Burst Image Restoration and Enhancement

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Single Image Processing

Single low-quality Images

Single Image Processing:

- Single image quality is limited due to the imaging sensor.
- Thus, limited information in captured in single image.
- Restoration/enhancement approaches are limited to improve the quality of single image.

Burst Image Processing

Burst of low-quality Images

Burst Image Processing

- Multiple sub-sampled images of the same scene.
- More information than single image.
- Easy to capture burst image due to smartphone advancement. E.g., live photos.
- Multi-frame information helps to get precise high-quality image compared to the single image.

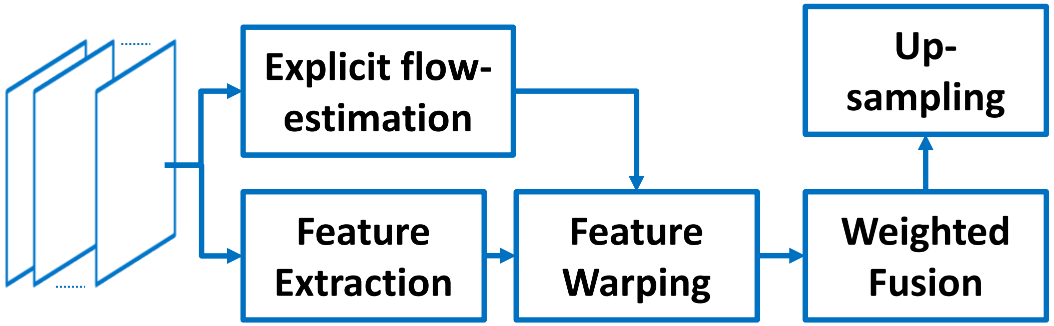
Challenges:

- Misalignment within multiple frames.
- How to merge multi-frame information to get single high-quality image.
- How to design a unified model that works in multiple scenarios.
- How to design compact and efficient model.

Burst Image Processing

Existing Architecture Designs

Explicit alignment and late feature fusion



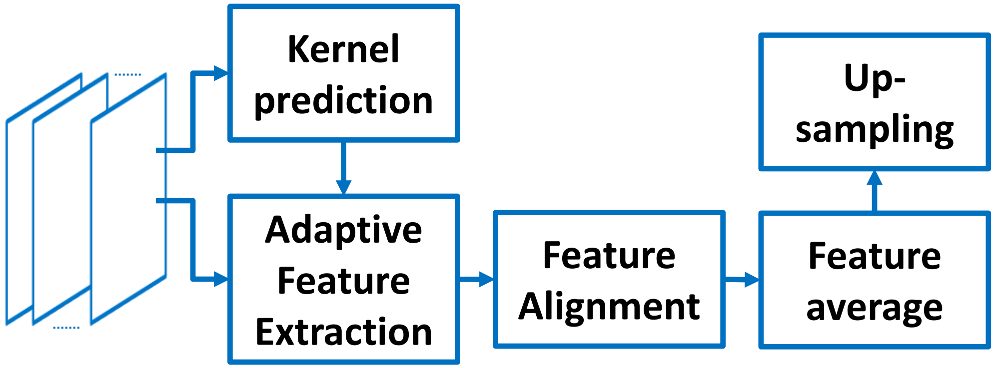
Issues

- Error propagation
- No access to multi-frame information in up-sampling
- No communication within frames

Burst Image Processing

Existing Architecture Designs

Adaptive feature extraction, Implicit alignment



Issues

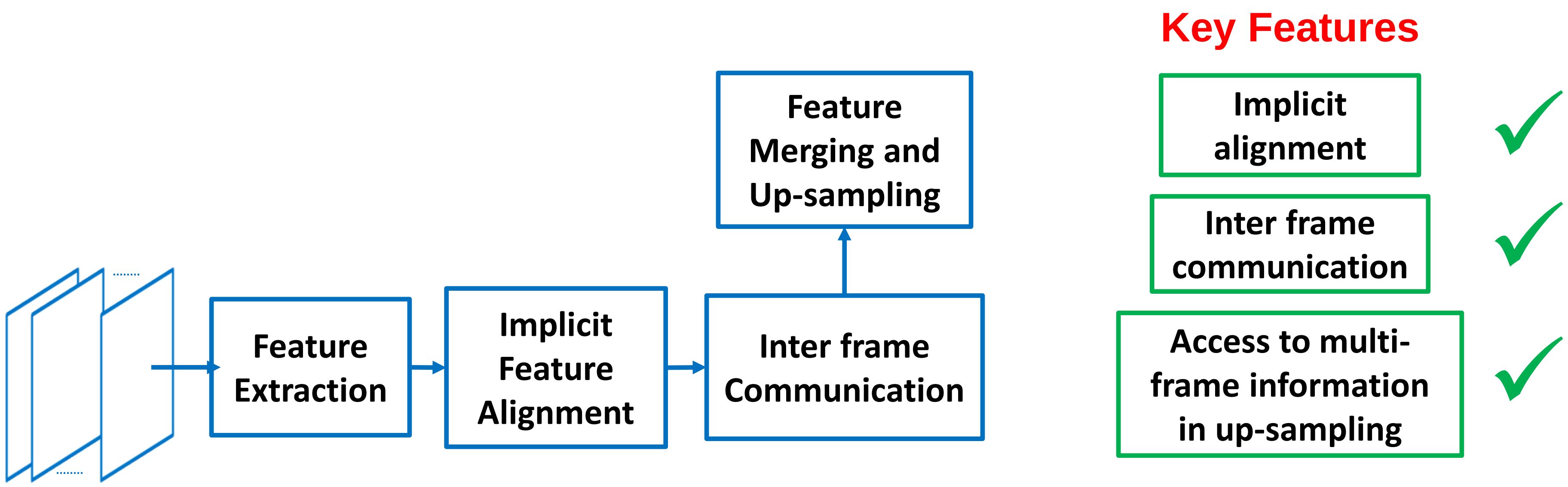
Bulky in nature

No communication within frames

No access to multi-frame information in up-sampling

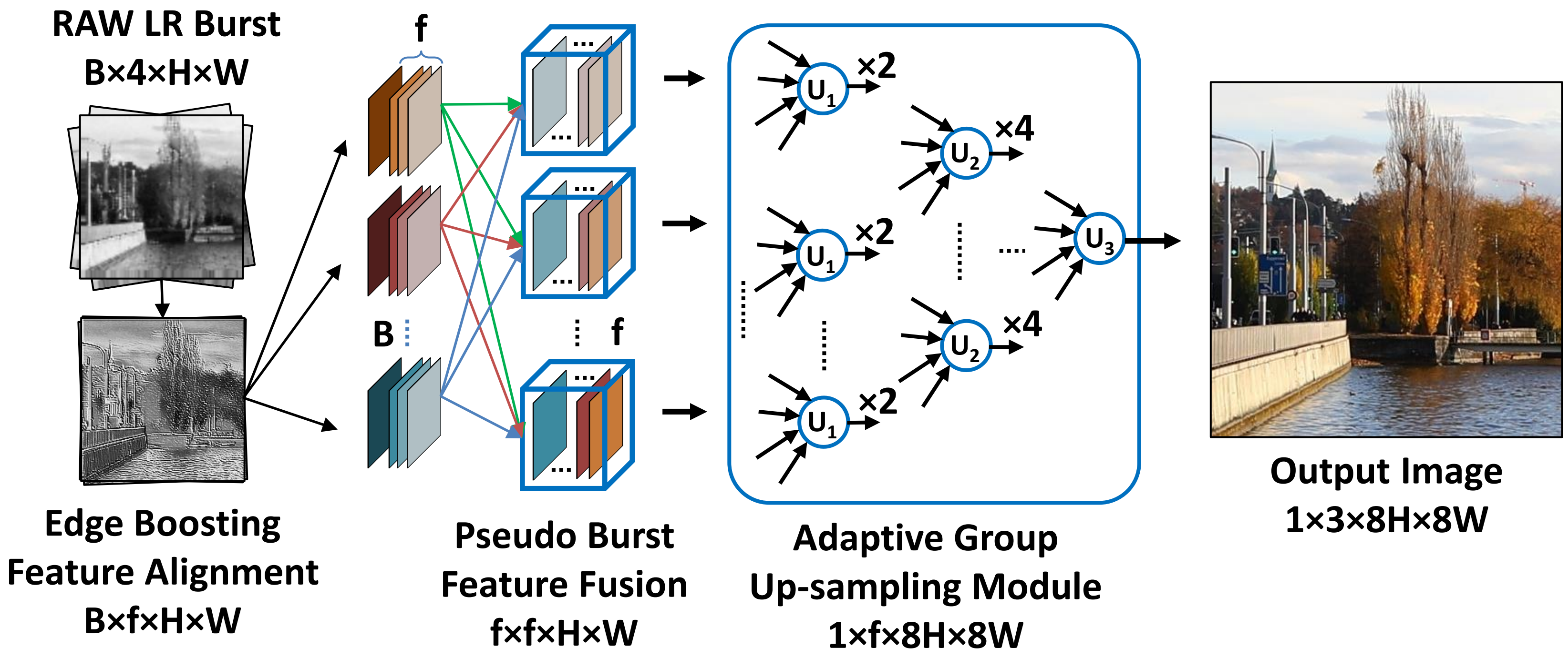
Akshay Dudhane, Waqas Zamir, Salman Khan, Fahad Khan, and Ming-Hsuan Yang:
***Burst Image Restoration and Enhancement*. CVPR 2022. Best paper Finalist.**

Proposed Approach: BIPNet



- An *edge boosting alignment technique* that removes spatial and color misalignment issues among the burst features.
- A novel *pseudo-burst feature fusion mechanism* to enable inter-frame communication and feature consolidation.
- An *adaptive group upsampling module* for progressive fusion and upscaling.

