NTIRE 2024 Challenge on Stereo Image Super-Resolution: Methods and Results

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Abstract

This paper summarizes the 3rd NTIRE challenge on stereo image super-resolution (SR) with a focus on new solutions and results. The task of this challenge is to super-resolve a low-resolution stereo image pair to a high-resolution one with a magnification factor of $\times 4$ under a limited computational budget. Compared with single image SR, the major challenge of this challenge lies in how to exploit additional information in another viewpoint and how to maintain stereo consistency in the results. This challenge has 2 tracks, including one track on bicubic degradation and one track on real degradations. In total, 108 and 70 participants were successfully registered for each track, respectively. In the test phase, 14 and 13 teams successfully submitted valid results with PSNR (RGB) scores better than the baseline. This challenge establishes a new benchmark for stereo image SR.

1. Introduction

Recently, dual cameras have been increasingly popular in AR/VR, mobile phones, autonomous vehicles and robots to record and perceive the 3D environment. For higher perceptual quality and finer-grained parsing of the real world, increasing the resolution of stereo images is highly demanded. To this end, stereo image super-resolution (SR) has been introduced to reconstruct a high-resolution (HR) stereo image pair with finer details from a low-resolution (LR) one.

Compared with a single image, stereo images can provide additional cues from a second viewpoint to better recover image details. However, since an object is projected onto different locations in left and right views, how to make full use of these cross-view information still remains challenging. On the one hand, stereo correspondence for objects at different depths can vary significantly. On the other hand, the occlusion between left and right views hinders correspondences to be incorporated.

To develop and benchmark stereo SR methods, stereo image SR challenge was hosted in the NTIRE 2022 and NTIRE 2023 workshops [1, 2]. The objective of previous challenges is to minimize the distortion between super-resolved stereo images and the groundtruth under both bicubic and realistic degradations. However, the computational cost of the stereo SR methods is not fully considered, which hinders these methods to be deployed on resource-limited devices.

Succeeding the previous years, NTIRE 2024 Stereo Image SR Challenge presents two competition tracks. These two tracks are inherited from the NTIRE 2023 challenge with an additional constraint of computational complexity. Specifically, both the memory and computational cost are considered for real-world applications.

This challenge is one of the NTIRE 2024 Workshop associated challenges on: dense and non-homogeneous dehazing [3], night photography rendering [4], blind compressed image enhancement [5], shadow removal [6], efficient super resolution [7], image super resolution ($\times 4$) [8], light field image super-resolution [9], stereo image super-resolution [10], HR depth from images of specular and transparent surfaces [11], bracketing image restoration and enhancement [12], portrait quality assessment [13], quality assessment for AI-generated content [14], restore any image model (RAIM) in the wild [15], RAW image super-resolution [16], short-form UGC video quality assessment [17], low light enhancement [18], and RAW burst alignment and ISP challenge.

2. Related Work

In this section, we briefly review recent advances in single image SR and stereo image SR.

2.1. Single Image SR

In the last decade, learning-based approaches have dominated the area of single image SR [19–23]. Dong *et al.*

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Section 7 provides the authors and affiliations of each team.
NTIRE 2024 webpage: https://cvlai.net/ntire/2024/
Challenge webpage (Track 1): https://codalab.lisn.upsaclay.fr/competitions/17245
Challenge webpage (Track 2): https://codalab.lisn.upsaclay.fr/competitions/17246
Github: https://github.com/The-Learning-And-Vision-Atelier-LAVA/Stereo-Image-SR/tree/NTIRE2024

[24] proposed the first CNN-based SR model (*i.e.*, SRCNN) to learn an LR-to-HR mapping. Following SRCNN, early methods focus on developing larger and more effective network architectures to achieve higher SR performance [25–27]. Specifically, Zhang *et al.* [28] proposed a residual dense network (*i.e.*, RDN) to fully use hierarchical features by combining residual connection [29] with dense connection [30]. Subsequently, Li *et al.* [31] suggested to use image features at different scales for single image SR, and proposed a multi-scale residual network (*i.e.*, MSRN). Dai *et al.* [32] proposed a second-order attention network (*i.e.*, SAN) for more powerful feature correlation learning, which achieves superior performance. Recently, the efficiency of SR models has drawn increasing interests, with numerous lightweight network architectures being developed [33–35]. For example, distillation blocks were proposed for feature learning in IDN [36]. Then, a cascading mechanism was introduced to encourage efficient feature reuse in CARN [37]. Different from these manually designed networks, Chu *et al.* [38] developed a compact architecture using neural architecture search (NAS).

