NTIRE 2024 Challenge on Bracketing Image Restoration and Enhancement: Datasets, Methods and Results

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Abstract

Low-light photography presents significant challenges. Multi-image processing methods have made numerous attempts to obtain high-quality photos, yet remain unsatisfactory. Recently, bracketing image restoration and enhancement has received increased attention. By leveraging the full potential of multi-exposure images, several tasks (including denoising, deblurring, high dynamic range enhancement, and super-resolution) can be jointly addressed. This paper reviews the NTIRE 2024 challenge on bracketing image restoration and enhancement. In the challenge, participants are required to process multi-exposure RAW images to generate noise-free, blur-free, high dynamic range, and even higher-resolution RAW images. The challenge comprises two tracks. Track 1 does not incorporate the super-resolution task, whereas Track 2 does. Each track featured five teams participating in the final testing phase. The proposed methods establish new state-of-the-art performance benchmarks.

1. Introduction

Low-light photography is a widely desired yet challenging problem. Recent years have witnessed significant advancements in enhancing low-light image quality through learning-based methods. In comparison with single-image restoration (*e.g.*, denoising [1, 9, 30, 45, 49, 94, 98, 99], deblurring [18, 62, 66, 74, 95, 97], and super-resolution (SR) [41, 46, 48, 51, 100, 102, 103]) and enhancement (*e.g.*, high dynamic range (HDR) reconstruction [15, 26, 42, 55, 69, 110]), multi-image processing methods offer more advantages in mitigating the ill-posed nature of this problem and can generate results with higher fidelity.

Several multi-image processing works are summarized in Tab. 1. Within these works, burst and dual-exposure images have limited dynamic range, making it difficult to restore underexposed or overexposed details. Multi-exposure images contain richer information, while most methods based on them require ideal prerequisites (*e.g.*, no noise or no blur). More recently, Zhang *et al.* [106] consider a more realistic situation of multi-exposure images, encompassing noisy, blurry, underexposed, overexposed content, as well as inter-frame misalignment. They utilize the complementarity of exposure bracketing images to integrate image restoration and enhancement tasks, thereby generating a noise-free, blur-free, HDR, and high-resolution image. This new objective, termed bracketing image restoration and enhancement, is proposed.

This paper reviews the NTIRE 2024 Challenge on Bracketing Image Restoration and Enhancement, which aims to foster further research and establish state-of-the-art benchmarks. Participants are tasked with generating noise-free, blur-free, HDR, and even higher-resolution RAW images from five multi-exposure RAW images. The challenge consists of two tracks: Track 1 and Track 2. Track 1 does not incorporate the super-resolution task, whereas Track 2 does. In the final testing phase, each track featured the participation of five teams. This report briefly describes their

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solutions and reports their performance. Their proposed methods have set new state-of-the-art benchmarks in bracketing image restoration and enhancement.

2. NTIRE 2024 Challenge

Bracketing Image Restoration and Enhancement is one of the NTIRE 2024 associated challenges (https://cvlai.net/ntire/2024/), which include dense and non-homogeneous dehazing [3], night photography rendering [4], blind compressed image enhancement [91], shadow removal [77], efficient super resolution [70], image super resolution (×4) [16], light field image super-resolution [80], stereo image super-resolution [78], HR depth from images of specular and transparent surfaces [93], bracketing image restoration and enhancement [107], portrait quality assessment [10], quality assessment for AI-generated content [53], restore any image model (RAIM) in the wild [47], RAW image super-resolution [19], short-form UGC video quality assessment [44], low light enhancement [54], and RAW burst alignment and ISP challenge.

2.1. Overview

The objectives of NTIRE 2024 Challenge on Bracketing Image Restoration and Enhancement are as follows: (1) highlighting the problems and promoting the research in bracketing image restoration and enhancement, (2) establishing high-quality benchmarks for bracketing image restoration and enhancement and facilitating comparisons between various methods, (3) providing a platform for academic and industrial participants to engage, discuss, and potentially establish collaborations.

The challenge has two tracks, *i.e.*, Track 1 (https://codalab.lisn.upsaclay.fr/competitions/17573) and Track 2 (https://codalab.lisn.upsaclay.fr/competitions/17574). Track 1 utilizes bracketing photography to unify basic restoration (*i.e.*, denoising and deblurring) and enhancement (*i.e.*, HDR reconstruction), named BracketIRE. Track 2 appends the ×4 super-resolution task, dubbed BracketIRE+. The inputs are five multi-exposure RAW images. The output should be a noise-free, blur-free, HDR, and even higher-resolution (only for Track 2) RAW image. Participants can develop novel network architectures and other techniques to achieve the goal. Besides, we provide a simple image signal processing (ISP) toolkit (https://github.com/cszhilu1998/BracketIRE/tree/master/NTIRE2024) for converting the output RAW images into 16-bit RGB images for evaluation and visualization. We also provide codes and pre-trained models of a baseline (*i.e.*, TMRNet [106]) at this URL.

