High Dynamic Range Imaging with Time-Encoding Spike Camera

Zhenkun Zhu[1], Ruiqin Xiong[1], Jiyu Xie[2], Yuanlin Wang[1], Xinfeng Zhang[3], Tiejun Huang[1]

[1]State Key Laboratory of Multimedia Information Processing, School of Computer Science, Peking University

[2]Shanghai Radio Equipment Research Institute, Shanghai, China

[3]School of Computer Science and Technology, University of Chinese Academy of Sciences

1. Movitation

(a) Two Approaches for Intensity Representation.

Neuromorphic camera uses the ratio of accumulated photons to time, i.e. the photon arrival rate, to represent light intensity. Two common approaches are typically adopted. The first approach accumulates the arrived photons N_p over a fixed time interval T, yielding a photon arrival rate of N_p/T. The second approach records the time duration T_t required for the accumulated photons to reach a fixed amount N_θ, resulting in a photon arrival rate of N_θ/T_t .

(b) Intensity Representation via Primitive Spikes.

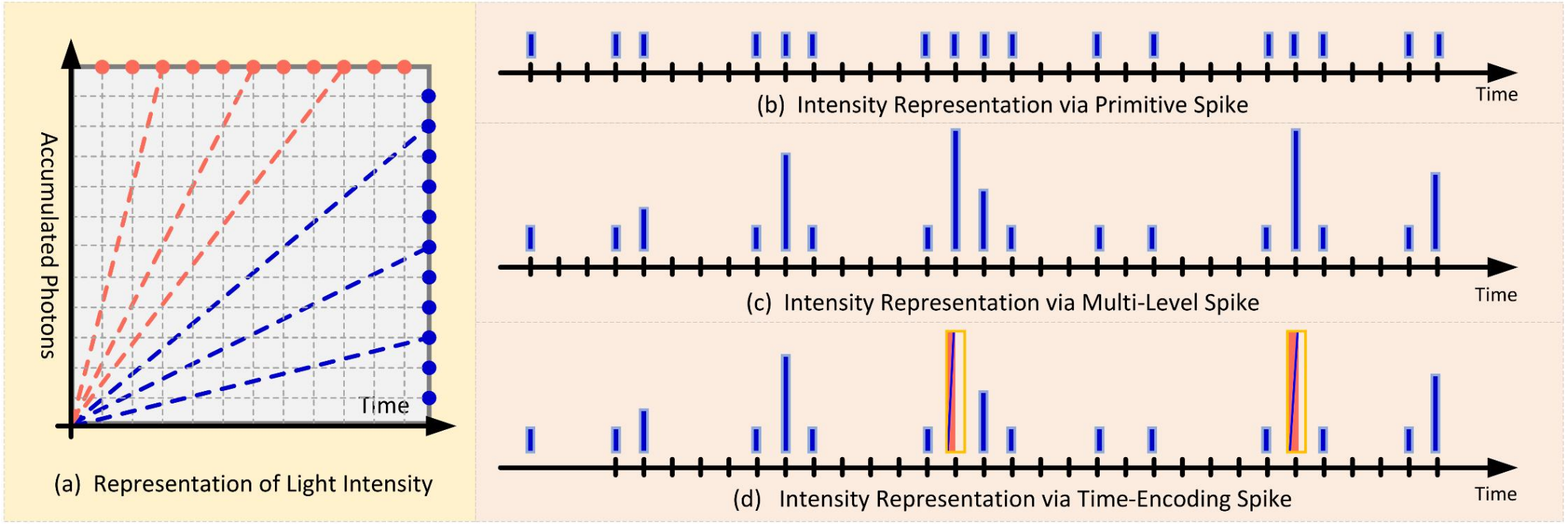
Each spike represents a fixed amount of photons, this mechanism uses the spike interval to represent intensity.

(c) Intensity Representation via Primitive Spikes.

This mechanism uses multi-level spike symbols to represent different amounts of photons.

(d) Intensity Representation via Primitive Spikes.

This mechanism represents intensity by recording the time required for photon accumulation to reach a specific photon amount.



2. Contribution

(1) we propose time-encoding (TE) spike camera, which transforms the counting of spikes to recording of the time at which a specific number of spikes (i.e., an overflow) is reached.

(2) To encode time information with as few bits as possible, instead of directly utilising a timer, we leverage a periodic timing signal with a higher frequency than the readout signal. Then the recording of overflow moment can be transformed into recording the number of accumulated timing signal cycles until the overflow occurs.