Inspired by the great success of Transformer in computer vision, Transformer has been widely studied to promote single image SR. Liang *et al.* [39] designed a SwinIR model for image restoration by applying Swin Transformer [40]. Lu *et al.* [41] proposed an effective super-resolution Transformer (*i.e.*, ESRT) for single image SR, which introduced a lightweight Transformer and feature separation strategy to reduce GPU memory consumption. Zamir *et al.* [42] proposed an encoder-decoder Transformer (*i.e.*, Restormer) for image restoration with multi-scale local-global representation learning.

2.2. Stereo Image SR

Jeon *et al.* [43] developed the first learning-based stereo image SR method termed StereoSR. This method incorporates cross-view information by concatenating the left image and a stack of right images with different pre-defined shifts. Later, Wang *et al.* [44, 45] developed PASSRnet by introducing a parallax attention module (PAM) to capture stereo correspondence along the epipolar line. Inspired by PASSRnet, Song *et al.* [46] further combined self-attention with parallax attention to better model global correspondence. Wang *et al.* [47] introduced a Siamese network with a bi-directional parallax attention module to simultaneously super-resolve left and right images in a symmetric manner. Guo *et al.* [48] proposed a new Transformer-based parallax fusion model called Parallax Fusion Transformer.

Instead of using parallax-attention mechanism, several efforts have also been made to employ stereo matching approach to capture stereo correspondence. Yan *et al.* [49] proposed a domain adaptive stereo SR network (DASSR) to incorporate cross-view information through explicit disparity estimation using a pre-trained stereo matching network. Dai *et al.* [50] proposed a feedback network to alternately solve disparity estimation and stereo image SR in a recurrent manner. Wan *et al.* [51] proposed a multi-stage network to progressively obtain cross-view features and an edge-guided supplementary branch to refine the cross-view features.

In the NTIRE 2022 Stereo Image SR Challenge, the champion team developed NAFSSR network [52] by using nonlinear activation-free network (NAFNet) for feature extraction and PAM for cross-view information interaction. In the NTIRE 2023 Stereo Image SR Challenge, the champion team of track 1 developed a Hybrid Transformer and CNN Attention Network (HTCAN), which employs a Transformer-based network for single image enhancement and a CNN-based network for stereo information aggregation. The champion team of track 2 proposed a Swin-FIRSSR by using Swin Transformer [40] and fast Fourier convolution [53]. The champion team of track 3 combined NAFSSR [54] with LTE [55] and proposed LTFSSR.

3. NTIRE 2024 Challenge

The objectives of the NTIRE 2024 challenge on example-based stereo image SR are: (i) to gauge and push the state-of-the-art in SR under given computational constraints; and (ii) to compare different solutions.

3.1. Dataset

Training Set. The training set of the Flickr1024 dataset [56] (with 800 images) is used as the training set of this challenge. Both original HR images and their LR versions will be released. The participants can use these HR images as ground-truth to train their models.

Validation Set. The validation set of the Flickr1024 dataset (with 112 images) is used as the validation set of this challenge. Similar to the training set, both HR and LR images in the validation set are provided. The participants can download the validation set to evaluate the performance of their developed models by comparing their super-resolved images with the HR ground-truth images. Note that the validation set should be used for validation purposes only but cannot be used as additional training data.

Test Set. To rank the submitted models, a test set consisting of 100 stereo images is provided. Unlike the training and validation sets, only LR images will be released for the test set. The participants must apply their models to the released LR stereo images and submit their super-resolved images to the server. It should be noted that the images in the test set (even the LR versions) cannot be used for training.

3.2. Tracks

- **Track 1: Constrained SR & Bicubic Degradation**

In this track, bicubic degradation (Matlab *imresize* function in bicubic mode) is used to generate LR images:

$$I^{LR} = I^{HR} \downarrow_s, \tag{1}$$

where I^{LR} and I^{HR} are LR and HR images, $\downarrow_s$ represents bicubic downsampling with scale factor s.

