Burst Image Restoration and Enhancement

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(Invited Paper)

Abstract—Burst Image Restoration aims to reconstruct a high-quality image by efficiently combining complementary inter-frame information. However, it is quite challenging since individual burst images often have inter-frame misalignments that usually lead to ghosting and zipper artifacts. To mitigate this, we develop a novel approach for burst image processing named BIPNet that focuses solely on the information exchange between burst frames and filter-out the inherent degradations while preserving and enhancing the actual scene details. Our central idea is to generate a set of pseudo-burst features that combine complementary information from all the burst frames to exchange information seamlessly. However, due to inter-frame misalignment, the information cannot be effectively combined in pseudo-burst. Thus, we initially align the incoming burst features regarding the reference frame using the proposed edge-boosting feature alignment. Lastly, we progressively upscale the pseudo-burst features in multiple stages while adaptively combining the complementary information. Unlike the existing works, that usually deploy single-stage up-sampling with a late fusion scheme, we first deploy a pseudo-burst mechanism followed by the adaptive-progressive feature up-sampling. The proposed BIPNet significantly outperforms the existing methods on burst super-resolution, low-light image enhancement, low-light image super-resolution, and denoising tasks. The pre-trained models and source code are available at https://github.com/akshaydudhane16/BIPNet.

Index Terms—Feature alignment, Feature fusion, Burst processing, Super-resolution, Denoising, Low-light image enhancement

1 INTRODUCTION

With the escalating popularity of built-in smartphone cameras, the demand for capturing high-quality images has drawn much attention. However, relative to the larger standalone cameras, e.g., a DSLR, smartphone cameras have several limitations due to the constraints placed on them in order to be integrated into a smartphone’s thin profile. The most eminent hardware limitations are the small camera sensor size and the associated lens optics that reduce their spatial resolution and dynamic range [15], thus making noise much more of a problem during smartphone capture. As a remedy for these hardware limitations and to improve the overall image quality on smartphones, image restoration, and enhancement techniques have become indispensable. Image restoration techniques are employed to rectify the deteriorated aspects of an image caused by noise, blurriness, or other artifacts introduced during the image capture process. On the other hand, image enhancement techniques focus on improving the visual appearance of an image such that the viewer deems it pleasant.

In the literature, various approaches for single image restoration and enhancement have been developed to improve image quality. Nevertheless, achieving a truly high-quality output can be challenging due to the limited scene information within a single image. A promising solution gaining traction is the adoption of burst photography, capturing a series of photos in rapid succession rather than relying on a single shot. Burst processing approaches capture multiple shifted images, which are then integrated into a single high-quality output image to retrieve the non-redundant high-frequency details. Three critical factors in designing a novel burst processing approach include feature alignment, fusion, and high-quality image restoration. Generally, the biggest challenge for any burst processing approach is the accuracy of the alignment process, as the scene motion of dynamically moving objects and camera motion results in blurry output. Thus, it is crucial to design a module to facilitate accurate alignment, as the subsequent fusion and reconstruction modules must be robust to misalignment to generate an artifact-free image. We further note that existing burst processing approaches [5], [6] extract and explicitly align the burst features by employing late feature fusion mechanisms, which can hinder flexible information exchange among multiple frames. To address these issues, we present a novel burst image processing approach named BIPNet, which enables inter-frame communication through the proposed pseudo-burst feature fusion mechanism. Specifically, a pseudo-burst is formed by exchanging information within frames, where each feature comprises complementary properties from all burst frames.

The success of the pseudo burst mechanism for inter-frame communication depends upon the alignment among the burst frames. Therefore, it is crucial to accurately align the input burst frames to aggregate the apt pixel-level cues in the later stages before creating pseudo-bursts. We observe that the existing works DBSR [5] and MFIR [6] generally deploy explicit motion estimation techniques (e.g., optical flow) for aligning the burst features, which are typically bulky pre-trained modules (trained on additional data) and cannot be fully blended within an end-to-end learnable pipeline. However, this can result in upstretching of the cascaded errors during the flow estimation stage, and its further propagation to the warping and processing stages.
Our main contributions are summarized as:

- We propose an edge-boosting feature alignment module to align burst features with respect to the reference frame. (Sec. 3.1)
- A novel pseudo-burst feature aggregation technique is proposed to enable the interaction within burst frames. (Sec. 3.2)
- To upscale the burst features, we propose an adaptive group upsampling strategy. (Sec. 3.3)

A preliminary version of this work has been published as a conference paper [19], where we validate the proposed BIPNet for burst super-resolution, burst denoising, and burst low-light image enhancement. In this work, we additionally test the proposed BIPNet on a new problem of burst low-light image super-resolution. Furthermore, we validate two lightweight variants of the proposed approach named BIPNet-16 and BIPNet-32 for the burst SR task to reduce the inference time. We investigate more comprehensive ablation studies and add additional visual analysis to emphasize the major determinant factors in BIPNet (Sec. 4, and Sec. 5). The detailed experiments show that the proposed BIPNet outperforms current state-of-the-art methods on real and synthetic datasets for all the discussed applications.