Proposed Approach: BIPNet



Proposed Approach: BIPNet

RAW LR Burst
B×4×H×W

Edge Boosting Feature Alignment

↓

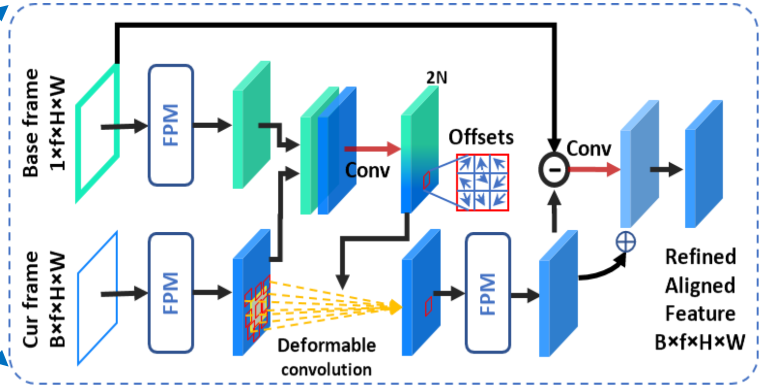
Pseudo Burst Feature Fusion

↓

Adaptive Group Up-sampling

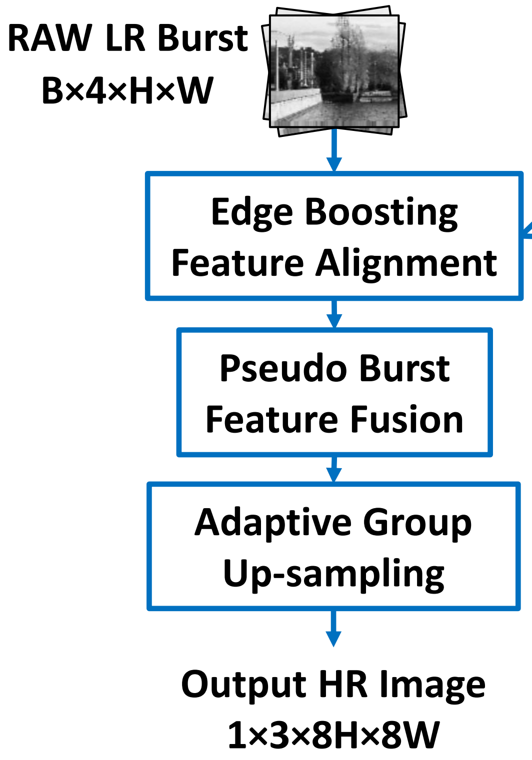
↓

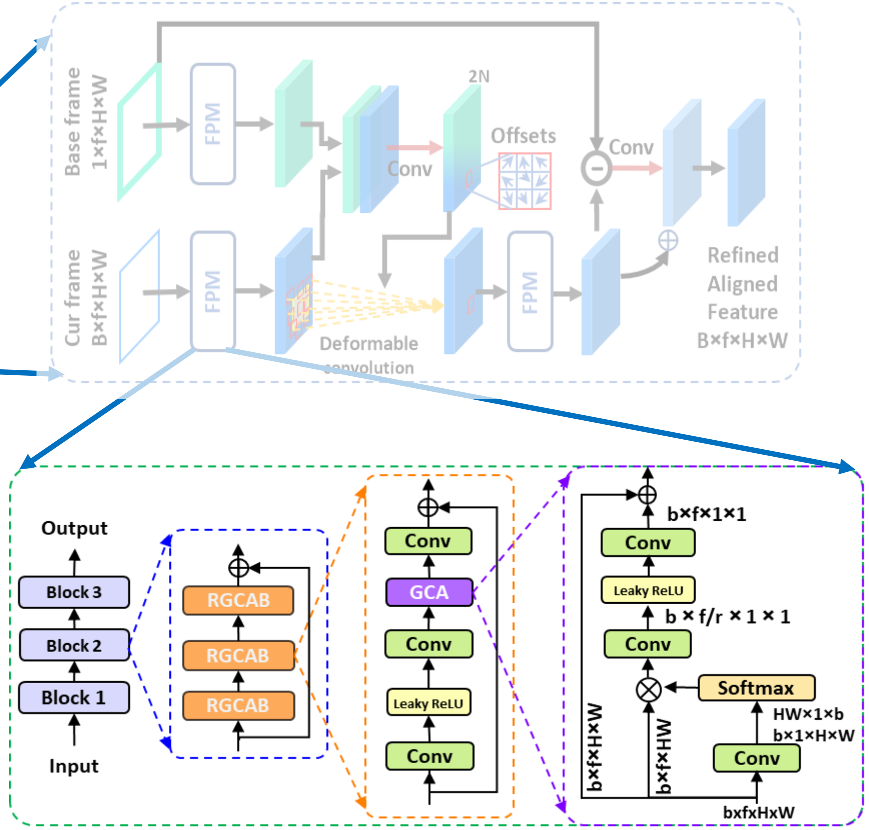
Output HR Image
1×3×8H×8W



Edge Boosting Feature Alignment

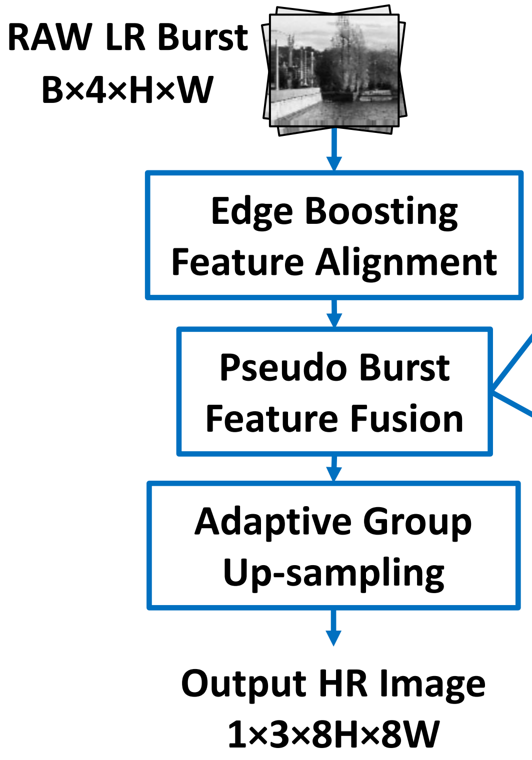
Proposed Approach: BIPNet

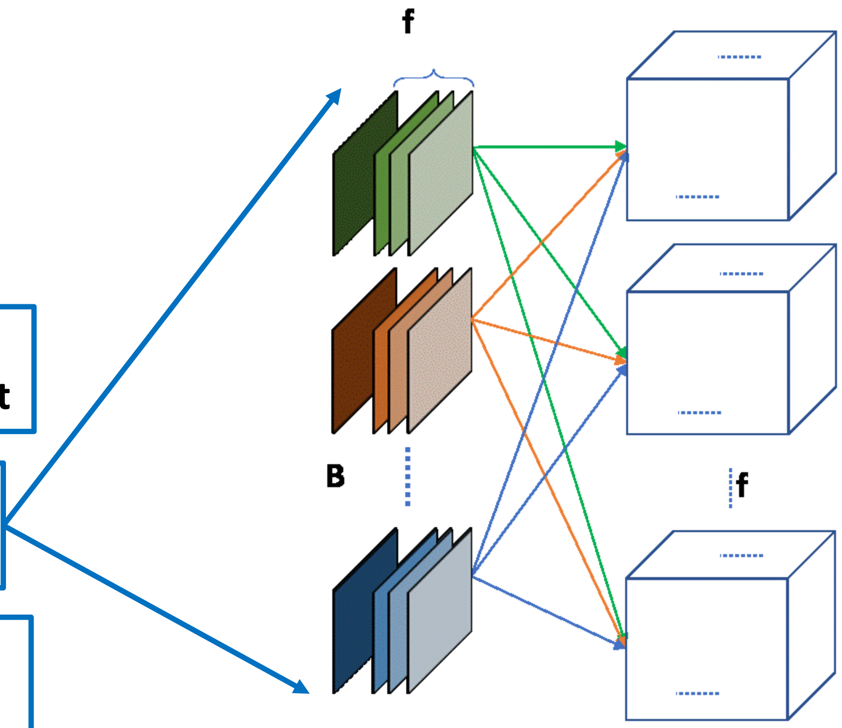




Feature Processing Module (FPM)

Proposed Approach: BIPNet

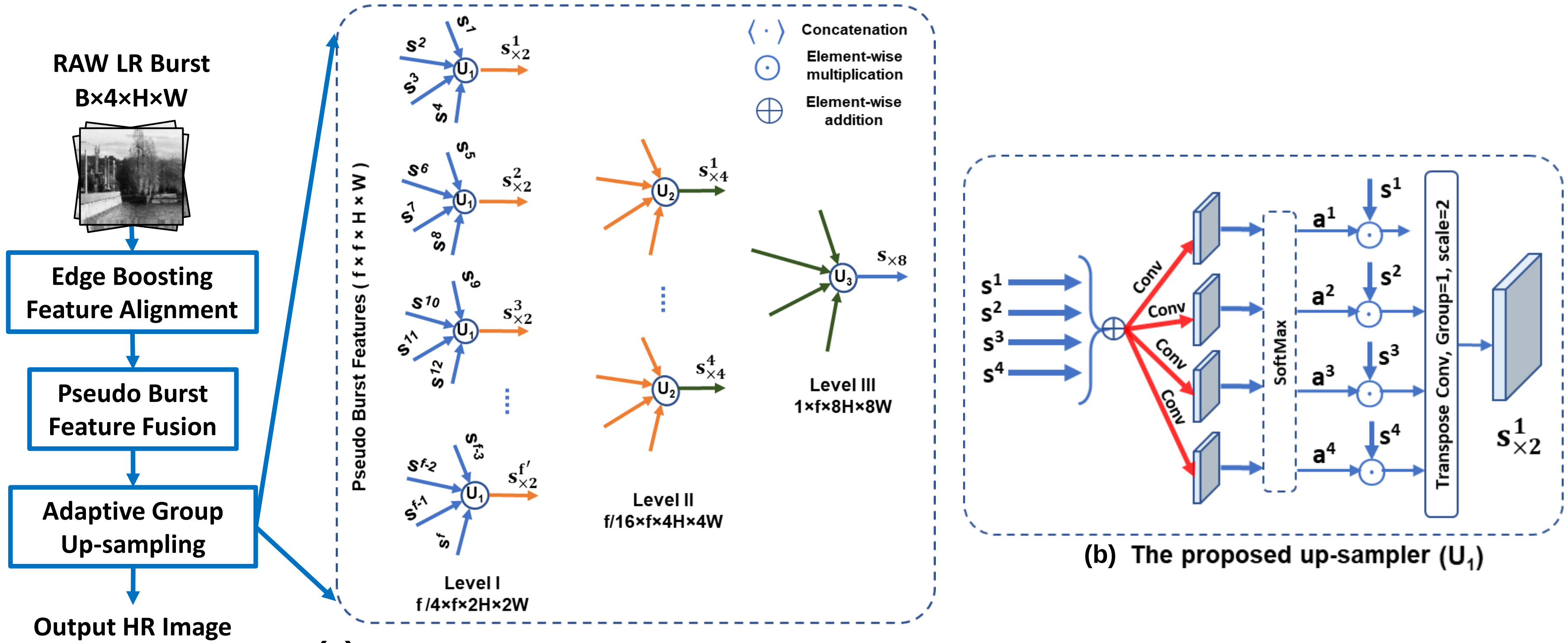




Pseudo Burst Feature Fusion Module (PBFF)

- Generates feature tensors by concatenating corresponding channel-wise features from all burst feature maps.
- Each feature tensor in the pseudo-burst contains complimentary properties of all actual burst image features.
- Processing inter-burst feature responses simplifies the representation learning task and merges the relevant information by decoupling the burst image feature channels.

Proposed Approach: BIPNet



(a) Adaptive Group Up-sampling (AGU)

(b) The proposed up-sampler (U_1)

- Effectively utilizes the information available in multiple frames to get into HR space.
- Handles pseudo-bursts features in groups and progressively performs upscaling.
- Sequentially divide pseudo-burst features into groups, which are up-sampled with up-sampler.