(3) we propose an image reconstruction scheme for TE spike camera, which leverages the multi-scale gradient features of spike data. This scheme includes a similarity-based pyramid alignment module to align spike streams across the temporal domain and a light intensity-based refinement module, which utilises the guidance of light intensity to fuse spatial features of the spike data.

(4) Experimental results demonstrate that TE spike camera effectively improves the dynamic range of spike camera.

Time-Encoding Spike Camera

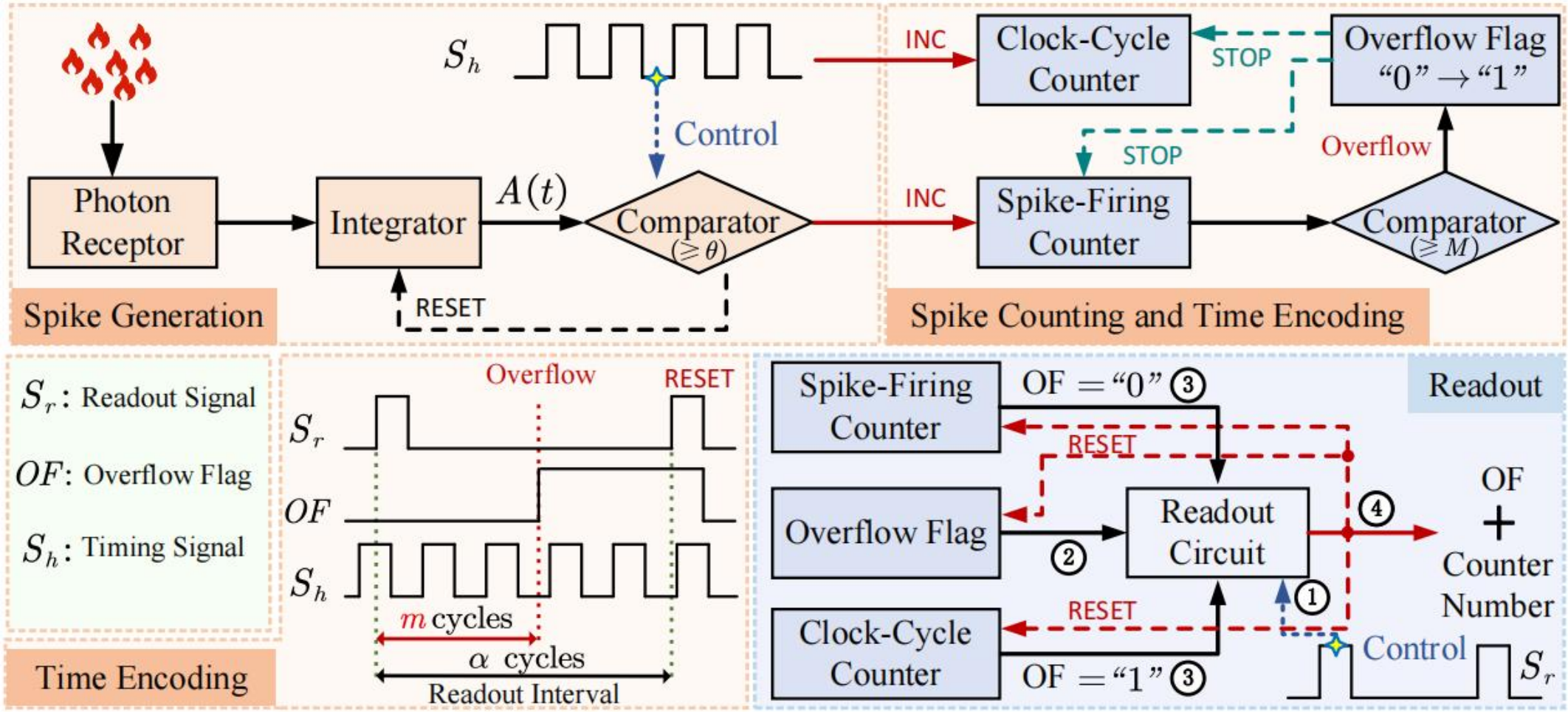
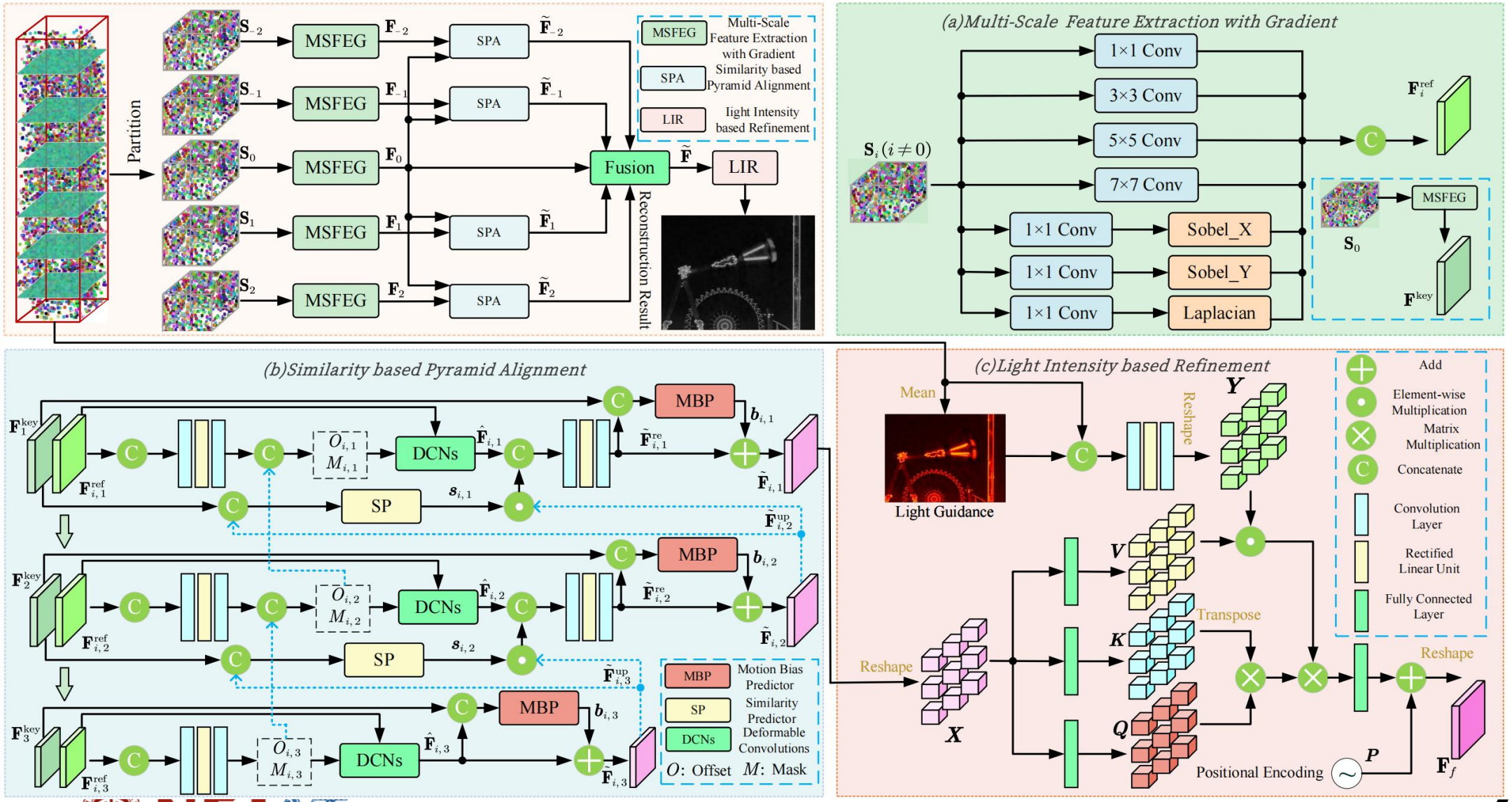