2 Related Work

2.1 Single Image Super-resolution (SISR)

Since the pioneering CNN-based work [17], data-driven approaches have achieved impressive performance gains over the conventional counterparts [21], [58]. The success of CNNs is mainly attributed to their architecture design [2], [62]. Given a low-resolution image (LR), early methods directly learn to generate latent SR image [17], [18]. In contrast, recent approaches learn to produce high-frequency residual to which LR image is added to generate the final SR output [27], [48], [49]. Other notable SISR network designs employ recursive learning [1], [30], progressive reconstruction [32], [56], attention mechanisms [14], [61], [64], [65], and generative adversarial networks [34], [44], [55]. However, the SISR approaches cannot handle multi-degraded frames from an input burst, and our proposed approach belongs to multi-frame SR that assists effective merging of the cross-frame information for a high-quality HR output.
2.2 Multi-Frame Super-Resolution (MFSR)
Tsai et al. [51] proposed the first frequency domain-based method for the MFSR task. It performs registration and fusion of the aliased LR images to generate an SR image. Since processing multi-frames in the frequency domain generates visual artifacts [51], other works improved results by incorporating image priors in the reconstruction process [46] and making algorithmic choices such as iterative back-projection [28], [43]. Farsui et al. [20] design a joint multi-frame demosaicking and SR approach that is robust to noise. MFSR techniques are devised for diverse uses, including handheld devices (Wronski et al., 2019), enhancing facial image spatial resolution (Ustinova et al., 2017), and satellite imagery applications (Deudon et al., 2020; Molini et al., 2019). Lecouat et al. [33] retains the interpretability of conventional approaches for inverse problems by introducing a deep-learning-based optimization process that alternates between motion and HR image estimation steps. Recently, Bhat et al. [5] propose a burst SR method that initially aligns the burst image features using an explicit PWCNet [47] and then performs an attention-based fusion mechanism to integrate the features. However, explicit motion estimation and image-warping techniques can pose difficulty in handling scenes with fast object motions. Recent works [50], [54] show that the deformable convolution [67] effectively handles inter-frame alignment issues due to being implicit and adaptive in nature. Unlike existing MFSR methods, we implicitly learn the inter-frame alignment, and aggregate the channel-wise information followed by adaptive upsampling, which optimally leverages multi-frame information.

2.3 Low-Light Image Enhancement
Images acquired in low-light conditions are generally darker, noisy, and color distorted. Addressing these issues involves long sensor exposure time, larger aperture lens, camera flash, and exposure bracketing [15], [63]. However, each of these possible solutions comes with its challenges. For instance, long exposure generates images with ghosting artifacts because of camera or object movements. Wide apertures are generally not available on smartphone devices, etc. See-in-the-Dark method [10] is the first attempt to replace the standard camera imaging pipeline with a CNN model. It takes a RAW image captured in extremely low light as input and learns to generate a well-lit sRGB image. Later, this work is further improved by employing a combined pixel-wise and perceptual loss [63] and a new CNN-based architecture [39]. Zaho et al. [66] proposes a recurrent convolutional network by using burst imaging to produce a noise-free bright sRGB image from a burst of RAW images. The results are further improved by Karadeniz et al. [29] via their two-stage approach: the first sub-network performs denoising, and the second sub-network generates a visually enhanced image. Though these studies exhibit noteworthy progress in low-light image enhancement, they do not effectively consider the inter-frame misalignment and information interaction that we address in this work.

2.4 Low-light Image Super-resolution
Along with the low illumination and noise, distortions in low-light images further increase with physical constraints of the smartphone cameras, such as small sensor size, which limits the spatial resolution of the captured image. Approaches [10], [15], [29], [39], [63], [66] discussed in Sec. 2.3 deals with low-light image enhancement alone, while distortions due to the spatial resolution are not considered. Recently, Han et al. [23] have proposed a super-resolution approach for infrared images captured under low-light conditions. Wang et al. [52], [53] have proposed a low-light image super-resolution approach for monochromatic low-resolution images. Further, cross-fusion U-Net architecture is proposed in [11] for sRGB low-light image super-resolution. Above discussed approaches jointly deal with image enhancement and super-resolution tasks but operate on a single image captured in low-light conditions. Unlike these approaches, we use multiple low-light images to upscale and enhance the details jointly.