Experiments

- **Burst Super-resolution**
- **Burst Low-light Image Enhancement**
- **Burst Denoising**

Experiments

Burst Image Super-resolution

Synthetic Burst Super-resolution

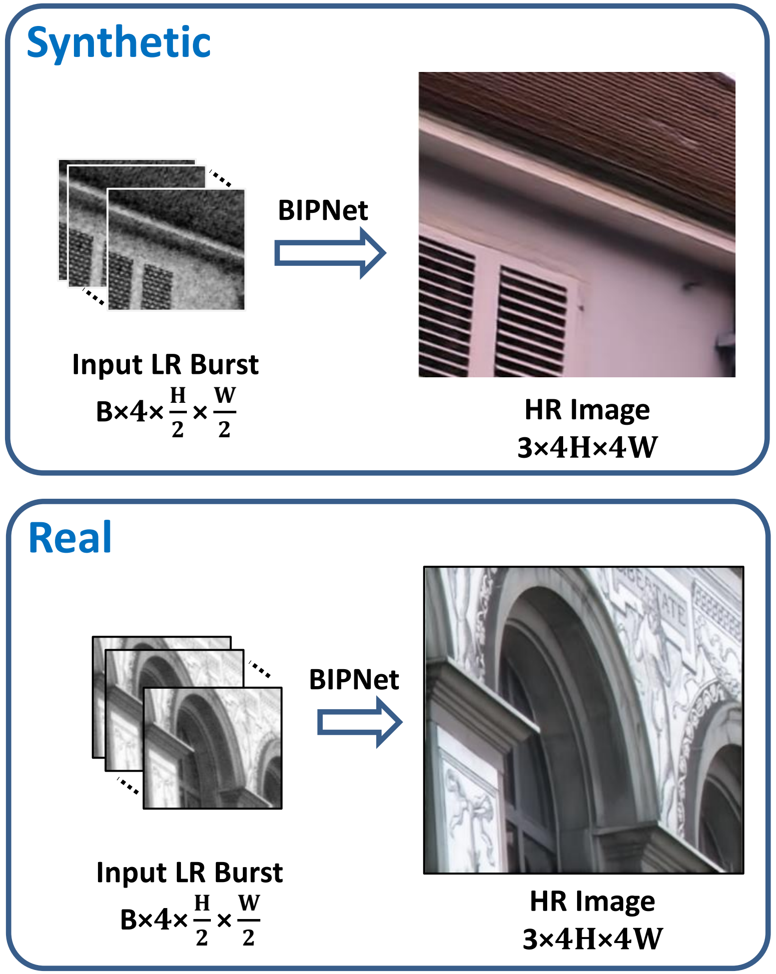
- Dataset: SyntheticBurst
- Train split (46839 synthetic bursts)
- Validation split (300 synthetic bursts)

Real Burst Super-resolution

- Dataset: BurstSR
- Train split (5405 real burst patches)
- Validation split (882 real burst patches)

Training details

- Loss function: L_1
- Optimizer: ADAM
- Schedular: Cosine annealing strategy
- Learning rate: 10^{-4} to 10^{-6}
- Network parameters: 6.67 M



Experiments

Quantitative comparison for x4 Burst SR

Methods	SyntheticBurst		(Real) BurstSR	
	PSNR	SSIM	PSNR	SSIM
Single Image	36.17	0.909	46.29	0.982
HighRes-Net [1]	37.45	0.92	46.64	0.98
DBSR [2]	40.76	0.96	48.05	0.984
LKR [3]	41.45	0.95	--	--
MFIR [4]	41.56	0.96	48.33	0.985
BIPNet (Ours)	**41.93**	**0.96**	**48.49**	**0.985**

[1] Michel Deudon et al., ***HighRes-net: recursive fusion for multi-frame super-resolution of satellite imagery*****.**

[2] Goutham Bhat et al., ***Deep burst super-resolution*****. In CVPR, 2021.**

[3] Bruno Lecouat et al., ***Lucas kanade reloaded: End-to-end super-resolution from raw image bursts*****. In ICCV, 2021**

[4] Goutham Bhat et al., ***Deep re-parametrization of multi-frame super-resolution and denoising*****. In ICCV, 2021**

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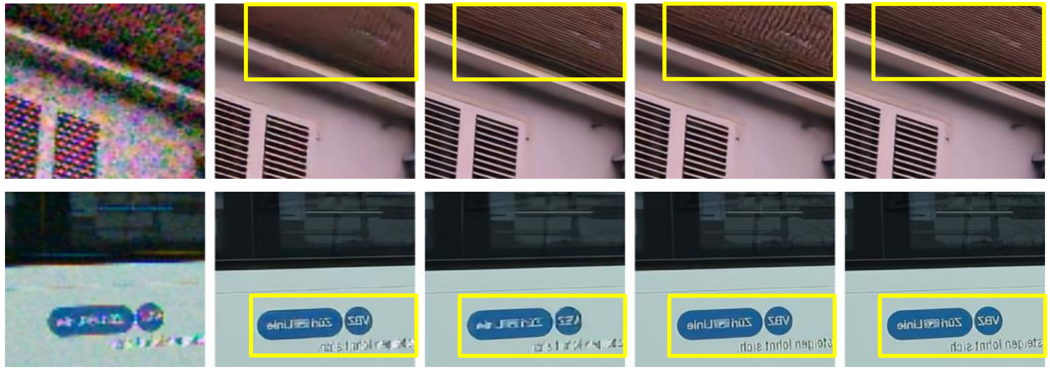
Visual comparison for SyntheticBurst SR



Base frame DBSR [2] LKR [3] MFIR [4] BIPNet (Ours)

Visual comparison for RealBurst SR

Base frame DBSR [2] MFIR [4] BIPNet (Ours) Reference

[1] Michel Deudon et al., *HighRes-net: recursive fusion for multi-frame super-resolution of satellite imagery*.
[2] Goutham Bhat et al., *Deep burst super-resolution*. In CVPR, 2021.
[3] Bruno Lecouat et al., *Lucas kanade reloaded: End-to-end super-resolution from raw image bursts*. In ICCV, 2021
[4] Goutham Bhat et al., *Deep re-parametrization of multi-frame super-resolution and denoising*. In ICCV, 2021

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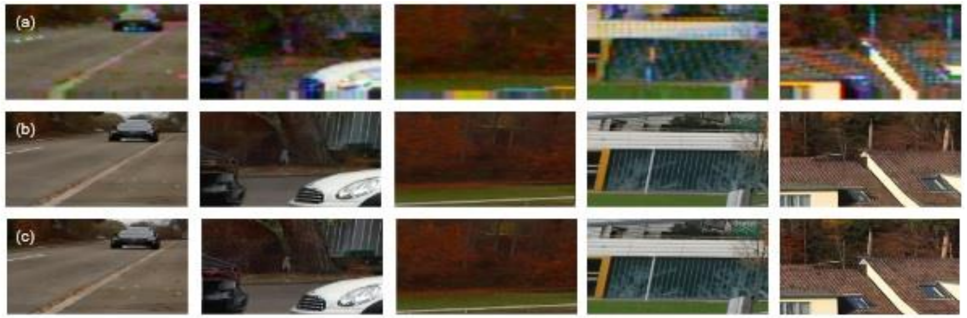
[1] Michel Deudon et al., *HighRes-net: recursive fusion for multi-frame super-resolution of satellite imagery*.

[2] Goutham Bhat et al., *Deep burst super-resolution*. In CVPR, 2021.

[3] Bruno Lecouat et al., *Lucas kanade reloaded: End-to-end super-resolution from raw image bursts*. In ICCV, 2021

[4] Goutham Bhat et al., *Deep re-parametrization of multi-frame super-resolution and denoising*. In ICCV, 2021

Visual comparison for x8 Burst SR

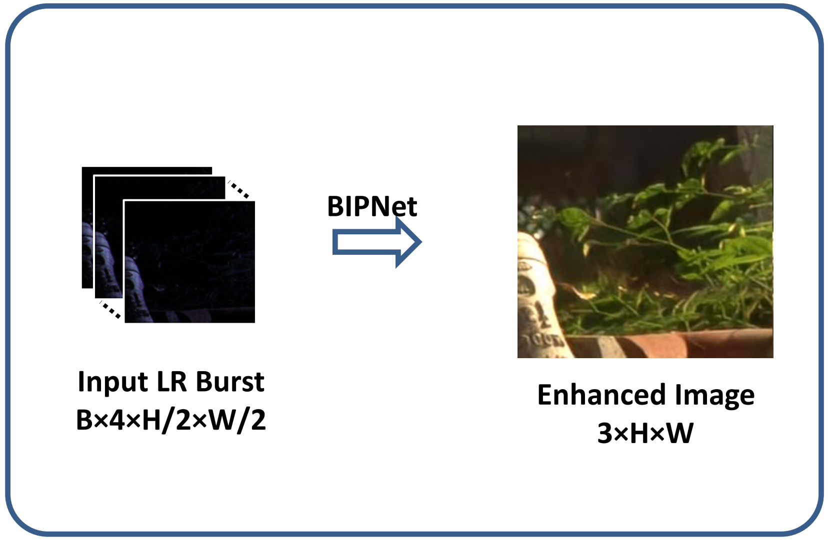


(a) Base frame (b) Ours (c) Ground-truth

Experiments

Burst Low-Light Image Enhancement

- Dataset: SID dataset (Sony subset)
- Train split (28k patches generated from 161 burst sequences)
- Validation split (50 burst sequences)



Training details

- Loss function: L_1
- Optimizer: ADAM
- Schedular: Cosine annealing strategy
- Learning rate: 10^{-4} to 10^{-6}
- Epochs: 50
- Network parameters: 6.67 M

Experiments

Quantitative comparison for Burst low-light image enhancement

Methods	PSNR	SSIM	LPIPS
Chen et al. [1]	29.38	0.892	0.484
Maharajan et al. [2]	29.57	0.891	0.484
Zamir et al. [3]	29.13	0.881	0.462
Zhao et al. [4]	29.49	0.895	0.455
Karadeniz et al. [5]	29.80	0.891	0.306
BIPNet (Ours)	**32.87**	**0.936**	**0.305**

[1] Chen Chen et al., *Learning to see in the dark*. In CVPR, 2018.

[2] Paras Maharjan et al., *Improving extreme low-light image denoising via residual learning*. In ICME, 2019

[3] Syed Waqas Zamir et al., *Learning digital camera pipeline for extreme low-light imaging*. Neurocomputing 2021

[4] Di Zhao et al., *End-to-end denoising of dark burst images using recurrent fully convolutional networks*. arXiv:1904.07483, 2019

[5] Ahmet Serdar Karadeniz et al., *Burst photography for learning to enhance extremely dark images*. arXiv:2006.09845, 2020.