• **Track 2: Constrained SR & Realistic Degradation**

In this track, a realistic degradation model consisting of blur, downsampling, noise, and compression is adopted to synthesize LR images:

$$I^{LR} = \mathcal{C}\left(\left(I^{HR} \otimes k\right) \downarrow_s + n\right), \tag{2}$$

where k is the blur kernel, n is additive Gaussian noise, and $\mathcal{C}$ represents JPEG compression.

In these two tracks, the model size (*i.e.*, number of parameters) is restricted to 1 MB, and the computational complexity (*i.e.*, number of MACs) is restricted to 400 G (a stereo image pair of size 320×180). Peak signal-to-noise ratio (PSNR) and structural similarity (SSIM) are used as metrics for performance evaluation. The average results of left and right views over all of the test scenes are reported. Note that only PSNR (RGB) is used for ranking.

3.3. Challenge Phases

Development Phase. The participants were provided with pairs of LR and HR training images and LR validation images of the Flickr1024 dataset. The participants had the opportunity to test their solutions on the LR validation images and to receive immediate feedback by uploading their results to the server. A validation leaderboard is available online.

Testing Phase. The participants were provided with the LR test images and were asked to submit their super-resolved images, codes, and a fact sheet for their methods before the challenge deadline. After the end of the challenge, the final results were released to the participants.

4. Challenge Results

4.1. Track 1: Fidelity & Bicubic Degradation

Among the 108 registered participants, 14 teams successfully participated the final phase and submitted their results, codes, and fact sheets. Table 1 reports the final test results, rankings of the challenge, and major details from the fact sheets of 14 teams. These methods are briefly described in Section 5 and the team members are listed in Section 7.

4.2. Track 2: Fidelity & Realistic Degradation

Among the 70 registered participants, 13 teams successfully participated the final phase and submitted their results, codes, and fact sheets. Table 2 reports the final test results, rankings of the challenge, and major details from the fact sheets of 13 teams. These methods are briefly described in Section 5 and the team members are listed in Section 7.

4.3. Summary

Architectures and main ideas. All the proposed methods are based on deep learning techniques. Transformers and the winner method in the NTIRE 2022 challenge (*i.e.*, NAFSSR) are widely used as the basic architecture. To exploit cross-view information, the idea of parallax-attention mechanism (PAM) are widely adopted in most solutions to capture stereo correspondence.

Data Augmentation. Widely applied data augmentation approaches such as random flipping and RGB channel shuffling are used for most solutions. In addition, random horizontal shifting, Mixup, CutMix, and CutMixup are also used in several solutions and help to achieve superior performance.

Ensembles and Fusion. Due to the constraints in computational complexity, ensemble strategy (data ensemble and model ensemble) is only adopted in a few solutions. Several solutions employ a limited number of transformed inputs for enhanced prediction. In addition, the champion solution in track 1 employs model exponential moving average for model ensemble without additional overhead during the inference phase.

Conclusions. By analyzing the settings, the proposed methods and their results, it can be concluded that: 1) The proposed methods strike better balance between accuracy and efficiency. 2) With recent renaissance of CNNs (*e.g.*, NAFNet), Transformers and CNNs are comparably popular in this challenge and produce competitive performance. 3) Cross-view information lying at varying disparities is critical to the stereo image SR task and helps to achieve higher performance. 4) To meet the efficiency requirements of the challenge, techniques like depth-wise convolution are widely applied and produce promising results. 5) One recent remarkable technique (*i.e.*, Mamba) has been introduced to achieve efficient image SR and produces promising results.

5. Challenge Methods and Teams

In this section, we present the challenge methods proposed by the winner teams. The solutions proposed by the other teams are presented in the supplemental material.

5.1. Davinci - Track 1★, Track 2★

Inspired by SwinFIR [57], HAT [58], and NAFSSR [52], they proposed SwinFIRSSR using Swin transformer [40] and fast fourier convolution [53], as shown in Fig. 2. HAT employs Residual Hybrid Attention Group (RHAG) to activate more pixel in image SR transformer to improve the performance. Each RHAG contains N hybrid attention blocks

Table 1. NTIRE 2024 Stereo Image SR Challenge (Track 1) results, rankings, and details from the fact sheets. Note that, PSNR (RGB) is used for the ranking. "Transf" denotes Transformer and "PAM" denotes parallax attention mechanism.