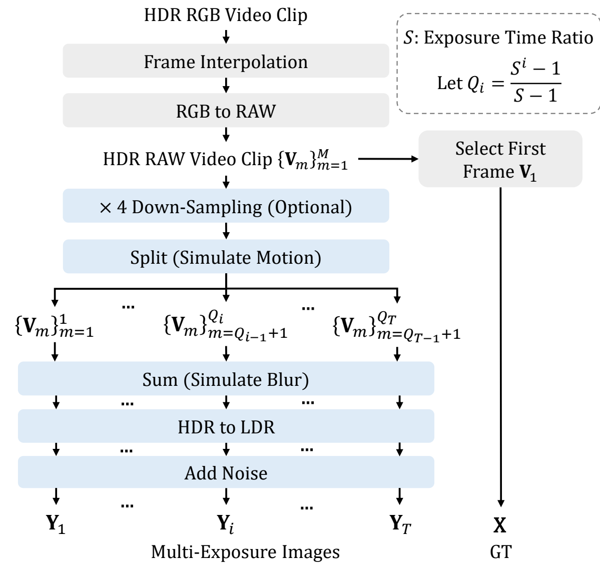


Figure 1. Overview of data simulation pipeline. HDR video is utilized to synthesize multi-exposure images $\{\mathbf{Y}_i\}_{i=1}^{T}$ and the corresponding GT image $\mathbf{X}$. S denotes the exposure time ratio between $\mathbf{Y}_i$ and $\mathbf{Y}_{i-1}$. $\mathbf{Y}_i$ is obtained by summing and processing S^{i-1} ($\{i–1\}$-th power of S) images from HDR raw video $\mathbf{V}$. Q_i denotes the total number of images from $\mathbf{V}$ that participate in constructing $\{\mathbf{Y}_k\}_{k=1}^{i}$.

2.2. Datasets

We follow the data simulation pipeline [106] to provide synthetic datasets for BracketIRE and BracketIRE+ tasks, as shown in Fig. 1. First, we perform ×32 frame interpolation with RIFE [34] on HDR videos from Froehlich *et al.* [28]. Then, we convert the RGB videos to RAW space, getting HDR RAW sequences$\{\mathbf{V}_m\}_{m=1}^{M}$.

Next, we introduce degradations to construct multi-exposure images, mainly including the following 5 steps. (1) Bicubic ×4 down-sampling is applied to obtain low-resolution images, which only serves for BracketIRE+ task. (2) Each video is split into T non-overlapped groups, where i-th group should be used to synthesize $\mathbf{Y}_i$. (3) Denote the exposure time ratio between $\mathbf{Y}_i$ and $\mathbf{Y}_{i-1}$ by S. We sequentially move S^{i-1} ($\{i-1\}$-th power of S) consecutive images into the above i-th group, summing them up to simulate blurry images. (4) We transform the HDR blurry images into low dynamic range (LDR) ones by cropping values outside the specified range and mapping the cropped values to 10-bit unsigned integers. (5) We add the heteroscedastic Gaussian noise [9, 32, 79] to LDR images to generate the final multi-exposure images (*i.e.*, $\{\mathbf{Y}_i\}_{i=1}^{T}$). The noise variance is a function of pixel intensity, whose parameters are estimated from the real-world images captured by Xiaomi 10S smartphone when ISO is set to 1,600.

The first frame $\mathbf{V}_1$ in HDR video clip is taken as a ground truth (GT) image, whose resolution is 1,920×1,080.

Table 1. Comparison between various multi-image processing manners.

Setting	Methods	Input Images	Supported Tasks Denoising	Deblurring	HDR	SR
Burst Denoising	[29, 31, 64, 71, 86]	Burst	✓			
Burst Deblurring	[2, 21, 68, 83]	Burst		✓		
Burst SR	[22, 82, 84]	Burst				✓
Burst Denoising and SR	[5–8, 24, 25, 39, 61, 63, 85]	Burst	✓			✓
Burst Denoising and HDR	[27, 33]	Burst	✓		✓	
Dual-Exposure Image Restoration	[12, 38, 65, 72, 92, 104, 108]	Dual-Exposure	✓	✓		
Basic HDR Imaging	[36, 57, 67, 75, 88, 89, 105]	Multi-Exposure			✓	
HDR Imaging with Denoising	[17, 52, 69]	Multi-Exposure	✓		✓	
HDR Imaging with SR	[73]	Multi-Exposure			✓	✓
HDR Imaging with Denoising and SR	[40]	Multi-Exposure	✓		✓	✓
BracketIRE	[106]	Multi-Exposure	✓	✓	✓	
BracketIRE+	[106]	Multi-Exposure	✓	✓	✓	✓

We set the exposure time ratio S to 4 and the frame number T to 5. Finally, we obtain 1,335 data pairs from 35 scenes. 1,045 pairs from 31 scenes are used for training, and the remaining 290 pairs from the other 4 scenes are used for testing. The validation set is selected from the testing set, including 29 pairs from 4 scenes.