2.5 Multi-Frame Denoising
Earlier works [12], [37], [38] provide extensions on top of the popular image denoising algorithm BM3D [13] to video. Buades et al. [9] estimated the noise level from the aligned images followed by the combination of pixel-wise mean and BM3D to perform denoising. A hybrid 2D/3D Wiener filter is used in [25] to denoise and merge burst images for high dynamic range and low-light photography tasks. Godard et al. [22] utilize recurrent neural network (RNN) and extend a single image denoising network for multiple frames. Mildenhall et al. [42] generate per-pixel kernels through the kernel prediction network (KPN) to merge the input images. In [40], authors extend the KPN approach to predict multiple kernels, while [57] introduces basis prediction networks (BPW) to enable the use of larger kernels. Recently, Bhat et al. [6] proposed a deep reparameterization of the maximum a posteriori formulation for the multi-frame SR and denoising.

3 Burst Processing Approach
This section describes our burst processing approach, which applies to different image restoration tasks, including burst super-resolution, burst low-light image enhancement, burst low-light image super-resolution, and burst denoising. The goal is to generate a high-quality image by combining information from multiple degraded images captured in a single burst. Burst images are typically captured with handheld devices, and it is often inevitable to avoid inter-frame spatial and color misalignment issues. Therefore, the main challenge of burst processing is to accurately align the burst frames, followed by combining their complementary information while preserving and reinforcing the shared attributes. To this end, we propose BIPNet in which different modules operate in synergy to jointly perform denoising, demosaic, feature fusion, and upsampling tasks in a unified model.
Overall pipeline. Fig. 1 shows three main stages in the proposed BIPNet. First, the input RAW burst is passed through the edge boosting feature alignment module to extract features, reduce noise, and remove spatial and color misalignment issues among the burst features (Sec. 3.1). Second, a pseudo-burst is generated by exchanging information such that each feature map in the pseudo-burst now
contains complimentary properties of all actual burst image features (Sec. 3.2). Finally, the multi-frame pseudo-burst features are processed with the adaptive group upsampling module to produce the final high-quality image (Sec. 3.3).

3.1 Edge Boosting Feature Alignment Module

One major challenge in burst processing is to extract features from multiple degraded images that are often contaminated with noise, unknown spatial displacements, and color shifts. These issues arise due to camera and/or object motion in the scene and lighting conditions. To align the other images in the burst with the base frame (usually the 1st frame), we propose an alignment module based on modulated deformable convolutions [67]. However, existing deformable convolution is not explicitly designed to handle noisy RAW data. Therefore, we propose a feature processing module to reduce noise in the initial burst features. Our edge boosting feature alignment (EBFA) module (Fig. 2(a)) does feature processing followed by burst feature alignment.

3.1.1 Feature Processing Module

The proposed feature processing module (FPM), shown in Fig. 2(b), employs residual-in-residual learning that allows abundant low-frequency information to pass easily via skip connections [64]. Since capturing long-range pixel dependencies which extract global scene properties is beneficial for a wide range of image restoration tasks [59] (e.g., image/video super-resolution [41] and extreme low-light image enhancement [3]), we utilize a global context attention (GCA) mechanism to refine the latent representation produced by residual block, as illustrated in Fig. 2(b). Let \( \{x^{b}\}_{b \in [1:B]} \in \mathbb{R}^{B \times f \times H \times W} \) be an initial latent representation of the burst having \( B \) burst images and \( f \) number of feature channels, our residual global context attention block (RGCAB in Fig. 2(b)) is defined as:

\[
y^{b} = \bar{x}^{b} + \omega_{1}(\alpha(\bar{x}^{b})),
\]

where \( \bar{x}^{b} = \omega_{3}(\gamma(\omega_{3}(\bar{x}^{b}))) \) and \( \alpha(\bar{x}^{b}) = \bar{x}^{b} + \omega_{1}(\gamma(\omega_{1}(\Psi(\omega_{1}(\bar{x}^{b}) \otimes \bar{x}^{b})))) \). Here, \( \omega_{k} \) represents a convolutional layer with \( k \times k \) sized filters and each \( \omega_{k} \) corresponds to a separate layer with distinct parameters, \( \gamma \) denotes leaky ReLU activation, \( \Psi \) is softmax activation, \( \otimes \) represents matrix multiplication, and \( \alpha(\cdot) \) is the global context attention.

3.1.2 Burst Feature Alignment Module

To effectively fuse information from multiple frames, these frame-level features need to be aligned first. We align the features of the current frame \( y^{b} \) with the base frame \( y^{b_{r}} \). EBFA processes \( y^{b} \) and \( y^{b_{r}} \) through an offset convolution layer and predicts the offset \( \Delta n \) and modulation scalar \( \Delta m \) values for \( y^{b} \). The aligned features \( \bar{y}^{b} \) computed as:

\[
\bar{y}^{b} = \omega^{d}\left(y^{b}, \Delta n, \Delta m\right), \quad \Delta m = \omega^{o}\left(y^{b}, y^{b_{r}}\right),
\]

where \( \omega^{d} \) and \( \omega^{o} \) represent the deformable and offset convolutions, respectively. More specifically, each position \( n \) on the aligned feature map \( \bar{y}^{b} \) is obtained as:

\[
\bar{y}^{b}_{n} = \sum_{i=1}^{K} \omega^{d}_{ni} y^{b}_{(n_{i} + \Delta n)} \cdot \Delta m_{n_{i}},
\]

where \( K=9 \), \( \Delta m \) lies in the range \([0, 1] \) for each \( n_{i} \in \{(-1, 1), (-1, 0), \ldots, (1, 1)\} \) is a regular grid of \( 3 \times 3 \) kernel.