Visual comparison for Grayscale Burst De-noising

Karadeniz et al. [2] | BIPNet (Ours) | Reference

Experiments

Burst Image Denoising

Grayscale burst denoising

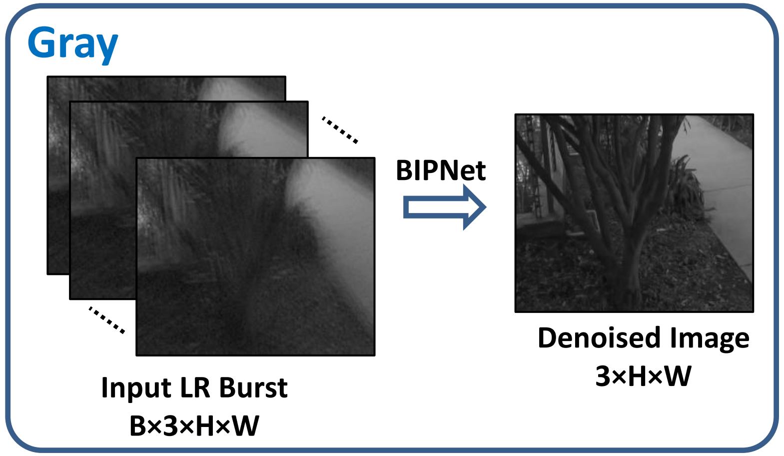
- Train split (20k from Open Images set)
- Validation split (73 Grayscale synthetic bursts)

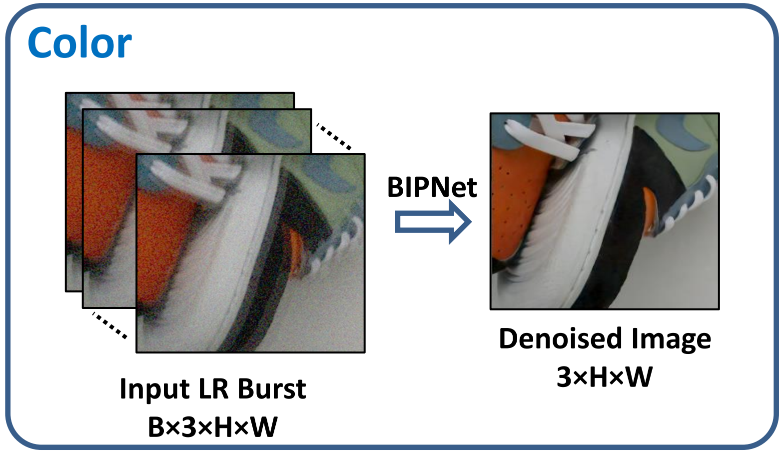
Color burst denoising

- Train split (20k from Open Images set)
- Validation split (100 Color synthetic bursts)

Training details

- Loss function: L_1
- Optimizer: ADAM
- Schedular: Cosine annealing strategy
- Learning rate: 10^{-4} to 10^{-6}
- Epochs: 50
- Network parameters: 6.67 M





Experiments

Quantitative comparison for Grascale Burst De-noising

Method	Gain α 1	Gain α 2	Gain α 4	Gain α 8	Average
KPN [1]	36.47	33.93	31.19	27.97	32.39
BPN [2]	38.18	35.42	32.54	29.45	33.9
MFIR [3]	39.37	36.51	33.38	29.69	34.74
BIPNet (Ours)	**41.26**	**38.74**	**35.91**	**31.35**	**36.81**

Quantitative comparison for Color Burst De-noising

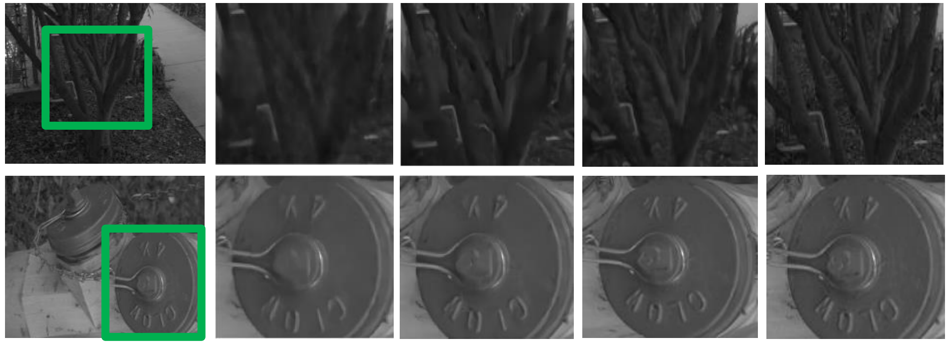
Method	Gain α 1	Gain α 2	Gain α 4	Gain α 8	Average
KPN [1]	38.86	35.97	32.79	30.01	34.41
BPN [2]	40.16	37.08	33.81	31.19	35.56
MFIR [3]	42.21	39.13	35.75	32.52	37.4
BIPNet (Ours)	**42.28**	**40.2**	**37.85**	**34.64**	**38.74**

[1] Ben Mildenhall et al., *Burst denoising with kernel prediction networks*. In CVPR, 2018

[2] Zhihao Xia et al., *Basis prediction networks for effective burst denoising with large kernels*. In CVPR, 2020

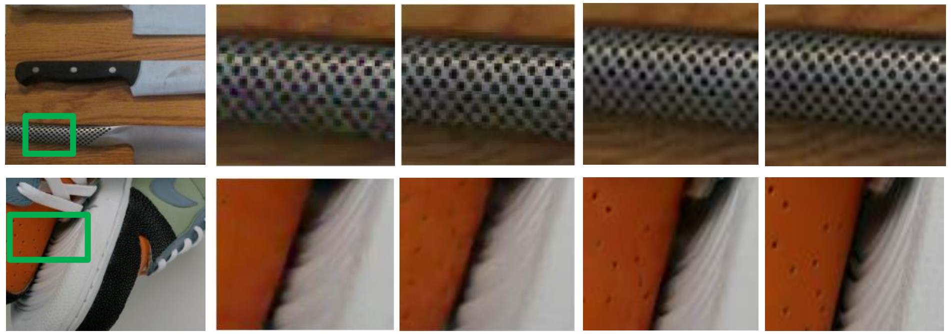
[3] Goutham Bhat et al., *Deep re-parametrization of multi-frame super-resolution and denoising*. In ICCV, 2021

Visual comparison for Grayscale Burst De-noising



BPN [2] MFIR [3] BIPNet (Ours) Reference

Visual comparison for Color Burst De-noising



BPN [2] MFIR [3] BIPNet (Ours) Reference

Summary

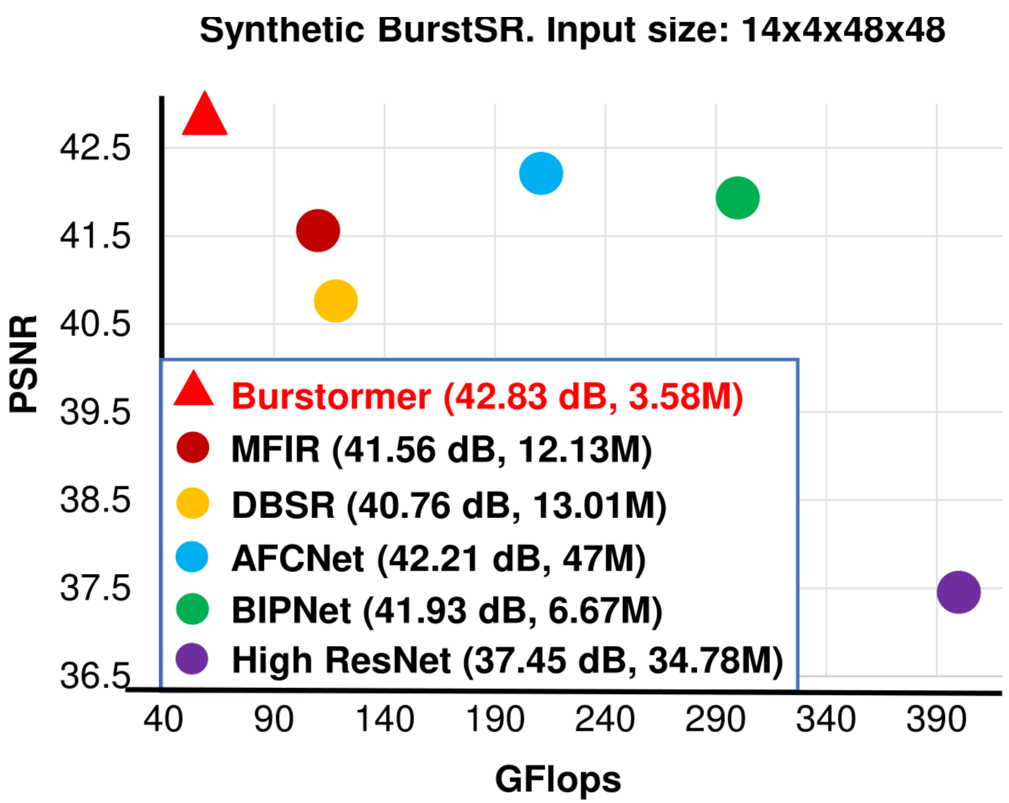
- A burst image restoration and enhancement framework which is developed to effectively fuse complimentary information from multiple burst frames.
- We propose the idea of pseudo-burst sequence that is created by combining the channel-wise features from individual burst frames.
- We introduce an edge-boosting burst alignment module that is robust to camera-scene movements.
- The pseudo-burst features are enriched using multi-scale information and later progressively fused to create up-sampled outputs.
- State-of-the-art results on three burst image restoration and enhancement tasks (super-resolution, low-light enhancement, denoising) corroborate the generality and effectiveness of BIPNet.

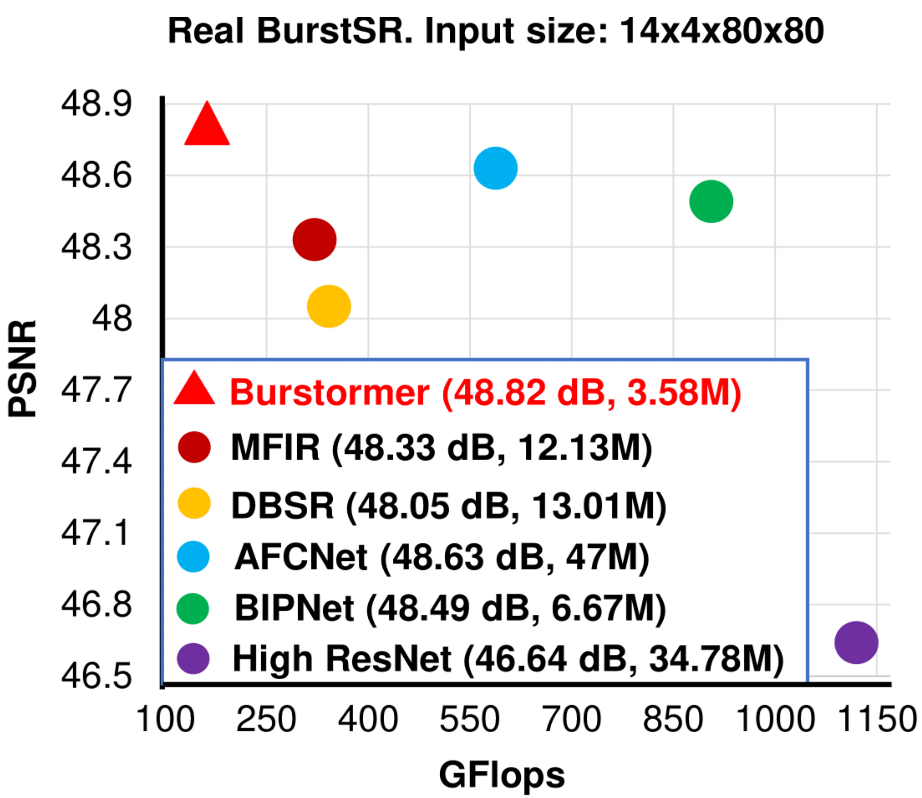
Akshay Dudhane, Syed Waqas Zamir, Salman Khan, Fahad Khan, Ming-Hsuan Yang: ***Burstormer: Burst Image Restoration and Enhancement Transformer***. **CVPR 2023**. **TUE-PM-150**.