Rank	Team	Authors	PSNR (RGB)	Architecture	Disparity	Ensemble
1	Davinci	Davinci and S. Zhang	23.6503	CNN+Transf	PAM	Data+Feature
2	HiSSR	R. Liao, R. Sheng, F. Li, H. Bai, R. Cong, and W. Zhang	23.6105	CNN	PAM	N.A.
3	MiVideoSR	Y. Yang, Z. Zhang, J. Yang, L. Bao, and H. Sun	23.6070	CNN+Transf	PAM	Data
4	webbzhou	Y. Zhou, W. Deng, X. Qiu, T. Wang, Q. Gao, and T. Tong	23.5941	CNN	PAM	N.A.
5	Qi5	Y. Zhu and Y. Li	23.5896	CNN+Transf	PAM	N.A.
6	WITAILab	Z. Chen, X. Lang, K. Zhao, and B. Zhu	23.5725	CNN+Transf	PAM	N.A.
7	Giantpandacv	W. Zou, Y. Li, Q. Wei, T. Ye, and S. Chen	23.5271	CNN	PAM	N.A.
8	JNU_620	W. Yuan, Z. Li, W. Kuang, and R. Guan	23.4851	CNN	PAM	N.A.
9	GoodGame	J. Wang, Y. Miao, B. Li, and K. Zhao	23.4598	CNN	PAM	N.A.
10	Fly_Flag	W. Luo, and J. Wu	23.4510	CNN+Transf	PAM	Data
11	Mishka	Y. Zhang, B. Li, S. Zhang, J. Zhang, J. Gao, and X. You	23.4270	CNN+Mamba	PAM	N.A.
12	LightSSR	Y. Guo and H. Xu	23.3888	CNN	N.A.	N.A.
13	DVision	S. Mistry, A. Shukla, S. Saini, A. Gupta, V. Jakhetiya, and S. Jaiswal	23.1895	CNN	PAM	N.A.
14	LVGroup_HFUT	Z. Zhang, B. Wang, S. Zhao, Y. Luo, and Y. Wei	23.0977	CNN	N.A.	Data

Table 2. NTIRE 2024 Stereo Image SR Challenge (Track 2) results, rankings, and details from the fact sheets. Note that, PSNR (RGB) is used for the ranking. "Transf" denotes Transformer and "PAM" denotes parallax attention mechanism.

Rank	Team	Authors	PSNR (RGB)	Architecture	Disparity	Ensemble
1	Davinci	Davinci and S. Zhang	21.8724	CNN+Transf.	PAM	Data+Feature
2	MiVideoSR	Y. Yang, Z. Zhang, J. Yang, L. Bao, and H. Sun	21.6983	CNN+Transf	PAM	Data
3	BUPTMM	K. Zhao, E. Zhang, H. Fu, and H. Ma	21.6702	CNN	PAM	N.A.
4	webbzhou	Y. Zhou, W. Deng, X. Qiu, T. Wang, Q. Gao, and T. Tong	21.6691	CNN	PAM	N.A.
5	JNU_620	W. Yuan, Z. Li, W. Kuang, and R. Guan	21.5935	CNN	PAM	N.A.
6	Liz620	Y. Chen, R. Deng, and Y. Deng	21.5655	CNN	PAM	N.A.
7	Mishka	Y. Zhang, B. Li, S. Zhang, J. Zhang, J. Gao, and X. You	21.5313	CNN+Mamba	PAM	N.A.
8	ECNU-IDEALab	J. Wang, Z. Wu, and D. Huang	21.5238	CNN+Transf	PAM	N.A.
9	Giantpandacv	W. Zou, Y. Li, Q. Wei, T. Ye, and S. Chen	21.4970	CNN	PAM	N.A.
10	HiYun	Y. Ye	21.1994	CNN	PAM	Data
11	GoodGame	J. Wang, Y. Miao, B. Li, and K. Zhao	20.7642	CNN	PAM	N.A.
12	Fly_Flag	W. Luo, and J. Wu	20.7518	CNN+Transf	PAM	Data
13	LVGroup_HFUT	Z. Zhang, B. Wang, S. Zhao, Y. Luo, and Y. Wei	20.6167	CNN	N.A.	Data

(HAB), an overlapping cross-attention block (OCAB) and a 3×3 convolutional layer. They replaced the convolution (3×3) with fast fourier convolution and a residual module to fuse global and local features, namely Spatial-frequency Block (SFB), to improve the representation ability of the model. They also followed NAFSSR to fuse left/right features using stereo cross-attention module (SCAM).