The convolution operation will be performed on the non-uniform positions \( (n_{i} + \Delta n_{i}) \), where \( n_{i} \) can be fractional. To avoid fractional values, the operation is implemented using bilinear interpolation.

The proposed EBFA module is inspired by the deformable alignment module (DAM) [50] with the following differences. Our approach does not provide explicit ground-truth supervision to the alignment module. Instead, it learns to perform implicit alignment. Furthermore, to strengthen the feature alignment and correct the minor alignment errors, we use FPM to obtain refined aligned features (RAF) and the high-frequency residue by taking the difference between the RAF and base frame features and adding it to the RAF. Adding this residue to RAF effectively boosts the edge content within the burst features. The overall process of our EBFA module is summarized as: \( e^{b} = \bar{y}^{b} + \omega_{3}(\bar{y}^{b} - y^{b_{r}}) \) where \( e^{b} \in \mathbb{R}^{B \times f \times H \times W} \) represents the aligned burst feature maps, and \( \omega_{3}(-) \) is a \( 3 \times 3 \) convolution layer. Although the deformable convolution is shown only once in Fig. 2(a) for brevity, we sequentially apply three such layers to improve the transformation capability of our EBFA module.

1. Here, we consider the first image of a given burst as the base frame.
employ our FPM instead of regular convolutions. We use shared weights in the U-Net and also pseudo-bursts. We use a lightweight (3-)
f-pseudo-burst of size ‘f’
where, ‘⟨·⟩’ represents concatenation,
image feature channels. Given the aligned burst feature set
and merge the relevant information by decoupling the burst
feature responses simplify the representation learning task
properties of all burst image features. Processing inter-burst
from all burst feature maps. Consequently, each feature
tensor in the pseudo-burst contains complimentary properties
of all frames. Pseudo bursts are processed with (shared) U-Net to extract
Existing burst image processing techniques [5], [6] separately extract and align features of burst images and usually employ late feature fusion mechanisms, which can hinder flexible information exchange between frames. We instead propose a pseudo-burst feature fusion (PBFF) mechanism (see Fig. 3 (a)). This PBFF module generates feature tensors by concatenating the corresponding channel-wise features from all burst feature maps. Consequently, each feature tensor in the pseudo-burst contains complimentary properties of all burst image features. Processing inter-burst feature responses simplify the representation learning task and merge the relevant information by decoupling the burst image feature channels. Given the aligned burst feature set
\[ e = \{ e^b_c \}_{c \in [1 : f]} \]
of burst size ‘B’ and ‘f’ number of channels, the pseudo-burst is generated by,
\[ S^c = \omega^o \left( \langle e^1_c, e^2_c, \cdots, e^B_c \rangle \right), \quad s.t. \quad c \in [1 : f], \]
where, ‘⟨·⟩’ represents concatenation, ‘e^i_c’ is the ‘i’th feature map of 1st aligned burst feature set ‘e^i’, ‘\omega^o’ is the convolution layer with ‘f’ output channel, and \[ S = \{ S^c \}_{c \in [1 : f]} \] is the pseudo-burst of size \( f \times f \times H \times W \). Here, we use \( f = 64 \).

Even after generating pseudo-bursts, obtaining their deep representation is essential. We use a lightweight (3-level) U-Net to extract multi-scale features (MSF) from pseudo-bursts. We use shared weights in the U-Net and also employ our FFM instead of regular convolutions.

3.2 Pseudo-Burst Feature Fusion Module

Upsampling is the final key step to generate the super-resolved image from LR feature maps. Existing burst SR methods [5], [6] use pixel-shuffle layer [45] to perform upsampling in one stage. However, in burst image processing, information in multiple frames can be exploited effectively to get into the HR space. To this end, we propose to adaptively and progressively merge multiple LR features in the upsampling stage. For instance, on the one hand, it is beneficial to have uniform fusion weights for texture-less regions to perform denoising among the frames. On the other hand, to prevent ghosting artifacts, it is desirable to have low fusion weights for any misaligned frame.