Image Reconstruction for Time-Encoding Spike Camera



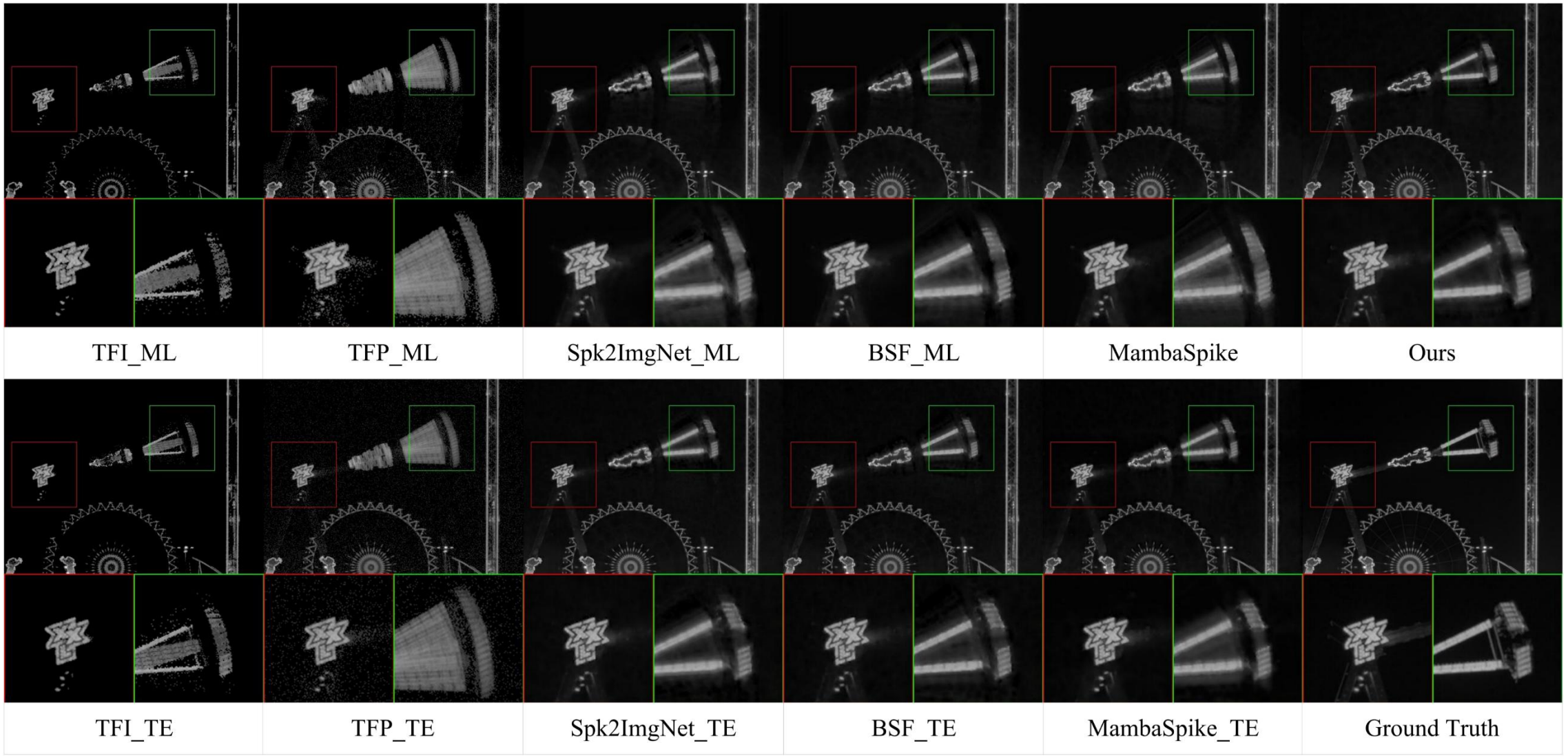
4. Experimental Results

Quantitative Results on the synthesized HDM-HDR-2014 dataset

ML Reconstruction	PSNR-μ ↑	SSIM-μ ↑	HDR-VDP↑	HDR-VQM↓	TE Reconstruction	PSNR-μ ↑	SSIM-μ ↑	HDR-VDP↑	HDR-VQM↓
TFI_ML	15.50	0.161	3.056	0.943	TFI_TE	17.37	0.235	3.367	0.933
TFP_ML	16.13	0.250	3.778	0.970	TFP_TE	17.74	0.317	3.412	0.970
Spk2ImgNet_ML	26.69	0.779	7.209	0.459	Spk2ImgNet_TE	29.64	0.830	7.892	0.357
BSF_ML	26.94	0.782	7.338	0.457	BSF_TE	29.64	0.826	7.825	0.370
MambaSpike ♠	25.76	0.755	7.081	0.545	MambaSpike_TE	28.94	0.828	7.802	0.400
MambaSpike	27.30	0.788	7.405	0.443	Ours	**30.86**	**0.853**	**8.055**	**0.325**