During the training phase, HR images were cropped to 128×384 sub-images. The Adam [59] optimizer with default parameters and the Charbonnier L1 loss [60] were employed for training. The initial learning rate was set to 2×10^{-4} and decayed at 600,000, 650,000, 700,000, 750,000 iterations. The batch size was 4 and patch size was 32×96. The models were implemented usingPyTorch 1.8.1, NVIDIA A6000 GPU with CUDA11.1. Random horizontal flip, vertical flip, rotation, RGB perm and mixup [61] were adopted for data augmentation.

Inspired by [62], model ensemble was employed to improve the performance. Widely-applied multi-model and data ensemble strategy inevitably introduces additional computational overhead. To remedy this, they proposed to conduct model ensemble from the perspective of network parameters, as illustrated in Fig. 1. Specifically, the parameters of several models are aggregated as:

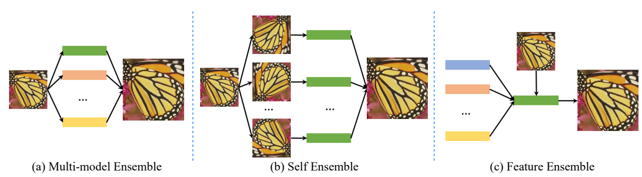

Figure 1. Comparison between different ensemble strategies. (a) Multi-model ensemble. (b) Data ensemble. (c) The proposed model ensemble. Rectangles with different colors represent different model parameters.

$$SwinFIRSSR(\theta) = \sum_{i=1}^{n} SwinFIRSSR(\theta)^i * \alpha^i, \quad (3)$$

where θ denotes the parameter sets of SwinFIRSSR, n is the numbers of models. α is the weight of each model and the $\alpha = \frac{1}{n}$ in our solution.

5.2. HiSSR - Track 1☆

Figure 3 depicts the network structure of the proposed method. Specifically, CVHSSR [63] is used as the backbone, which consists of a cross-hierarchy information mining block (CVIM) and a cross-hierarchy information mining block (CHIMB). CHIMB leverages both spatial and

