is better;  $\downarrow$ : lower is better. GT-\* rows indicate an upper bound when the corresponding method is fed with ground-truth grayscale inputs; these rows are excluded when determining the best and second-best results. Best is in **bold**, second-best is underlined.

Methods	TartanAir [28]			KITTI [17]		
	AbsRel $\downarrow$	RMSE $\downarrow$	$\delta_1\uparrow$	AbsRel $\downarrow$	RMSE $\downarrow$	$\delta_1\uparrow$
Base-DEFOM [13]	0.1695	2.5187	0.8795	0.4477	<u>4.8843</u>	0.9427
Refine-DEFOM [13]	<b>0.0940</b>	<b>1.7852</b>	<b>0.9202</b>	<b>0.4288</b>	<b>4.1719</b>	<b>0.9630</b>
GT-DEFOM [13]	0.0498	1.5839	0.9438	0.4219	4.0963	0.9655
Base-CRE [15]	0.1631	<u>2.2064</u>	0.8737	0.4746	6.4855	0.9262
Refine-CRE [15]	0.1126	2.3595	<u>0.9153</u>	0.4523	5.6236	<u>0.9486</u>
GT-CRE [15]	0.0609	1.6524	0.9335	0.4441	5.5583	0.9507
Spike-T [32]	0.9675	8.2092	0.2731	0.8000	13.5509	0.3233
STIR [7]-DepthAnythingV2 [31]	0.4839	14.1810	0.5483	0.4412	6.6630	0.9116
GT-DepthAnythingV2 [31]	0.4830	14.1307	0.5406	0.4304	6.4323	0.9191
STIR [7]-DepthPro [2]	<u>0.1085</u>	2.2625	0.8573	<u>0.4409</u>	5.4297	0.9302
GT-DepthPro [2]	0.0731	1.6028	0.9164	0.3399	4.8738	0.9345

edge the inherent asymmetry in this comparison. However, in the absence of an open-source video decoupling method, the improved depth estimation results obtained from our binocular videos confirm that our monocular solution achieves enhanced accuracy without increasing data requirements. For monocular depth estimation benchmarks, we selected frame-based DepthAnythingV2 [31], DepthPro [2] and spike-based Spike-T [32].

#### 4.1. Evaluation on binocular video

We first evaluate binocular video decoupling on synthetic data. As shown in Tab. 2, our full model significantly outperforms the baseline decoupling method across all image quality metrics. This demonstrates the powerful restoration capability of our network. As shown in Fig. 6, we present the mixed frame reconstructed directly from spike streams as input. Our method successfully recovers high-quality binocular videos for both views. In the first row of Fig. 6, our approach accurately reconstructs the moving vehicle with preserved details. The second row demonstrates faithful recovery of architectural textures, while the

third row shows clear reconstruction of vegetation contours.

#### 4.2. Evaluation on depth estimation.

We now evaluate the utility of our decoupled videos for the downstream task of depth estimation.

**Results on synthetic data.** Tab. 1 presents the quantitative results on TartanAir and KITTI. For stereo-based approaches, we provide the baseline decoupling results, our refined results, and the ground truth grayscale stereo pairs (GT-\*). For monocular methods, we evaluate them on inputs reconstructed from spike streams (e.g., STIR [7]-DepthPro) and on ground truth grayscale images. For DepthAnythingV2 and DepthPro, we aligned their outputs with the ground truth depth for scale correction, since they take single-channel inputs. After excluding the ideal GT-\* results, which serve as an upper bound, our Refine-DEFOM method demonstrates best performance. Our baseline is highly competitive on its own, and the refinement network provides a significant boost, bringing our results close to the theoretical upper bound. As shown in Fig. 7, our baseline decoupling paired with a stereo estimator already produces high-quality visual results. The refinement further enhances this performance, yielding sharper and more accurate depth maps. While DepthAnythingV2 and DepthPro also deliver strong and visually competitive outputs, their accuracy degrades for distant scenes.

**Results on real-world data.** Qualitative results are shown in Fig. 8. We feed the baseline decoupling and refined results into the DEFOM and CREStereo models, respectively. We also apply monocular methods to the spike streams. The results show that both the DepthPro and Spike-T methods are largely ineffective. While DepthAnythingV2 recovers the relative depth relationships well, its output lacks distinct depth stratification, resulting in a visually flat appearance. Among stereo estimators, DEFOM generally outperforms CREStereo. For DEFOM, the difference between baseline