Fig. 3(b) shows the proposed adaptive group upsampling (AGU) module that processes the feature maps \( S = \{ S^c \}_{c \in [1 : f]} \) produced by the pseudo-burst fusion module and provides an HR output via three-level progressive upsampling. In AGU, we sequentially divide the pseudo-burst features into groups of 4, instead of following any complex selection mechanism. These groups of features are upsampled with the architecture depicted in Fig. 3(c) that first computes a dense attention map (‘\( a^o \)’) (attention weights for each pixel). The dense attention maps are element-wise applied to the respective burst features. Finally, the upsampled response for a given group of features \( S^g = \{ S^i : i \in ([g - 1] * 4 + 1 : g * 4) \}^{g \in [1 : f / 4]} \) \( \subset S \) and associated attention maps \( a^g \) at the first upsampling level.
We perform SR experiments for scale factor $\times 4$. Burst Super-resolution are provided in the supplementary material.

Augmentation. Additional network details and visual results during training. We use horizontal and vertical flips for data aligning aligned $L$ with pre-trained weights on the SyntheticBurst dataset using LKR, and MFIR results contain splotchy textures and compromise image details.

**4 Experiments**

We evaluate the proposed BIPNet and other approaches on real and synthetic datasets for (a) burst super-resolution, (b) burst low-light image enhancement, (c) burst low-light image super-resolution, and (d) burst denoising.

**4.1 Implementation Details.**

Our BIPNet is end-to-end trainable and needs no pre-training of any module. For network parameter efficiency, all burst frames are processed with shared BIPNet modules (FPM, EBFA, PBFF and AGU). Overall, the proposed network contains 6.67M parameters. We train separate models for burst SR, burst low-light image enhancement, burst low-light image SR, and burst denoising using $L_1$ loss only. While for burst SR on real data, we fine-tune our BIPNet with pre-trained weights on the SyntheticBurst dataset using aligned $L_1$ loss [5]. The models are trained with an Adam optimizer. Cosine annealing strategy [36] is employed to steadily decrease the learning rate from $10^{-4}$ to $10^{-6}$ during training. We use horizontal and vertical flips for data augmentation. Additional network details and visual results are provided in the supplementary material.

**4.2 Burst Super-resolution**

We perform SR experiments for scale factor $\times 4$ on the SyntheticBurst and (real-world) BurstSR datasets [4].

**4.2.1 Datasets**

1. **SyntheticBurst** dataset consists of 46,839 RAW bursts for training and 300 for validation. Each burst contains 14 LR RAW images (each of size $48 \times 48$ pixels) that are synthetically generated from a single sRGB image. Each sRGB image is first converted to the RAW space using the inverse camera pipeline [7]. Next, the burst is generated with random rotations and translations. Finally, the LR burst is obtained by applying the bilinear downsampling followed by Bayer mosaicking, sampling and random noise addition operations.

2. **BurstSR** dataset consists of 200 RAW bursts, each containing 14 images. To gather these burst sequences, the LR images and the corresponding (ground-truth) HR images are captured with a smartphone camera and a DSLR camera, respectively. From 200 bursts, 5,405 patches are cropped for training and 882 for validation. Each input crop is of size $80 \times 80$ pixels.

**4.2.2 SR results on synthetic data**

The proposed BIPNet is trained for 300 epochs on the training set while evaluated on a validation set of SyntheticBurst dataset [4]. We compare our BIPNet with the several burst SR methods such as HighResNet [16], DBSR [5], LKR [33], and MFIR [6] for $\times 4$ upsampling. Table 1 shows that our method performs favorably well. Specifically, our BIPNet achieves PSNR gain of 0.37 dB over the previous best MFIR [6] and 0.48 dB over the second best approach [33].

Visual results provided in Fig. 5 show that the SR images produced by BIPNet are sharper and more faithful than those of the other algorithms. Our BIPNet is capable of reconstructing structural content and fine textures without introducing artifacts and color distortions. Whereas DBSR, LKR, and MFIR results contain splotchy textures and compromise image details.

To show the effectiveness of our method BIPNet on large scale factor, we perform experiments for the $\times 8$ burst SR. We synthetically generate LR-HR pairs following the same procedure as we described above for the SyntheticBurst dataset consist of 200 bursts, 5,405 patches for training and 882 for validation. Each input crop is of size $80 \times 80$ pixels.
dataset. Visual results in Fig. 6 show that our BIPNet is capable of recovering rich details for such large-scale factors as well, without any artifacts. Additional examples can be found in the supplementary material.

4.2.3 SR results on real data

The LR input bursts and the corresponding HR ground truth in the BurstSR dataset suffer from minor misalignment as they are captured with different cameras. To mitigate this issue, we used aligned L1 loss for training and aligned PSNR/SSIM for evaluating our model, as in previous works [5], [6]. We fine-tuned the pre-trained BIPNet for 15 epochs on the training set while evaluating on the validation set of the BurstSR dataset. The image quality scores are reported in Table 1. Compared to the previous best approach MFIR [6], our BIPNet provides a performance gain of 0.16 dB. The visual comparisons in Fig. 7 show that our BIPNet is more effective in recovering fine details in the reproduced images than other competing approaches.