2.3. Challenge Rules

To ensure fairness and equitable comparisons to the greatest extent possible, the following competition rules are established: (1) Reproducibility of methods is a must. (2) The method should input multi-exposure RAW images and output an HDR RAW image. (3) The participants cannot change the provided ISP. (4) During inference, the number of network parameters should be less than 100M, GPU memory should be controlled within 24G and the use of a self-ensemble strategy is prohibited. (5) Each participant can only join one team. Each team can only submit one algorithm for final ranking. (6) Any testing adaptive strategies are not permitted. In other words, the model cannot be fine-tuned using data related to the test images. For example, using the testing results of Track 1 to fine-tune the model of Track 2 is prohibited.

2.4. Challenge Phases

There are two phases in the challenge: (1) development and validation phase, (2) testing phase.

Development and Validation Phase. Participants have access to both the training data and validation data (refer to Sec. 2.2 for dataset details). Note that the training data includes multi-exposure images and the corresponding GT images, while the validation data only includes the input multi-exposure images. Participants can upload their results to the validation server to calculate PSNR metrics and receive feedback.

Testing Phase. Participants have access to the testing multi-exposure images to generate final results. Note that the GT images are not available for them. They can submit their results to the server and email their code and fact sheet to the organizers. The organizers executed the provided code to verify the results, which were then shared with participants at the end of the challenge.

3. Challenge Results

There are 100 and 92 participants registered for Track 1 and Track 2, respectively. Each track has five teams submitting the final testing results (including model outputs, codes, and fact sheets). Their solutions are described in Sec. 4.

3.1. Evaluation Metrics

The restored RAW images are post-processed to 16-bit RGB ones by the provided ISP. We evaluate the results on the 16-bit RGB domain. The widely used PSNR [35], SSIM [81] and LPIPS [101] are employed as the quantitative evaluation metrics. The ranking is based on the PSNR metric of the full images. Besides, given that several pixels around the image are invalid, we also calculate the metrics on the cropped images that exclude the invalid pixels. To compare the inference cost, #FLOPs, testing time, and GPU memory are measured when generating a 1920×1080 RAW image on a single NVIDIA RTX A6000 GPU. The number of model parameters is also measured. In addition, the performance of a baseline model (*i.e.*, TMRNet [106]) is reported for reference.

3.2. Track 1: BracketIRE

Tab. 2 shows that all teams outperform the baseline (*i.e.*, TMRNet[106]) with a large margin, improving PSNR results ranging from 0.27dB to 2.35dB. In particular, Samsung team achieves the best performance, obtaining 2.35dB

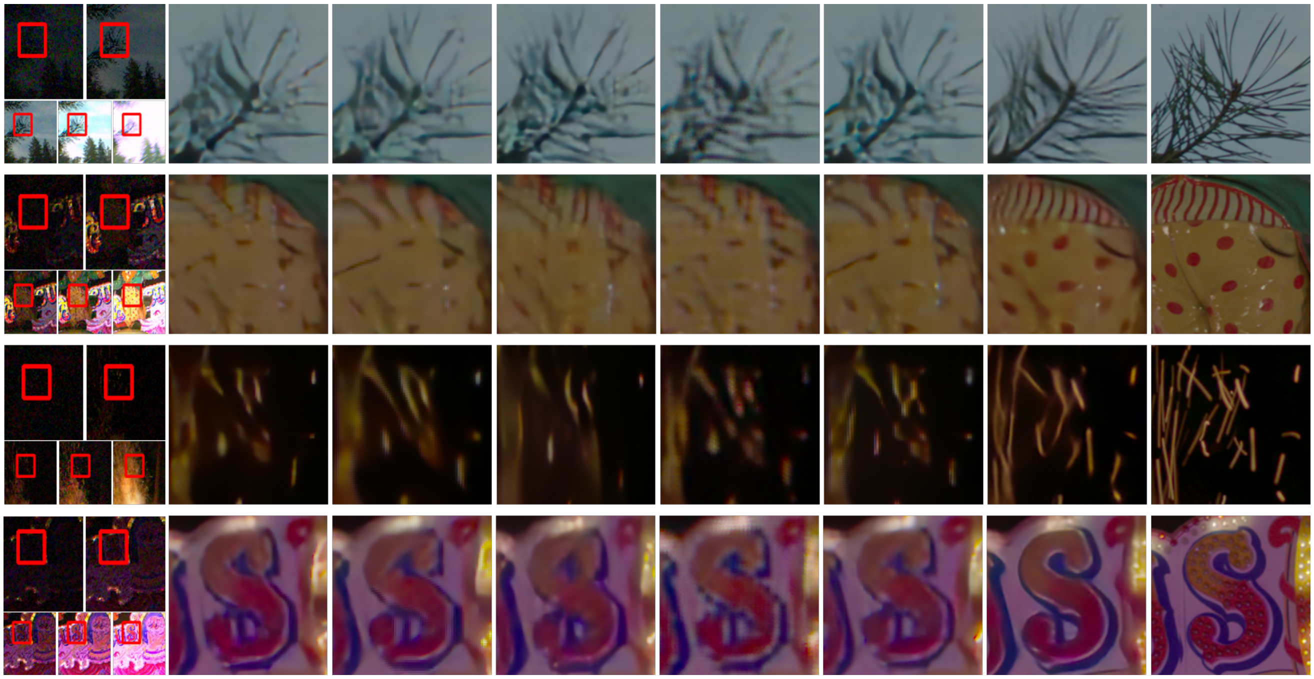
Figure 2. Qualitative results on Track 1 of Bracketing Image Restoration and Enhancement Challenge.