Proposed Approach: Burstormer

- A transformer-based design, named Burstormer, for burst-image restoration and enhancement that leverages multi-scale local and non-local features for improved alignment and feature fusion.
- It enables inter-frame communication in the burst neighborhoods for information aggregation and progressive fusion while modeling the burst-wide context.
- Its flexible design allows processing bursts of variable sizes.
- Burstormer is efficient and outperforms state-of-the-art methods on burst super-resolution, burst denoising and burst low-light enhancement.

Proposed Approach: Burstormer





MFIR: Bhat G et al., “Deep reparametrization of multi-frame super-resolution and denoising”. In ICCV 2021.
DBSR: Bhat G et al., “Deep burst super-resolution”. In CVPR 2021.
AFCNet: Mehta N. et al., “Adaptive feature consolidation network for burst super-resolution”. In CVPRW-22.
BIPNet: Dudhane A. et al., “Burst image restoration and enhancement”. In CVPR-22.
HighResNet: Deudon M. et al., “Highres-net: Recursive fusion for multi-frame super-resolution of satellite imagery”. arXiv-2020.

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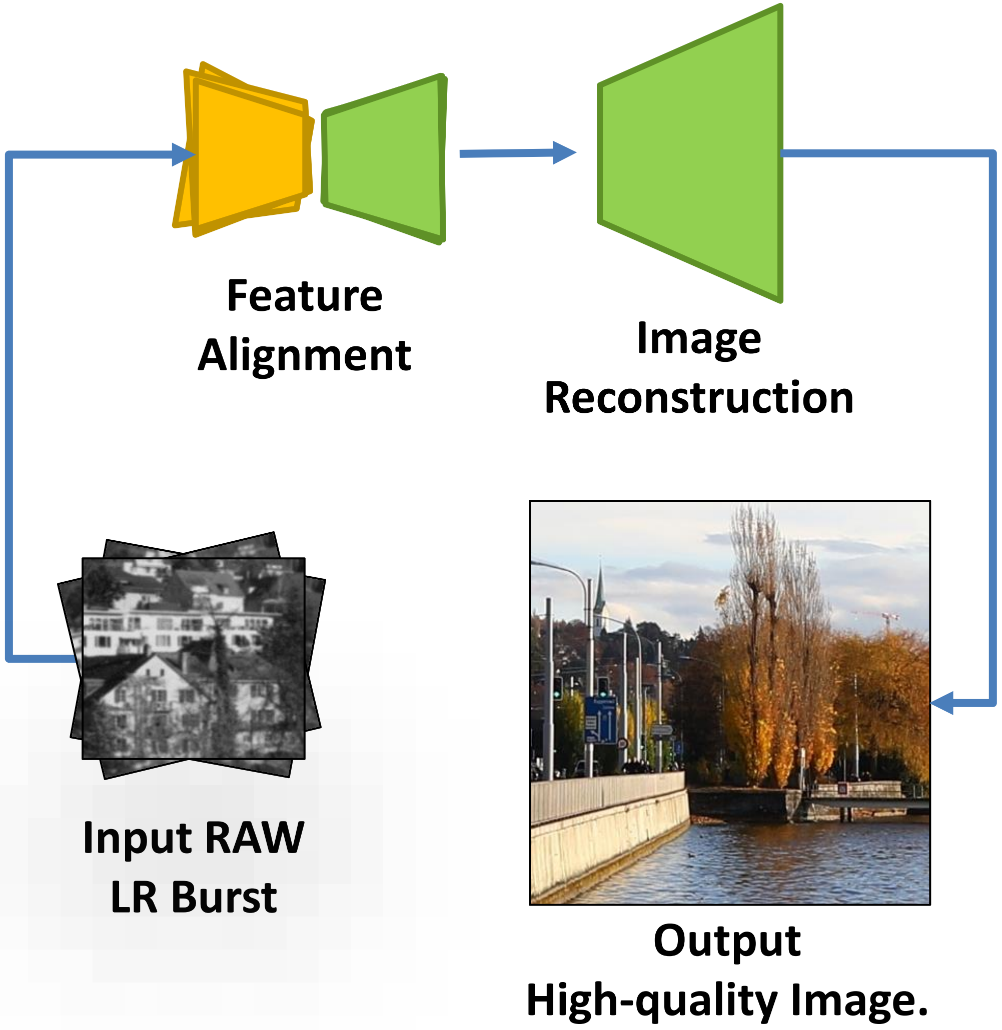


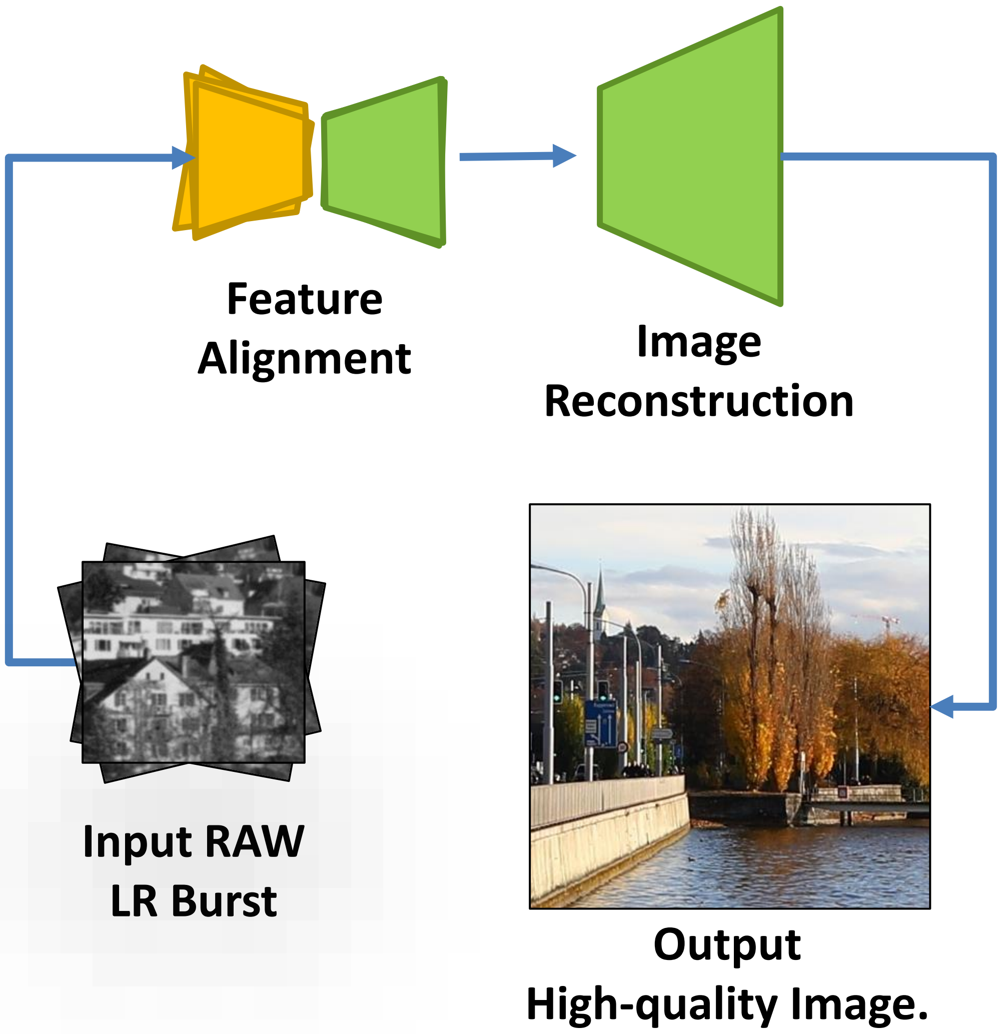
Contributions:

- **Enhanced Deformable alignment**: Aligns burst features implicitly with base frame, boosts the edges.
- **Image reconstruction**: Establishes strong inter-frame communication and integrates complementary information available within multiple frames. Neighboring frame features are used for spatial upscaling.

Applications:

- Proposed modules are validated for Burst **Super-resolution**, Burst **Low-light** Image **Enhancement**, Burst **De-noising**.

Proposed Approach: Burstormer



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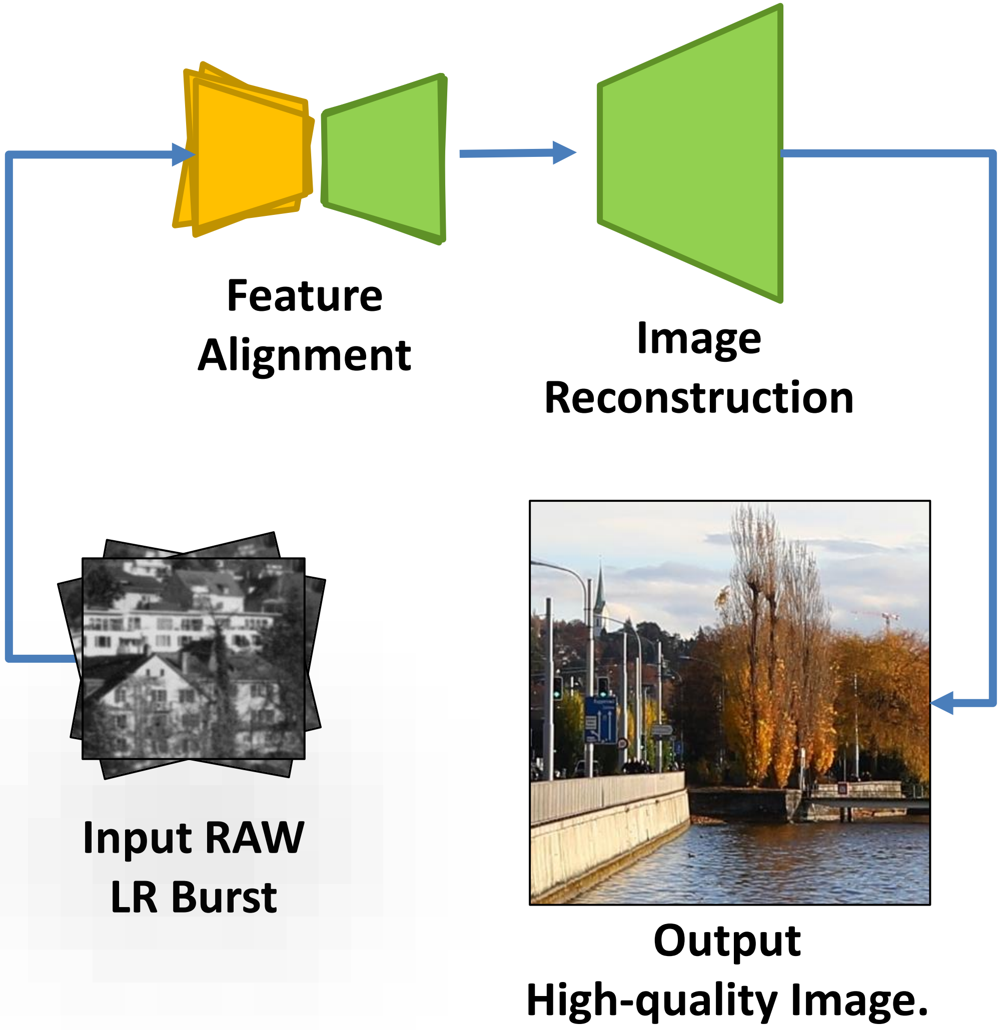