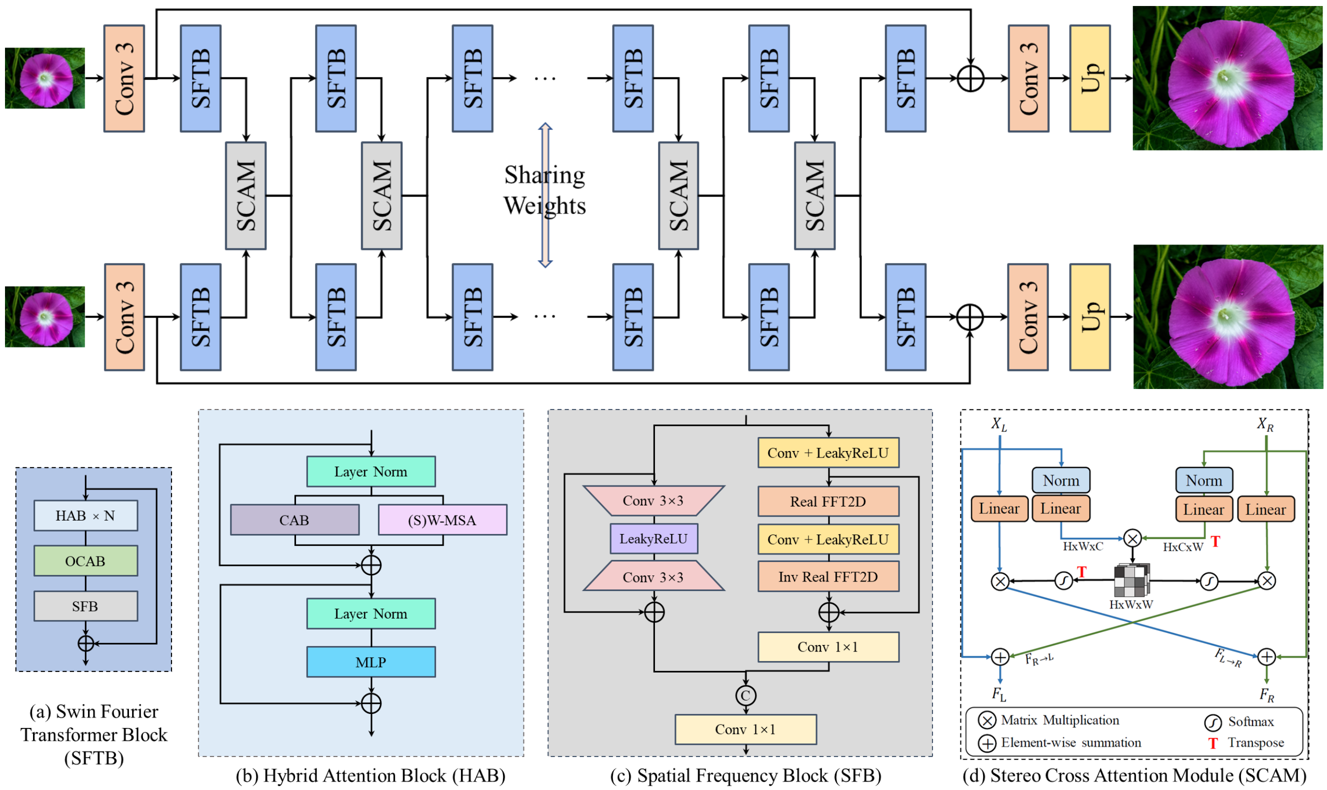

Figure 2. Davinci: The structure of the proposed SwinFIRSSR.

channel-wise attention mechanisms to model information at different levels within a single view. Meanwhile, CVIM integrates similar information across different views through cross-view attention. They employed CHVIMB to extract both global and local information from a single view, while CVIM is utilized to integrate analogous information across each views. Following CFSR [64], they further reparameterized the depth-wise convolution in the Information Refinement Feedforward Block in CHIMB. To further enhance the model's performance, they introduced an iterative interaction mechanism, leveraging the restoration results as reference images to enhance the performance.

Training Settings. The number of CHIMB in RIISSR is set to 20, while the channels of all the convolutional layers are set to 48. Residual connections are inserted between every four blocks. The number of parameters in the model is 0.918M, and the MACs are 235.28G for a 320×180 stereo image pair. During training, HR images were cropped into (30×90) patches with a stride of 10. Random horizontal, flips, rotations, mixup and RGB channel shuffle were adopted for data augmentation. The AdamW with $\beta_1 = 0.9$ and $\beta_2 = 0.99$ was used for optimization. The learning rate was initialized to (1×10^{-3}) and decreased using the multi-step strategy with γ set to 0.5. The proposed model was trained for (2.4×10^5) iterations with a batch size of 24. A $2\times$ SR model was first trained from scratch, which was then used to initialize the $4\times$ SR model.

5.3. MiVideoSR - Track 1★, Track 2★

Transformer-like methods have achieved advanced performance on low-level tasks. Motivated by NAFSSR [52], HAT [58] and SRFormer [65], this team proposed a HCASSR by plugging the SCAM of NAFSSR into the HAT to aggregate features from two views, as illustrated in Fig. 4. In addition, to improve the performance and efficiency of the model, they replaced the self-attention module with permuted self-attention (PSA) [65] to transfer the spatial information to the channel dimension.

Training Settings. The proposed model was first trained with a Charbonnier loss using an Adam optimizer and stopped after 400k iterations. Then, the resultant model was fine-tuned with the MSE loss. The batch size was set to 16 and the patch size was first set to 96×96 and then enlarged to 192×192 for fine-tuning. The learning rate was initialized as 5×10^{-4} and updated using a cosine annealing strategy. Data augmentation was performed through horizontal/vertical flipping, RGB channel random shuffing, and Mixup operations.