Table 2. Quantitative results on Track 1 of Bracketing Image Restoration and Enhancement Challenge. Quantitative metrics are calculated on the full images and the cropped images that exclude the surrounding 10 invalid pixels. #FLOPs, inference time, and GPU memory are measured when generating a 1920×1080 RAW image. We use NVIDIA RTX A6000 GPU to calculate the inference time and adopt THOP [109] toolkit to calculate #FLOPs. The ranking is based on the PSNR metric of the full images.

Rank	Team	Full Images PSNR ↑ / SSIM↑ / LPIPS↓	Cropped Images PSNR ↑ / SSIM↑ / LPIPS↓	#Params (M)	#FLOPs (T)	Time (s)	Memory (GB)
1	Samsung	40.54 / 0.9637 / 0.077	41.77 / 0.9633 / 0.076	94.34	48.238	3.102	20
2	MegIRE	39.78 / 0.9556 / 0.102	39.82 / 0.9550 / 0.105	19.75	30.751	2.383	16
3	UPN1	39.03 / 0.9500 / 0.117	39.02 / 0.9493 / 0.120	13.32	10.409	1.090	6
4	CVG	38.78 / 0.9543 / 0.102	39.89 / 0.9557 / 0.104	33.40	21.340	7.518	11
5	FZU_DXW	38.46 / 0.9527 / 0.105	39.61 / 0.9540 / 0.107	14.04	22.283	1.829	16
-	TMRNet [106]	38.19 / 0.9488 / 0.112	39.06 / 0.9498 / 0.115	13.29	21.340	1.874	15

Table 3. Quantitative results on Track 2 of Bracketing Image Restoration and Enhancement Challenge. Quantitative metrics are calculated on the full images and the cropped images that exclude the surrounding 16 invalid pixels. #FLOPs, inference time, and GPU memory are measured when generating a 1920×1080 RAW image. We use NVIDIA RTX A6000 GPU to calculate the inference time and adopt THOP [109] toolkit to calculate #FLOPs. The ranking is based on the PSNR metric of the full images.

Rank	Team	Full Images PSNR ↑ / SSIM↑ / LPIPS↓	Cropped Images PSNR ↑ / SSIM↑ / LPIPS↓	#Params (M)	#FLOPs (T)	Time (s)	Memory (GB)
1	Samsung	34.26 / 0.8913 / 0.206	34.80 / 0.8913 / 0.208	95.00	5.285	0.813	5
2	NWPU	30.59 / 0.8728 / 0.268	29.93 / 0.8633 / 0.274	13.37	1.426	0.887	3
3	FZU_DXW	29.82 / 0.8537 / 0.282	31.35 / 0.8660 / 0.277	14.34	1.500	0.493	3
4	CYD	29.66 / 0.8598 / 0.284	30.27 / 0.8632 / 0.285	17.60	1.560	0.751	4
5	CVG	29.25 / 0.8521 / 0.278	30.63 / 0.8645 / 0.275	71.82	6.898	0.679	4
-	TMRNet [106]	28.91 / 0.8572 / 0.273	30.65 / 0.8725 / 0.270	13.58	1.441	0.489	4



Input Frames TMRNet [106] CVG CYD FZU_DXW NWPU Samsung GT

Figure 3. Qualitative results on Track 2 of Bracketing Image Restoration and Enhancement Challenge.

and 0.76dB PSNR improvements than the baseline and second-place team (*i.e*., MegIRE), respectively. Besides, #Params and GPU Memory of all teams meet the challenge rules. The visual comparisons are shown in Fig. 2. It can be seen that the results from Samsung team have more photo-realistic details, and are more consistent with the GTs.