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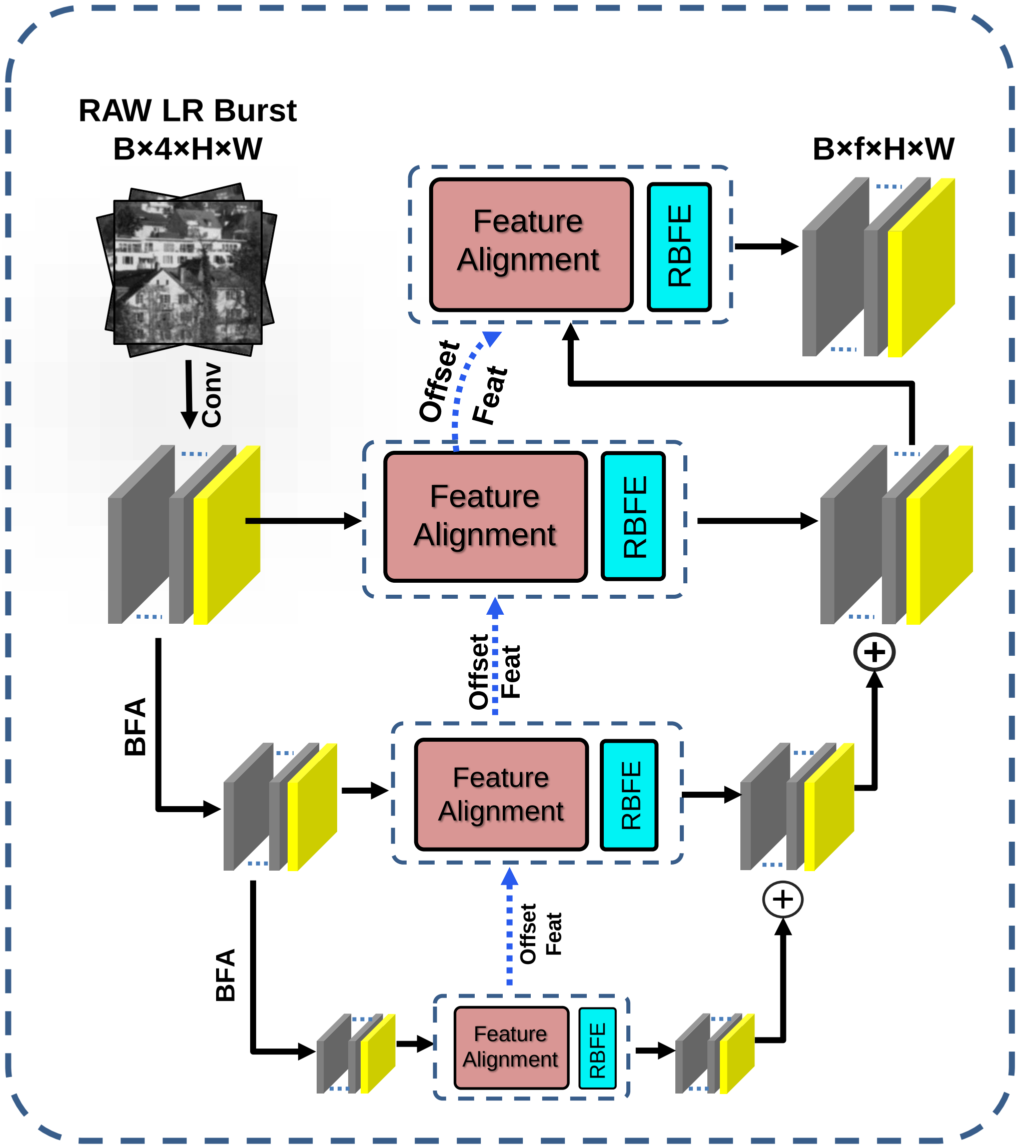
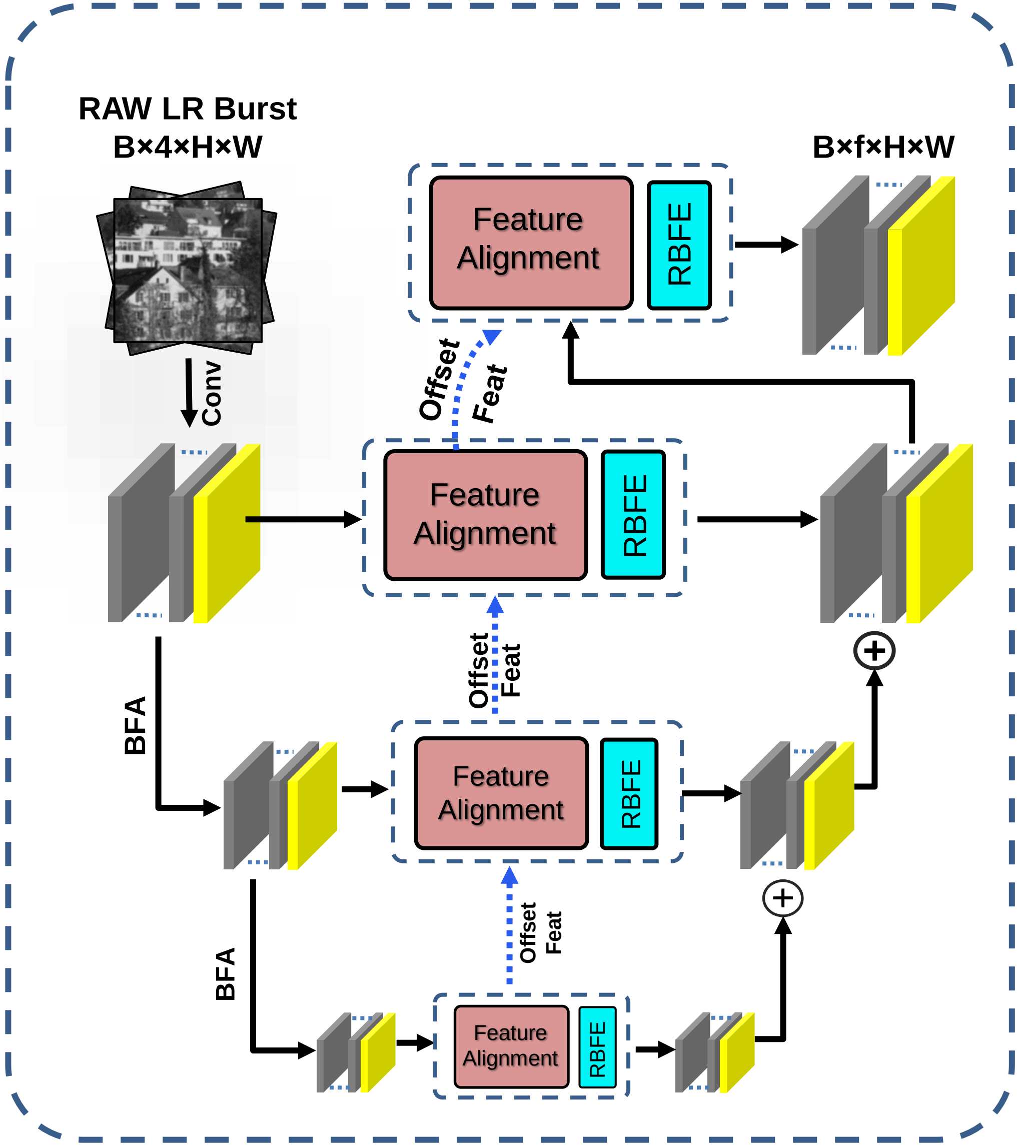


Enhanced Deformable Alignment (EDA)

- Feature Alignment (FA).
- Reference based feature Enrichment (RBFE).

Proposed Approach



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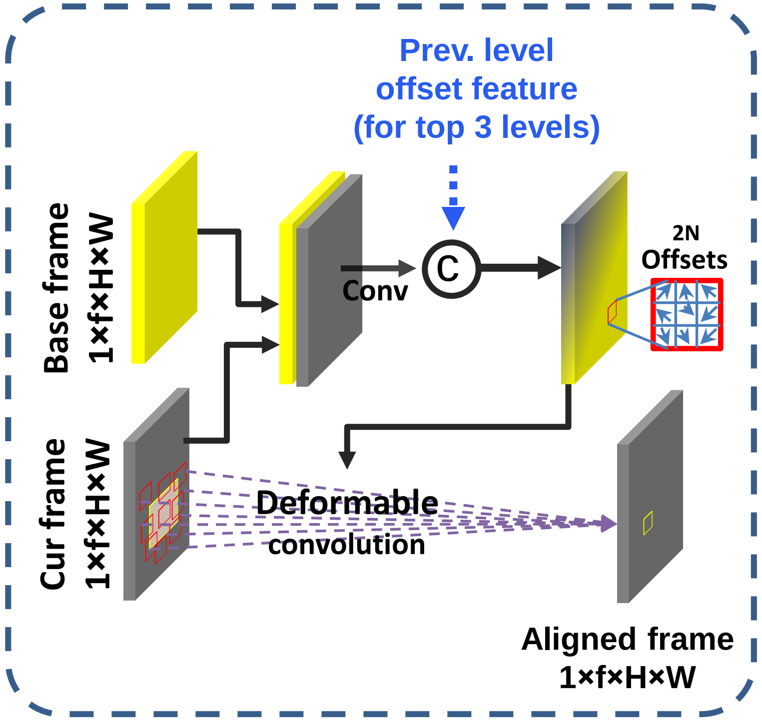
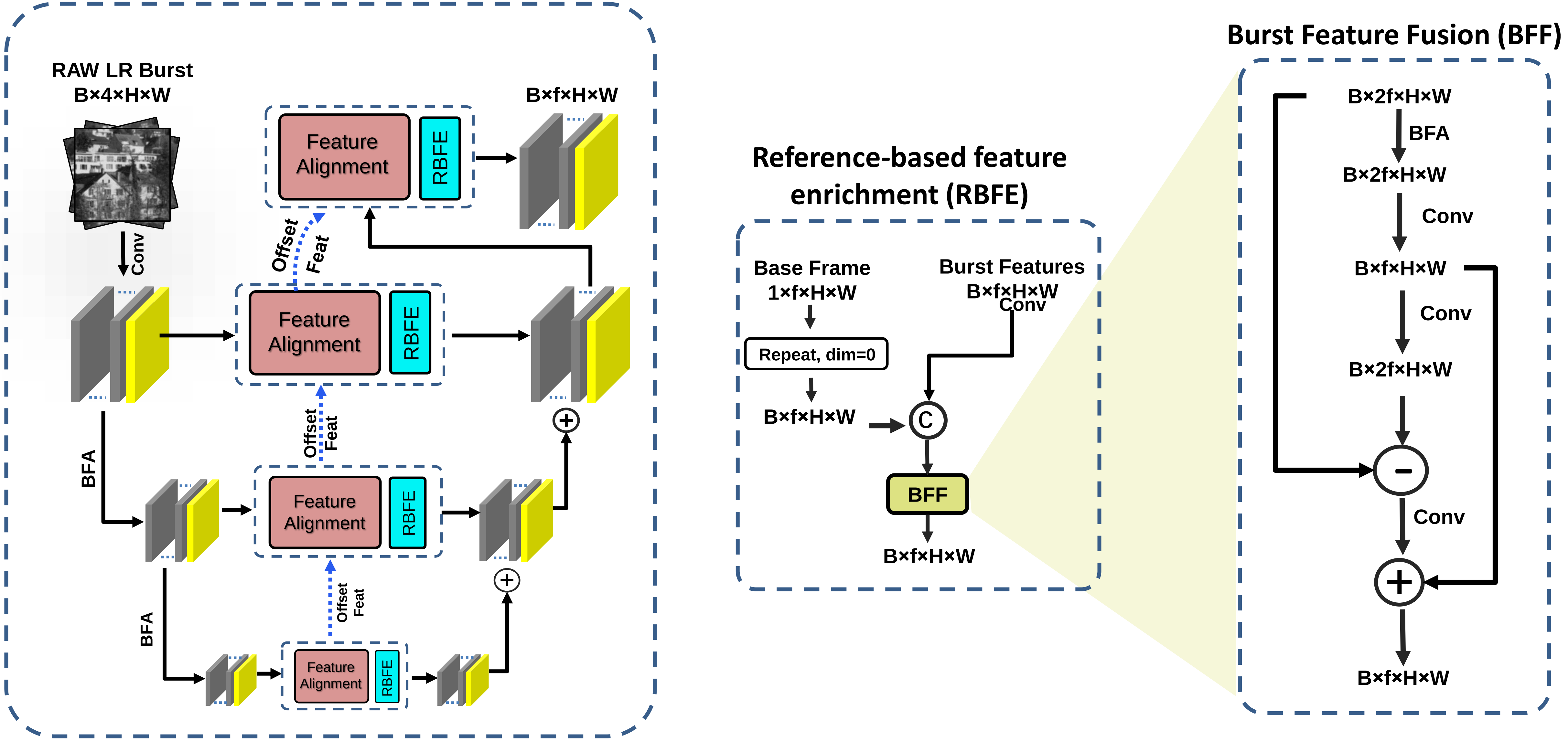
Feature Alignment (FA)