4.3 Light-weight BIPNet for Burst SR

The proposed BIPNet is designed with 64 filters in each convolution layer. It has 6.67M parameters and 300 GFlops. To reduce the GFlops and increase the burst processing speed, we obtain two lightweight versions, BIPNet-32 and BIPNet-16, by reducing the convolution filters from 64 to 32 and 64 to 16, respectively. Compared to BIPNet (6.67M, 300 GFlops), BIPNet-32 (1.8 M, 54.3 GFlops) has 73% fewer parameters and 81% fewer GFlops. While BIPNet-16 (0.5 M, 12 GFlops) has 93% fewer parameters and 96% fewer
Fig. 7: Comparisons for ×4 burst super-resolution on Real BurstSR dataset [5]. Our BIPNet produces more sharper and clean results than other competing approaches.

Fig. 8: Burst low-light image enhancement on Sony subset [10]. BIPNet better preserves color and structural details.

| Methods   | PSNR  | SSIM  | LPIPS |
|-----------|-------|-------|-------|
| SID [10]  | 29.38 | 0.892 | 0.484 |
| ELID [39] | 29.57 | 0.891 | 0.484 |
| LDCP [63] | 29.13 | 0.881 | 0.462 |
| RFCN [66] | 29.49 | 0.895 | 0.455 |
| LEED [29] | 30.04 | 0.890 | 0.308 |
| BIPNet (Ours) | 32.87 | 0.936 | 0.305 |

TABLE 2: Burst low-light image enhancement methods evaluated on the SID dataset [10]. Our BIPNet advances state-of-the-art by 2.83 dB.

While BIPNet-16 is comparatively less accurate (achieves 39.8 dB PSNR), it is extremely efficient with only 36.16 ms inference time, 503K parameters, and 12 GFlops, reducing 91%↓ inference time, 96%↓ parameters and 89%↓ GFlops compared to the existing baseline DBSR [5] approach.

4.4 Burst Low-Light Image Enhancement

To further demonstrate the effectiveness of BIPNet, we perform experiments for burst low-light image enhancement. Given a low-light RAW burst, our goal is to generate a well-lit sRGB image. Since the input is mosaicked RAW burst, we use one level AGU to obtain the output.

4.4.1 Dataset

SID dataset [10] consists of short-exposure burst raw images taken under extremely dark indoor (0.2-5 lux) or outdoor (0.03-0.3 lux) scenes and their corresponding ground truth sRGB images. Burst RAW images are acquired with three GFlops. In Fig. 4, we compare PSNR, inference time (in Milliseconds), and GFlops of the proposed light-weight BIPNet versions with the existing networks on the SyntheticBurst [4] dataset for burst SR task. As shown in Fig. 4, the proposed BIPNet-32 has an inference time of 45.85 ms, 54.3 GFlops, and achieves 41.12 dB PSNR which is better than the recent DBSR [5] approach (431 ms, 118 GFlops, 40.76 dB).
Fig. 9: Comparisons for $\times 4$ burst low-light image super-resolution on SID-SR [10] dataset. Our BIPNet produces sharper and enhanced results compared to the other approaches.

**Methods** | **PSNR ↑** | **SSIM ↑** | **LPIPS ↓**
--- | ---: | ---: | ---: |
LDCP [63] | 26.43 | 0.62 | 0.58 |
DBSR [5] | 26.71 | 0.74 | 0.51 |
MFIR [6] | 27.61 | 0.76 | 0.48 |
LEED [29] | 27.30 | 0.76 | 0.51 |
BIPNet (Ours) | 29.16 | 0.81 | 0.43 |

TABLE 3: Burst low-light image super-resolution methods evaluated on the SID-SR dataset [10].
ratio to align the exposure. After pre-processing, each burst patch is of size $256 \times 256 \times 4 \times B$ while ground truth sRGB patch is of size $512 \times 512 \times 3$, where $B$ denotes the number of burst images ranging from 2 to 8. Further, to mold the SID dataset for the low-light super-resolution (LSR) task, we apply bilinear downsampling by a factor $\times 4$ on the pre-processed burst to get the LR burst of size $64 \times 64 \times 4 \times B$.

4.5.2 LSR results

We compare the proposed BIPNet with existing base methods from burst super-resolution: DBSR [5], MFIR [6] and burst low-light image enhancement: LDCP [61], LEED [29] for $\times 4$ LSR task. For LDCP [61], and LEED [29] methods, we have deployed a pixel-shuffle layer to upscale the burst features. We train the proposed and existing methods for 100 epochs on a training set of the SID-SR dataset. Table 3 shows that the proposed BIPNet outperforms the other methods by a large margin. Visual results given in Fig. 9 show that the proposed BIPNet produces more enhanced results when compared with the existing methods.