3.3. Track 2: BracketIRE+

This track appends $\times 4$ super-resolution task based on Track 1, making it more challenging. The results are shown in Tab. 3. It can be seen that all teams perform better than the baseline (*i.e*., TMRNet[106]). Among all teams, Samsung team performs best and outperforms other methods by a large margin. Compared with the baseline, it obtains 5.35dB PSNR gains. Compared with the second-place team (*i.e*., NWPU), it achieves 3.67dB improvements. Besides, the inference cost of all methods follows the challenge requirements. The visual comparisons in Fig. 3 show that Samsung team produces more fine-scale details and fewer artifacts.

4. Challenge Methods

4.1. Track 1: BracketIRE

4.1.1 Samsung Team †

The team proposes a high quality Reference feature for Two stage bracketing Image Restoration and Enhancement Network, called RT-IRENet [87]. Specifically, the first module is based on TMRNet [106] which fuses 5 RAW images into the coarse restored result. The second module is based on NAFNet [14] which refines the output of the first module into the final result with much more details.

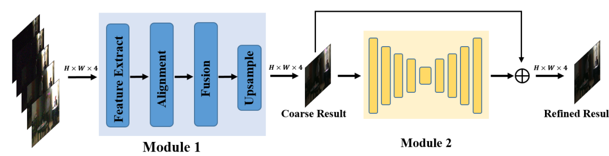


Figure 4. Structure of RT-IRENet proposed by Samsung team.

Network Architecture. The network architecture is shown in Fig. 4. For the first module, the team increases the number of channels from 64 to 96 in TMRNet [106]. Furthermore, the team chooses the second frame instead of the first frame of input as a reference frame. The reason for this is that the second frame has less noise and acceptable blur, which is beneficial in avoiding noise information from the first frame feature on the fused feature. It's worth noting that the second frame has only a tiny position misalignment with ground truth, thus such an operation has less impact on calculating loss terms. For the second module, the team adopts NAFNet [14], and changes the number of input and output channels to 4.

Inference Strategy. During inference, the team crops surrounding 5 pixels for input RAW images and feeds the cropped images to the model. Then they pad 5 pixels for

† Full name: Samsung MX (Mobile eXperience) Business & Samsung Research China - Beijing (SRC-B).

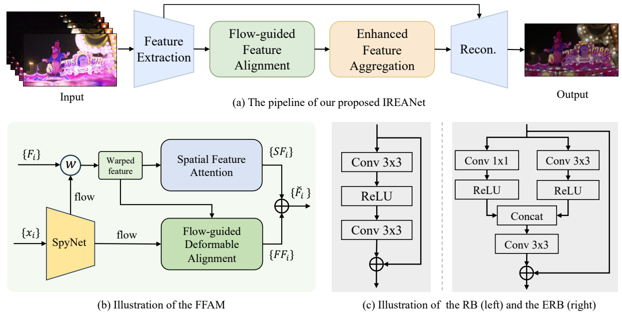


Figure 5. Illustration of IREANet proposed by MegIRE team.

the output RAW image. This ensures a high-quality output around the image.

Training Details. The team uses AdamW [59] optimizer ($\beta_1 = 0.9$, $\beta_2 = 0.999$) with a weight decay of 0.01. They adopt the cosine annealing strategy where the learning rate gradually decreases from 1×10^{-4} to 1×10^{-6} for 1000 epochs. They utilize PSNR loss to optimize. The batch size is 4, and the input patch size is 256×256. The experiments are conducted on the NVIDIA A100 GPU.

4.1.2 MegIRE Team

The team utilizes flow-guided feature alignment and enhanced feature aggregation to propose IREANet, which is shown in Fig. 5.

Flow-Guided Feature Alignment. It is designed as a dual-branch architecture to perform feature alignment, as shown in Fig. 5(b). The first branch is flow-guided deformable alignment [11], which is also adopted in TMRNet [106]. The second branch performs spatial feature attention on the flow-guided aligned features, obtaining spatial attention features. The spatial attention mechanism has been proven to effectively reduce noise and undesired contents caused by foreground object movement [57, 88]. The features from the two branches can be seen as complementary and are then combined using element-wise addition to acquire the final aligned features.