4. Experimental Results

Visualization Results on the synthesized HDM-HDR-2014 dataset



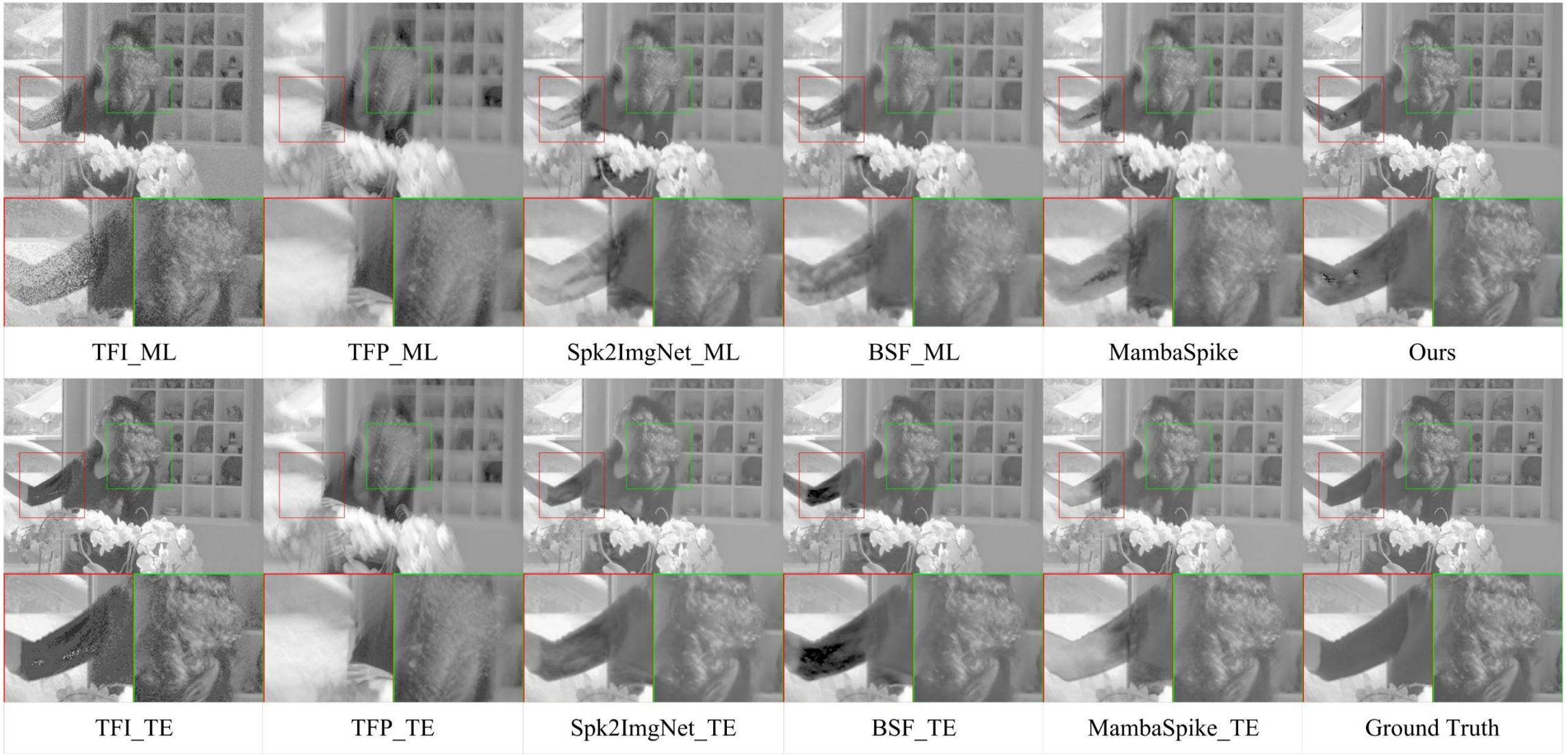
4. Experimental Results

Quantitative Results on the synthesized Kalantari13 dataset

ML Reconstruction	PSNR-μ ↑	SSIM-μ ↑	HDR-VDP↑	HDR-VQM↓	TE Reconstruction	PSNR-μ ↑	SSIM-μ ↑	HDR-VDP↑	HDR-VQM↓
TFI_ML	24.55	0.539	3.777	1.222	TFI_TE	27.52	0.740	3.882	1.228
TFP_ML	22.38	0.699	3.232	1.288	TFI_TE	23.88	0.737	3.321	1.288
Spk2ImgNet_ML	26.76	0.863	8.512	0.361	Spk2ImgNet_TE	30.29	0.937	9.587	0.138
BSF_ML	28.28	0.872	8.619	0.345	BSF_TE	31.74	0.937	9.586	**0.132**
MambaSpike ♠	25.87	0.854	8.557	0.343	MambaSpike_TE	29.06	0.929	9.516	0.151
MambaSpike	27.85	0.874	8.689	0.325	Ours	**33.65**	**0.943**	**9.606**	0.139

4. Experimental Results

Visualization Results on the synthesized Kalantari13 dataset



4. Experimental Results

Ablation Studies

Case	MSFE	Gradient	DCNs	SP	MBP	LIR	PSNR-μ ↑	SSIM-μ ↑
1	✓						25.68	0.680
2	✓	✓					26.35	0.697
3	✓	✓	✓				29.54	0.818
4	✓	✓	✓	✓			30.04	0.828
5	✓	✓	✓	✓	✓		30.32	0.824
6	✓	✓	✓	✓	✓	✓	**30.86**	**0.853**