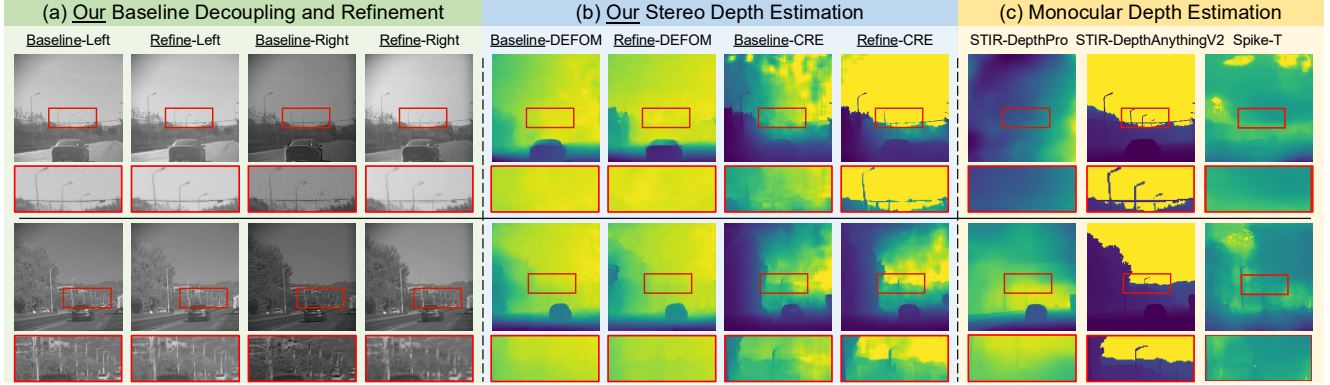


Figure 8. We show decoupled stereo results on real-world data and compare downstream depth estimation performance. Additional video results are provided in the supplementary material.

Table 2. Ablation study of the three modules (ABC, CBA, and RSF).  $\checkmark$ : denotes enabled. We report PSNR / SSIM / LPIPS, (Left/Right) and stereo errors (Bad 3.0/ EPE) on TartanAir [28] and KITTI [17]. Best is in **bold**, second-best is underlined.

	Proposed Modules			TartanAir [28]					KITTI [17]				
	ABC	CBA	RSF	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	Bad 3.0 $\downarrow$	EPE $\downarrow$	PSNR $\uparrow$	SSIM $\uparrow$	LPIPS $\downarrow$	Bad 3.0 $\downarrow$	EPE $\downarrow$
Baseline				26.53/16.54	0.857/0.775	0.162/0.266	5.372	13.71	25.48/17.78	0.850/0.764	0.107/0.212	5.580	0.964
+ABC	$\checkmark$			32.13/28.22	0.953/0.922	0.038/0.093	5.327	11.44	30.77/25.94	0.935/0.895	0.046/0.085	3.290	0.819
+CBA		$\checkmark$		28.90/19.97	0.958/0.899	0.041/0.111	5.266	11.40	29.10/22.25	0.932/0.881	0.052/0.091	3.600	0.819
+RSF			$\checkmark$	32.00/32.29	0.975/0.964	0.025/0.042	4.789	10.25	32.77/31.53	0.959/0.947	0.034/0.045	2.090	0.668
+ABC+CBA	$\checkmark$	$\checkmark$		33.66/29.73	0.964/0.926	0.038/0.084	5.232	11.13	31.26/27.33	0.937/0.897	0.049/0.078	3.630	0.808
+ABC+RSF	$\checkmark$		$\checkmark$	<u>36.20/35.45</u>	<u>0.977/0.968</u>	<b>0.023/0.038</b>	<b>4.691</b>	<u>10.07</u>	<u>34.36/32.88</u>	<u>0.960/0.950</u>	<b>0.030/0.040</b>	2.080	0.664
+CBA+RSF		$\checkmark$	$\checkmark$	31.55/32.15	0.976/0.966	0.025/0.039	4.971	<b>9.98</b>	32.72/31.60	<u>0.960/0.949</u>	0.032/0.041	<u>2.010</u>	0.658
Ours	$\checkmark$	$\checkmark$	$\checkmark$	<b>36.97/35.73</b>	<b>0.978/0.968</b>	<u>0.024/0.038</u>	4.791	10.08	<b>35.00/32.75</b>	<b>0.963/0.953</b>	<u>0.032/0.039</u>	<b>1.890</b>	<b>0.644</b>

and refined inputs is subtle. For CREStereo, the refined output yields clearly better depth. Fig. 8(a) shows that SMS-Net restores brightness consistency and recovers fine textures in the right view.

### 4.3. Ablation study

Since our network consists of three functionally distinct components, we conduct systematic ablation studies to evaluate the individual and combined contributions of each module. The evaluation is performed from two perspectives: image restoration quality and disparity estimation accuracy, with experiments carried out on TartanAir and KITTI datasets. As shown in Tab. 2, compared to the baseline solution, incorporating any of the three modules, *i.e.*, ABC, CBA, or RSF brings significant performance improvements. RSF contributes most substantially to the framework. Moreover, any two-module combination outperforms using a single module alone. Integrating ABC, CBA, and RSF addresses key decoupling challenges and achieves top performance. Overall, these extensive ablation experiments robustly validate the necessity and the synergistic benefits of our architectural design choices.

## 5. Conclusion

We presented a monocular solution for achieving 240FPS stereo vision from mixed spikes. By introducing temporal

optical modulation into one view and capturing the resulting mixed spikes, our camera system effectively encodes stereo cues in the spatial and temporal domain. A two-stage approach comprising a baseline decoupling strategy and a learning-based refinement network (SMS-Net) enables efficient and accurate reconstruction of binocular videos from mixed spikes. Experiments on both synthetic and real-world datasets demonstrate that our approach achieves high-quality stereo reconstruction while maintaining hardware compactness and data efficiency.

**Limitations:** In our current implementation, our LCD modulator is constrained to approximately 60 Hz due to inherent physical and operational principles. Faster modulators would enable decoupling at higher frame rates.

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