Enhanced Feature Aggregation. Similar to TMRNet [106], a unidirectional recurrent network is utilized to aggregate temporal features. Furthermore, they introduce an enhanced feature aggregation module, which takes the proposed enhanced residual block as a basic component, as shown in Fig. 5 (c). The proposed module increases the network's nonlinearity and enables better convergence, thus allowing for more effective aggregation of temporal features.

Training Details. The team uses a random combination of Bayer preserving augmentation [50] (see Fig. 6), vertical flip, horizontal flip, and rotation to augment the training data. They adopt AdamW [59] optimizer and the cosine annealing strategy of learning rate. The batch size is 8 and the input patch size is 128×128. Experiments are conducted on 4 NVIDIA TITAN Xp GPUs.

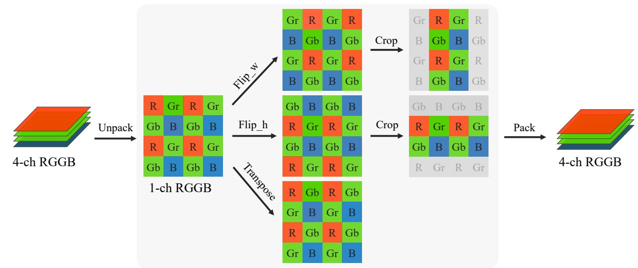


Figure 6. Illustration of Bayer preserving augmentation.

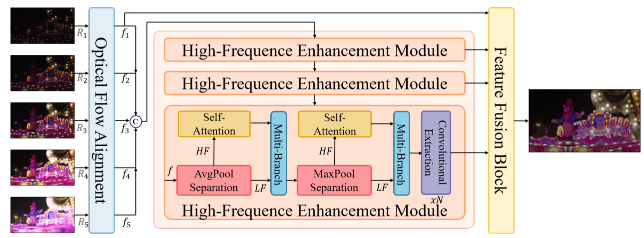


Figure 7. Overview of CRNet proposed by UPN1 team.

4.1.3 UPN1 Team

For the task, image details are of paramount importance. Moreover, to be applicable on edge devices, the inference time and the GPU memory footprint when generating images should also be carefully considered. The team proposes a Convolutional Restoration Network (CRNet) [90] (see Fig. 7), which can produce high-quality image details and has significant advantages in terms of inference time and GPU memory usage.

Network Architecture. TMRNet adopts a frame-by-frame processing manner. However, as the network deepens and the number of input frames increases, the team experimentally observes that this manner may lead to the network gradually forgetting the earlier frames and focusing more on the later frames, resulting in poor image quality. Instead, the team concatenates the five aligned images together for subsequent processing. First, the aligned images go through 3 high-frequency enhancement modules. Each module starts with two different pooling layers to separate high and low-frequency information [60] and enhance them separately, and ends with N convolutional extraction blocks. The frequency separation module utilizes self-attention to enhance the precious high-frequency information and deploys multi-branch [76] blocks to fuse high and low-frequency information. The convolutional extraction block can be seen as a high-frequency filter, and it utilizes large-kernel depth-wise separable convolutions [56] and convolutional FFN [23] for computationally friendly feature enhancement. Then, they

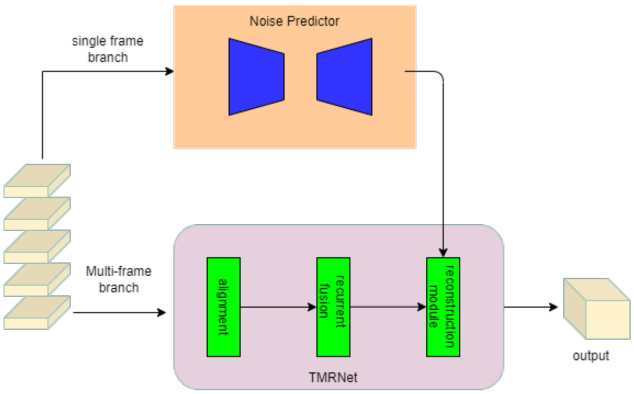


Figure 8. Network architecture proposed by CVG team.

use simple convolutional blocks to fuse the features from the 3 high-frequency enhancement modules and the reference frame to output the final result.

Implemental Details. They adopt the AdamW [59] optimizer with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. The learning rate is initially set to 10^{-4} and decays by half every 80 epochs. The model is trained on 4 NVIDIA A100 GPUs for 500 epochs for 3 days. Additionally, they utilize Hugging Face's Accelerator for parallel training.

4.1.4 CVG Team

In the process of image restoration, denoising is crucial to balance detail and noise. Given the promising capabilities of diffusion models, the team integrates a single-frame diffusion module and a multi-frame processing module, thus proposing a two-branch network (see Fig. 8).