4.6 Burst Denoising

Here, we demonstrate the effectiveness of the proposed BIPNet on the burst denoising task. BIPNet processes the input noisy sRGB burst and obtains a noise-free image. Since there is no need to up-sample the extracted features, transpose convolution in the proposed AGU is replaced by a simple group convolution while the rest of the network architecture is kept unmodified.

4.6.1 Dataset

We evaluate our approach on the grayscale and color burst denoising datasets introduced in [42] and [57]. These datasets contain 73 and 100 burst images, respectively. In both datasets, a burst is generated synthetically by applying random translations to the base image. The shifted images are then corrupted by adding heteroscedastic Gaussian noise [26] with variance $\sigma_t^2 + \sigma_s x$. The networks are then evaluated on 4 different noise gains $(1, 2, 4, 8)$, corresponding to noise parameters $(\log(\sigma_t), \log(\sigma_s)) \rightarrow (-2.2, -2.6)$, $(-1.8, -2.2)$, $(-1.4, -1.8)$, and $(-1.1, -1.5)$, respectively. Note
Particularly, our BIPNet provides a PSNR boost of training levels. A similar performance trend can be observed the previous best method MFIR [6] by 0.91 dB on the denoising dataset [42]. Specifically, the BIPNet outperforms significantly advances state-of-the-art on grayscale burst training it on extra data). Table 4 shows that our BIPNet that uses a custom optical flow sub-network (without pre-supervision, we consider the results of the MFIR [6] variant the proposed BIPNet is trained without any extra data or both for grayscale and color burst denoising tasks. Since approaches (KPN [42], MKPN [40], BPN [57] and MFIR [6])

We compare the proposed BIPNet with several previous methods on the grayscale burst denoising set [42] in terms of PSNR. The results for existing methods are from [6]. Our approach outperforms BPN on the highest noise level by 0.58 dB.

that the noise parameters for the highest noise gain (Gain ∝ 8) are unseen during training. Thus, performance on this noise level indicates the generalization of the network to unseen noise. Following [6], we utilized 20k samples from the Open Images [31] training set to generate the synthetic noisy bursts of burst-size eight and spatial size 128 × 128. Our BIPNet is trained for 50 epochs for the grayscale and color burst denoising tasks and evaluated on the benchmark datasets [42] and [57] respectively.

### 4.6.2 Burst Denoising results

We compare the proposed BIPNet with several previous approaches (KPN [42], MKPN [40], BPN [57] and MFIR [6]) for grayscale and color burst denoising tasks. Since the proposed BIPNet is trained without any extra data or supervision, we consider the results of the MFIR [6] variant that uses a custom optical flow sub-network (without pre-training it on extra data). Table 4 shows that our BIPNet significantly advances state-of-the-art on grayscale burst denoising dataset [42]. Specifically, the BIPNet outperforms the previous best method MFIR [6] by 0.91 dB on the highest noise level (Gain ∝ 8), which is unseen during training levels. A similar performance trend can be observed in Table 5 for color denoising on color burst dataset [57]. Particularly, our BIPNet provides a PSNR boost of 0.58 dB over the previous best method MFIR [6] for the highest noise level (Gain ∝ 8). In Figure 10, BIPNet’s reproduced images appear cleaner and sharper than other methods.

### 4.7 Ablation Study

Here we present ablation experiments to demonstrate the impact of each individual component of our approach. All

2. In conference version [19] of this work, we mistakenly calculated the PSNR before post-processing [6]. This paper rectifies the error, and the corrected PSNR scores can be found in Tables 4 and 5.

#### 4.7.1 Importance of individual components

We compare the proposed BIPNet with several previous methods on the color burst denoising set [57] in terms of PSNR. The results for existing methods are from [6]. Our approach outperforms BPN on the highest noise level by 0.58 dB.

#### 4.7.2 Importance of BIPNet modules

Table 6 shows the importance of BIPNet modules evaluated on SyntheticBurst validation set for ×4 burst SR.

### 4.8 Visual analysis

In addition to conducting a quantitative ablation study, we analyze restored results to validate the efficacy of the proposed Edge Boosting Feature Alignment (EBFA) module. We use checkerboard image for ease of understanding. We obtain a burst of sub-pixel shifted checkerboard images with the process described in Sec. 4.2.1 (1). Finally, the synthetically generated checkerboard burst is processed through the proposed EBFA module, which aligns all the neighboring frames with respect to the base frame

#### 4.9 Importance of the proposed alignment, fusion, and up-sampling modules

Table 7 reports the PSNR and SSIM scores for different alignment, fusion, and up-sampling methods on SyntheticBurst validation set for ×4 burst SR.