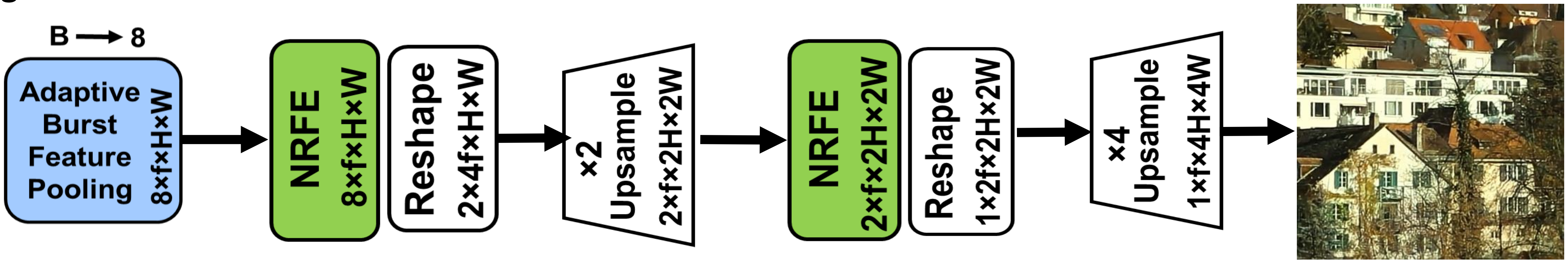
Proposed Approach



Enhanced Deformable Alignment

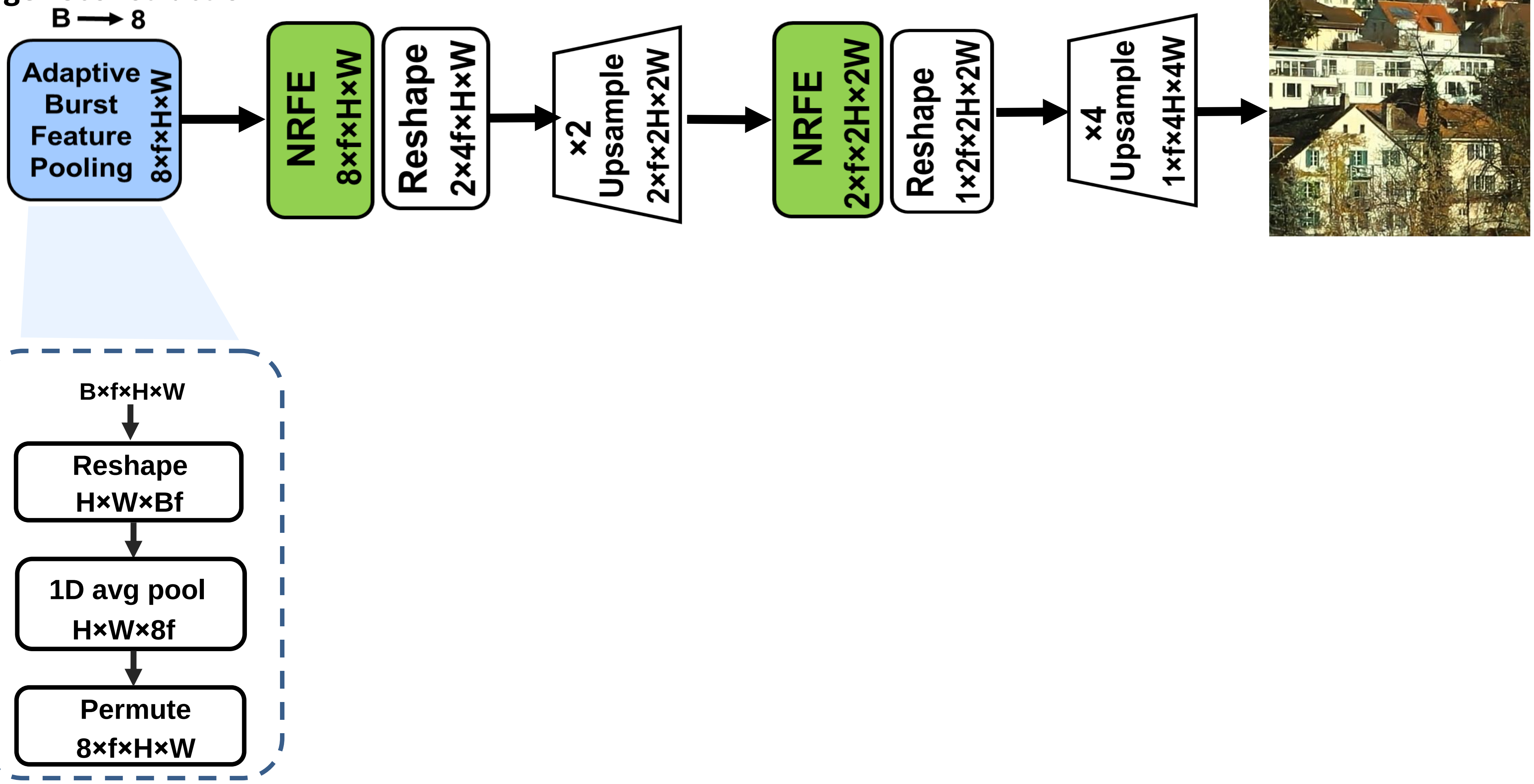
Proposed Approach

Image reconstruction



Proposed Approach

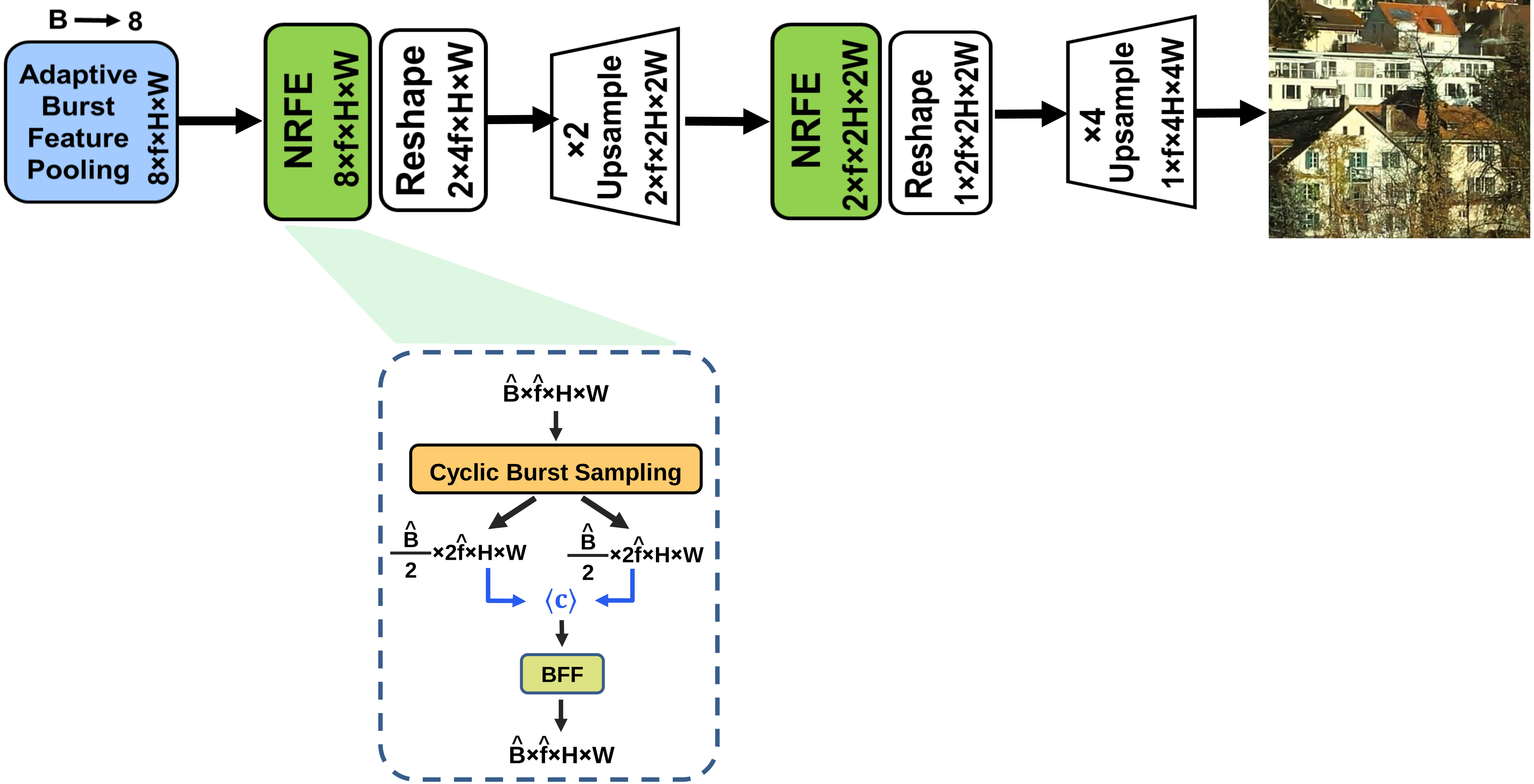
Image reconstruction



Adaptive Burst pooling

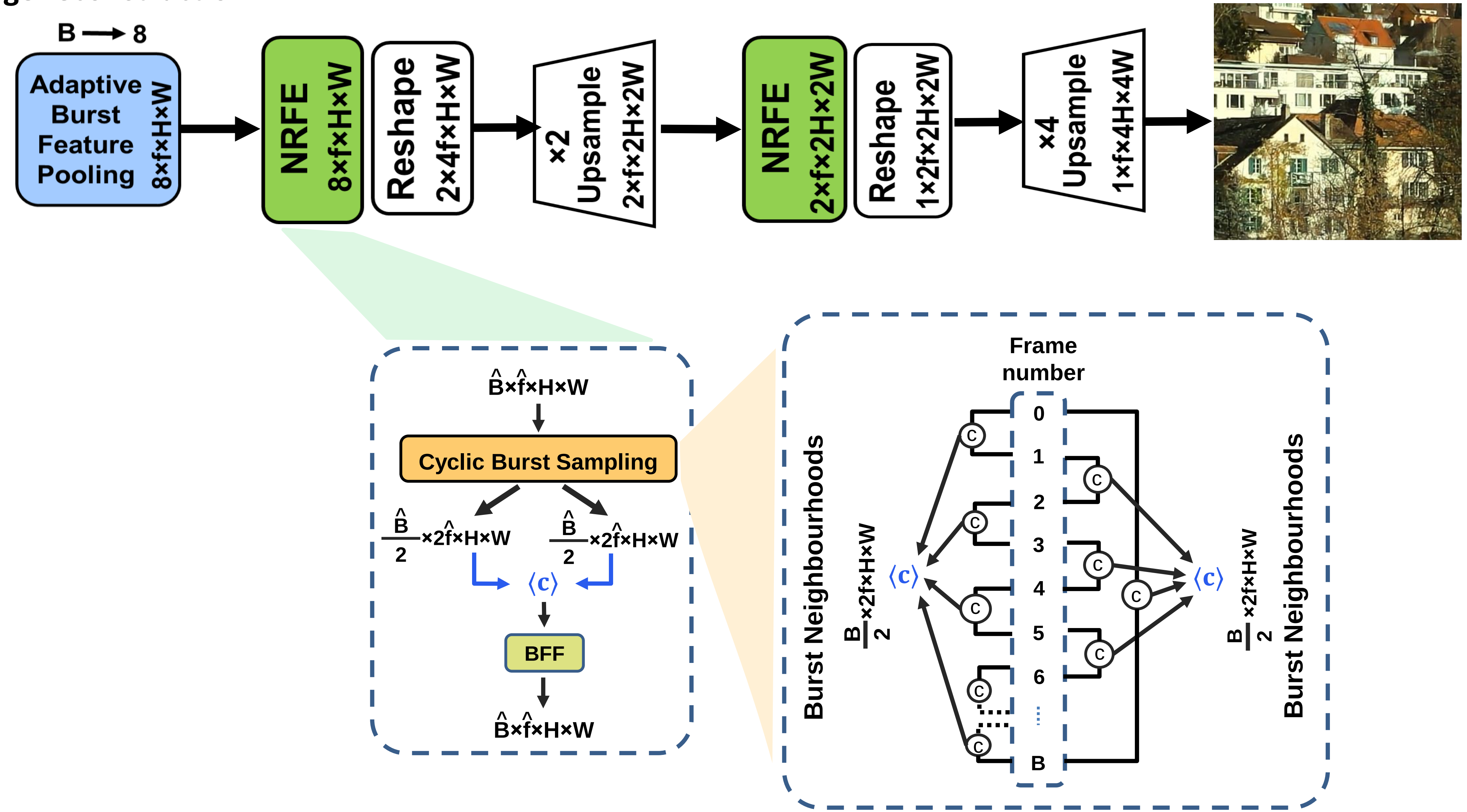
Proposed Approach

Image reconstruction



Proposed Approach

Image reconstruction



Cyclic Burst Sampling

Experiments

Burst Super-resolution

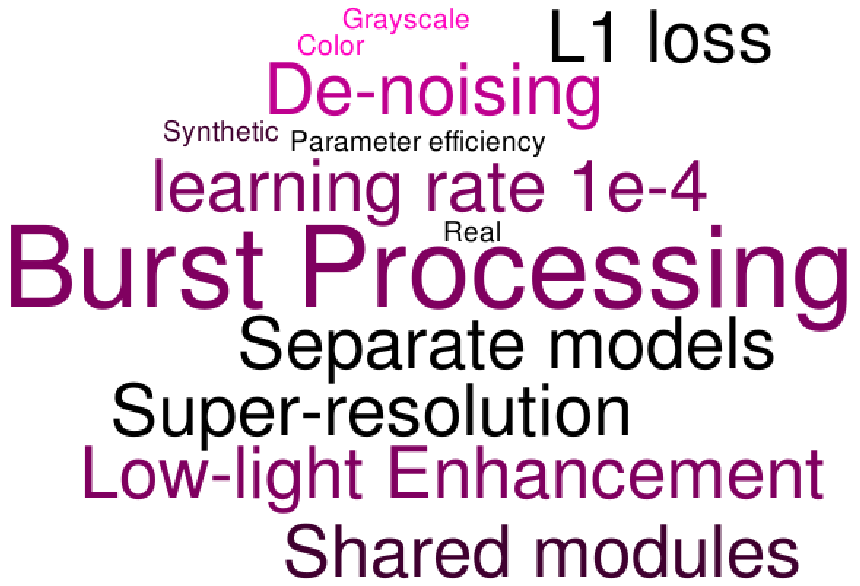
Datasets →	Synthetic Burst	BurstSR
Training set	46k	5405
Validation	1204	882

Burst De-noising

Datasets →	Color set	Grayscale set
Training set	20k	20k
Validation	100	73

Burst Low-light Image Enhancement

Datasets →	SONY
Training set	6.5k
Validation	93



Experiments

Burst low-light image enhancement evaluation on the SID dataset

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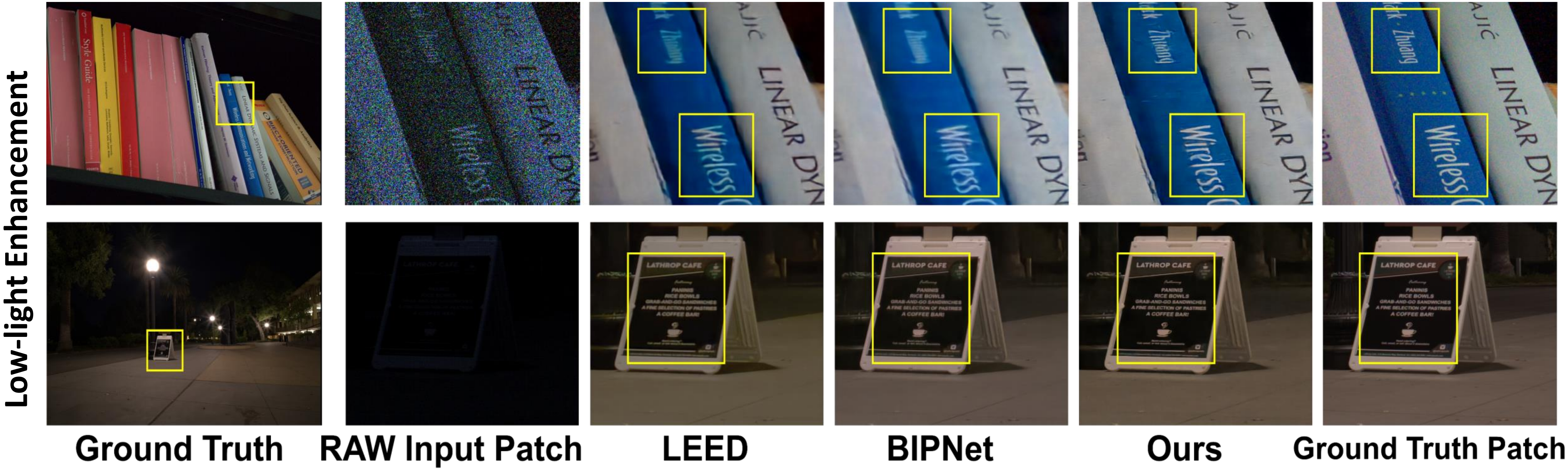
Zhao *et al.* [45]	29.49	0.895	0.455
LEED [18]	29.80	0.891	0.306
BIPNet [9]	32.87	0.936	0.305
Ours	**33.34**	**0.941**	**0.285**

[6]: Chen C at al., “Learning to see in the dark”. In CVPR 2018.
[9]: Dudhane A. et al., “Burst image restoration and enhancement”. In CVPR-22.
[18]: Karadeniz As et al., “Burst photography for learning to enhance extremely dark images”. IEEE TIP 2021.
[28]: Maharjan P et al., “Improving extreme low-light image denoising via residual learning”. In ICME 2019.
[43]: Zamir SW et al., “Learning digital camera pipeline for extreme low-light imaging”. Neurocomputing 2021.
[45]: Zhao D et al., “End-to-end denoising of dark burst images using recurrent fully convolutional networks”. arXiv 2019.

Experiments



Summary

- A transformer-based framework for burst image processing, capable of generating a single high-quality image from a given burst of noisy images having pixel misalignments among them.