Network Architecture. In the multi-frame branch, the team adopts TMRNet [106]. In the single-frame branch, the team uses a diffusion-based framework to process the reference frame. They utilize both noise-domain and image-domain loss terms to train the diffusion module for conducting stable sampling during inference. Finally, the output of the diffusion-based branch is connected to the reconstruction module in TMRNet.

Training Details. The team first trains the diffusion module for about 300 epochs. Then they optimize the multi-frame branch module for about 1000 epochs. When they train the multi-frame branch, they fix the weight of the diffusion module. The optimizer is Adam [37] with an initial learning rate of 10^{-4}. The batch size is 16 and the patch size is 48×48. Experiments are conducted on 2 NVIDIA Tesla A800 GPUs for about 4 days.

4.1.5 FZU_DXW Team

The team proposes an efficient aggregation restoration network for leveraging inter-frame complementary information effectively, named LGSTANet [20], as shown in Fig. 9.

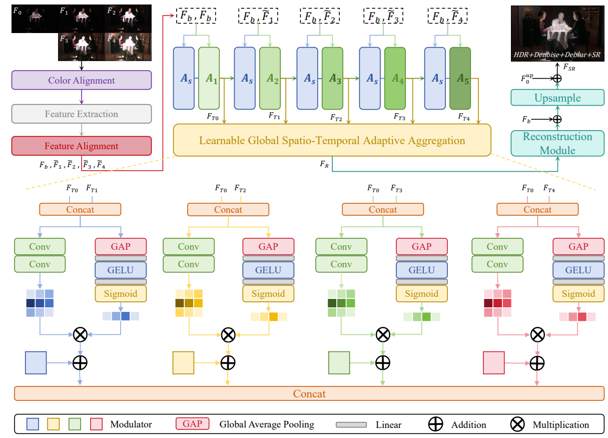


Figure 9. Structure of LGSTANet proposed by FZU_DXW team.

Network Architecture. Inspired by video restoration methods, the team adopts an efficient architecture of alignment, aggregation, and reconstruction. Additionally, they introduce a learnable global spatio-temporal adaptive aggregation module to help effectively aggregate inter-frame complementary information. Furthermore, they propose an adaptive restoration modulator to address specific degradation disturbances of various types, thus achieving high-quality restoration outcomes.

Training Details. The team adopts the progressive training strategy [96], which increases patch size and reduces batch size during training. The patch size of the training includes [128, 160, 192, 256, 320, 384]. They adopt AdamW [59] optimizer with $\beta_1 = 0.9$ and $\beta_1 = 0.999$ for training 800 epochs. The initial learning rate was set to 10^{-4}. Cosine annealing strategy [58] is employed to decrease the learning rates to 10^{-6}. All experiments are conducted on a single NVIDIA GeForce RTX 3090 GPU.

4.2. Track 2: BracketIRE+

4.2.1 Samsung Team †

The solution is roughly the same as stated in Sec. 4.1.1. Some differences are as follows: (1) The first module of RT-IRENet further adds ×4 upsampling operation. (2) During inference, they crop 2 pixels for the input raw images and pad 16 pixels for the output. (3) During training, they utilize model weights from Track 1 to initialize the model weights for Track 2. The input patch size is set to 64 × 64.

4.2.2 NWPU Team

The team proposes a CNN-based model named BSCCNet based on TMRNet[106].

Network Architecture. The model includes three components: alignment, reconstruction, and upsampling module.

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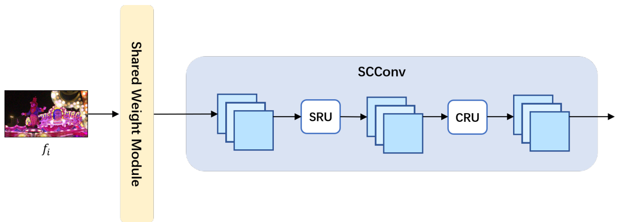

Figure 10. Structure of reconstruction module in BSCCNet proposed by NWPU team. f_i refers to the i^{th} feature after alignment.

In the alignment module, they use flow-guided deformable alignment [11], which is also adopted in TMRNet [106]. In the reconstruction module, they adopt a recurrent mechanism similar to TMRNet, progressively constructing the image through frame-by-frame processing. Fig. 10 shows the reconstruction process. Initially, each frame passes through a convolutional module with shared weights, followed by their respective feature extraction modules. Different from TMRNet, they choose SCConv (Spatial and Channel reconstruction Convolution) [43] as their feature extraction module to emphasize the uniqueness of each frame more. SCConv consists of two units: the Spatial Reconstruction Unit (SRU) and the Channel Reconstruction Unit (CRU), which can help suppress spatial and channel redundancy, aiding in learning more representative features. SCConv not only improves performance but also significantly reduces the model's complexity and computational cost by minimizing redundant features. In the subsequent up-sampling stage, they add the reference frame and use bilinear interpolation to increase the resolution.

