Supplementary Material: Data Association between Event Streams and Intensity Frames under Diverse Baselines

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6 Appendix

Positional Encoding 6.1

In the Transformer module of LSparse-Net and SDense-Net, we apply the 2D extension of positional encoding following [1] as:

$$PE(x,y)^{i} := \begin{cases} \sin(\omega_{k} \cdot x), i = 4k \\ \cos(\omega_{k} \cdot x), i = 4k + 1 \\ \sin(\omega_{k} \cdot y), i = 4k + 2 \\ \cos(\omega_{k} \cdot y), i = 4k + 3 \end{cases}$$
(7)

where $\omega_k = \frac{1}{10000^{(2k/d)}}$, d is the number of channels which are applied with positional encoding, and i is the index for feature channels.

6.2Mutual Nearest Neighbor Filtering

Scores on two directions form matches are calculate through Softmax:

$$s_p = \frac{\exp(M^l)}{\sum_{i,j} \exp(M^l(i,j,m,n))}$$
 and $s_e = \frac{\exp(M^l)}{\sum_{m,n} \exp(M^l(i,j,m,n))}$, (8)

We believe that $I_p^l(\hat{i},\hat{j})$ matches $I_e^l(\hat{m},\hat{n})$ when the following equation (Eq. (9)) is satisfied. We denote the final match matrix as \overline{M}^l .

$$(\hat{m}, \hat{n}) = \underset{m,n}{\operatorname{arg\,max}} s_p(i, j, m, n) \quad \text{and} \quad (\hat{i}, \hat{j}) = \underset{i,j}{\operatorname{arg\,max}} s_e(i, j, m, n). \tag{9}$$

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6.3 Dataset Preparation

We sample a part of the synthetic ScanNet [2] dataset for training to synthesize event streams by V2E [3]. Indexes for the sub-set range from 0 to 699. When generating the event stream corresponding to each intensity frame, we include the latest 20,000 events earlier than the timestamp of the intensity frame.

6.4 Additional Results

Pose Estimation. To better demonstrate the performances of our framework on pose estimation, we show additional results for data association on the synthetic data of ScanNet [2] dataset in Fig. 5. It is shown that, in scenes with large baselines and sparse textures, our framework can establish correct matches between event streams and intensity frames.



Fig. 5. Additional examples for pose estimation on the synthetic data. Our model can establish sound data association even when the views of the event streams and the intensity frames differ largely.

Stereo Depth Estimation. We further illustrate the capability of our framework to establish data association under small baselines by showing more results in Fig. 6 on the Indoor Flying dataset from MVSEC [4]. Our framework is adaptive to the task of stereo depth estimation, as it outputs results close to the ground truths.



Fig. 6. Additional qualitative comparison on the Indoor Flying dataset of MVSEC [4]. The first and third columns show the ground truth, whereas the second and fourth columns show the outputs of our framework. We only select frames from sequence 1. In the first and second columns, from top to bottom, we select frame 150, 400, 700, and 925. In the third and fourth columns, from top to bottom, we select frame 250, 550, 850, and 1185.

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