- Burstormer employs a *multi-scale hierarchical module EDA* that, at each scale, first generates denoised features encoding local and non-local context, and then aligns each burst frame with the reference frame.

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Summary

- A transformer-based framework for burst image processing, capable of generating a single high-quality image from a given burst of noisy images having pixel misalignments among them.

- Burstormer employs a *multi-scale hierarchical module EDA* that, at each scale, first generates denoised features encoding local and non-local context, and then aligns each burst frame with the reference frame.

- To fix any remaining minor alignment issues, we incorporate a reference-based feature enrichment RBFE module in EDA that enables additional interaction of the features of each frame with the base frame features.

- In the *image reconstruction stage*, we repeatedly apply the no-reference feature enrichment NRFE and upsampling modules in tandem until the final image is obtained. NRFE progressively and adaptively fuses each pair of frame features that are obtained with the proposed cyclic burst sampling.

Future Directions

- To develop a reference frame selector algorithm which will adaptively select the reference-frame for a given burst rather than assuming first frame as a reference frame.

- To come up with a self-supervised burst processing technique which overcome the pre-training on synthetic data and domain adaptation.

- To validate the proposed network modules for other multi-frame applications such as, satellite image processing, medical image analysis etc., where feature alignment, fusion and reconstruction plays a crucial role in systems performance.

Acknowledgements

- Akshay Dhudhane
- Syed Waqas Zamir
- Salman Khan
- Nancy Mehta
- Subrahmanyam Murala
- Ming-Hsuan Yang

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Thanks