Training Details. The team opts for the Adam [37] optimizer with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. The initial learning rate is set to 10^{-4}. They employ the cosine warm-up method for learning rate reduction with $lr_{min} = 10^{-6}$ and $warmup_t = 5$. The training lasted for 200 epochs and took approximately 120 hours on four NVIDIA A100 GPUs.

4.2.3 FZU_DXW Team

The solution is roughly the same as stated in Sec. 4.1.5. Some differences are as follows: (1) The upsampling operation is added at the end of the proposed model. (2) They first train the ×2 SR model whose weights are initialized with the best model from Track 1. Then they take the pre-trained weights of ×2 SR model to initialize the ×4 SR model. (3) The ×2 and ×4 SR models are trained for 400 and 801 epochs, respectively. The batch size is set to 8 and progressive training strategies are not used.

4.2.4 CYD Team

The proposed model of the team is called HLNet [13], as shown in Fig. 11. The team mainly improves the aggregation module of TMRNet [106].

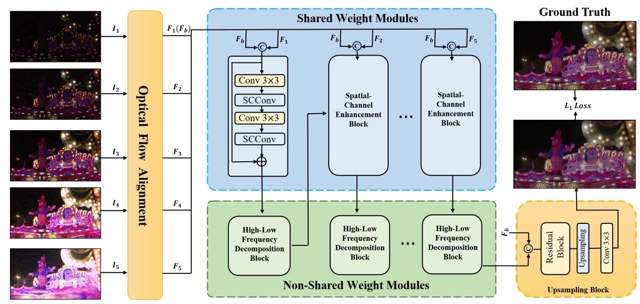

Figure 11. Structure of HLNet proposed by CYD team.

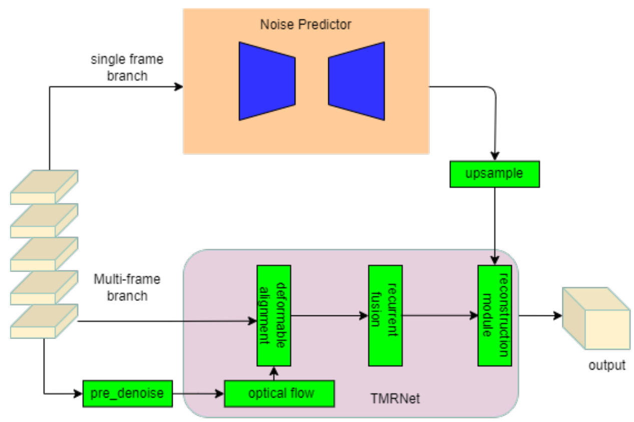

Figure 12. Network architecture proposed by CVG team.

Network Architecture. The aggregation module in TMRNet includes a shared module for all frames and a specific module only for i^{th} frame, which are composed of simple residual blocks. The team replaces the residual blocks of the two modules with Spatial-Channel Enhancement Blocks (SCEB) and High-Low Frequency Separation Blocks (HLFSB), respectively. Specifically, SCEB alternately uses regular convolution and SCConv [43]. SCConv can utilize spatial and channel redundancy and reduce the number of parameters effectively. HLFSB is inspired by ESRT [60], where high- and low- frequency information are processed separately. For high-frequency information, HLFSB adopts small convolution kernels and dense connections, which can better focus on local information, thereby restoring the details of the image. For low-frequency information that requires global information to restore the background and contours of the image, HLFSB adopts multi-scale feature extraction and Transformers to obtain long-distance dependencies. To compensate for the detail loss caused by downsampling, HLFSB fuses features of different scales based on wavelet transform.

Training Details. The team adopts AdamW [59] optimizer with $\beta_1 = 0.9$ and $\beta_2 = 0.999$. The initial learning rate is set to 10^{-4}, and they use a cosine warmup strategy for learning rate decay. The model is trained for 200 epochs for 6 days on 4 NVIDIA A100 GPUs.

4.2.5 CVG Team

The solution is roughly the same as stated in Sec. 4.1.4. Some differences are as follows: (1) The upsampling operation is added to the end of the proposed two-branch module. (2) For image alignment in the multi-frame branch, they train a noise pre-processing module using extra RAW data collected by the Xiaomi 13 smartphone, as shown in Fig. 12. (3) The multi-frame branch module is trained for about 400 epochs.

Acknowledgements

This work was partially supported by the Humboldt Foundation. We thank the NTIRE 2024 sponsors: Meta Reality Labs, OPPO, KuaiShou, Huawei and University of Würzburg (Computer Vision Lab).

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