### 5 Conclusion

In conclusion, we present BIPNet, a novel end-to-end burst denoising network that employs a combination of feature alignment and fusion modules to significantly improve the performance of burst denoising. We demonstrate that our approach achieves state-of-the-art performance on both grayscale and color burst denoising datasets, outperforming existing methods by a significant margin. Our work opens up new avenues for research in the field of burst denoising, with potential applications in various domains such as video processing, still image denoising, and medical imaging.

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**TABLE 4:** Comparison of our method with prior approaches on the grayscale burst denoising set [42] in terms of PSNR. The results for existing methods are from [6].

| Modules     | A1 | A2 | A3 | A4 | A5 | A6 | A7 | A8 |
|-------------|----|----|----|----|----|----|----|----|
| Baseline    | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  |
| FPM (§3.1.1) | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  |
| DAM (§3.1.2) | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  |
| RAF (§3.1.2) | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  |
| PBFF (§3.2) | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  |
| MSF (§3.2) | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  |
| AGU (§3.3) | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  |
| EBFA (§3.1) | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  | ✓  |

**Parameters (M)**: 5.27, 5.64, 6.23, 6.27, 6.35, 6.44, 6.57, 6.67

| PSNR | 36.38 | 36.54 | 38.39 | 39.10 | 39.64 | 40.33 | 41.25 | 41.55 |
|------|-------|-------|-------|-------|-------|-------|-------|-------|

**TABLE 5:** Comparison with previous methods on the color burst denoising set [57] in terms of PSNR.

| Modules | Gain ∝ 1 | Gain ∝ 2 | Gain ∝ 4 | Gain ∝ 8 |
|---------|----------|----------|----------|----------|
| KPN [42] | 38.86    | 35.97    | 32.79    | 30.01    |
| BPN [57] | 40.16    | 37.08    | 33.81    | 31.19    |
| MFIR [6] | 41.90    | 38.85    | 35.48    | 32.29    |
| BIPNet (Ours) | 40.58    | 38.13    | 35.30    | 32.87    |

**TABLE 6:** Importance of BIPNet modules evaluated on SyntheticBurst validation set for ×4 burst SR.

| Modules | PSNR ↑ | SSIM |
|---------|--------|------|
| (a) Alignment | Explicit [5] | 39.26 | 0.944 |
|           | TDAN [50] | 40.19 | 0.957 |
|           | EDVR [54] | 40.46 | 0.958 |
| (b) Fusion | Addition | 39.18 | 0.943 |
|           | Concat   | 40.13 | 0.956 |
|           | DBSR [5] | 40.16 | 0.957 |
| (c) Up-sampling | Pixel-shuffle [45] | 40.35 | 0.951 |
| (d) BIPNet (Ours) | 41.55 | 0.960 |

**TABLE 7:** Importance of the proposed alignment, fusion, and up-sampling modules on SyntheticBurst validation set for ×4 burst SR.
Fig. 11: Illustration of the feature maps with and without the proposed Edge Boosting Feature Alignment (EBFA) module. The upper row shows the unaligned burst features, whereas the lower row displays the corresponding aligned burst features. The EBFA module significantly reduces the noise and aligns the neighboring frames with the base frame.

Fig. 12: Visualization of the BIPNet results utilizing various base frames. The left side showcases a heavily distorted base frame alongside its restored image, whereas the right side displays a moderately distorted base frame and its restored image. This analysis shows that the final result gets influenced with respect to the base frame distortions.

(First frame). Fig. 11 shows the feature representations of the base and neighboring frames with and without the inclusion of the EBFA module. These results facilitate us to gain deeper insights into the functionality of the EBFA module. Notably, in the absence of feature alignment, the neighboring frames exhibit noticeable sub-pixel shifts compared to the base frame. Conversely, employing the EBFA module for feature alignment results in minimal sub-pixel shifts for the neighboring frame feature and a notable reduction in noise compared to the base frame.

Moreover, the proposed network's modules could extend to the applications where challenges are in feature alignment, fusion, and reconstruction, testing the modules' robustness and adaptability.

6 Conclusion

We have proposed a novel burst restoration and enhancement approach for effectively fusing complementary information from multiple burst frame features. Unlike the existing late feature fusion methods, which combine the multi-frame feature information in the late part of the pipeline, we present a novel concept of pseudo-burst arrangement by individually integrating the channel-wise attentive features from each burst frame. To avert any sort of mismatch among the generated pseudo-burst features, we design an edge-boosting burst alignment module to implicitly align the frames by being robust to the camera-scene motions. Subsequently, the generated pseudo-burst features are refined by utilizing multi-scale information and later progressively fused for generating the upsampled reconstructed output. Extensive experiments on four burst restoration and enhancement tasks (super-resolution, low-light enhancement, low-light image super-resolution, and denoising) validate the authenticity and potency of BIPNet.

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