Data Ensemble. Due to the limitation of the number of parameters, model ensemble strategy was abandoned. Be-

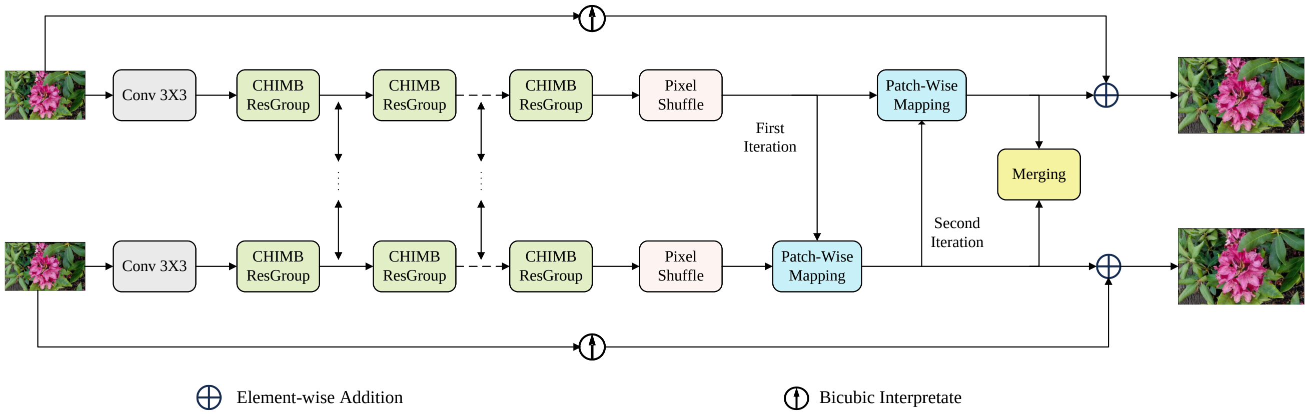

Figure 3. HiSSR: The structure of the proposed RISSR.

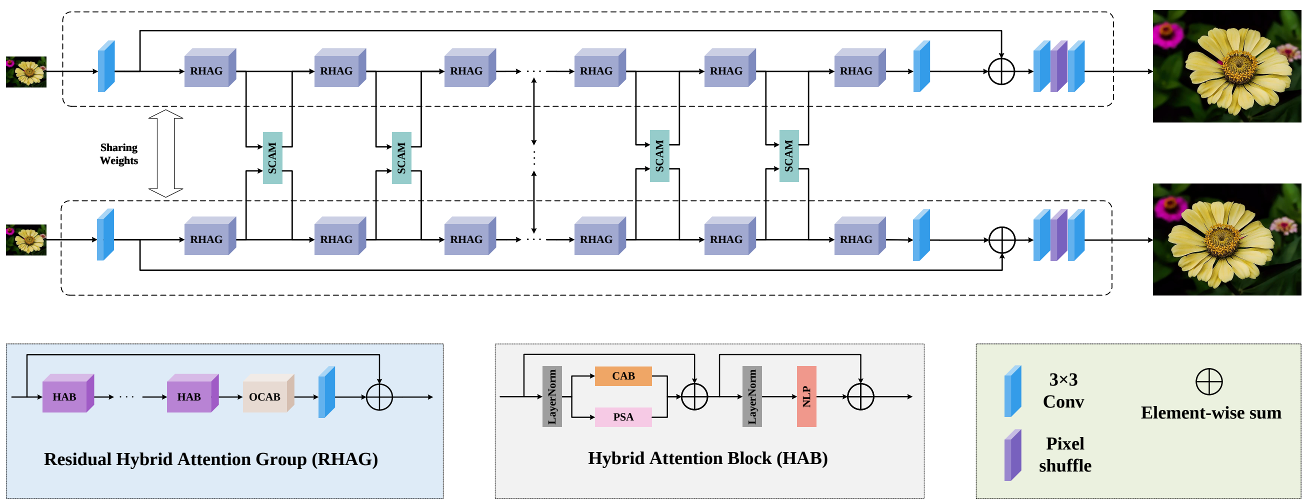

Figure 4. MiVideoSR: The structure of the proposed HCASSR.

sides, due to the limitation of the computational complexity, only horizontal flipping and vertical flipping were used to generate three images for data ensemble.

5.4. BUPTMM - Track 2★

This team developed a Cross-View Hierarchy Network for Stereo Image Super-Resolution (CVHSSR) [63] by leveraging the complementary information between different viewpoints (Fig. 5). CVHSSR consits of two modules: the Cross-Hierarchy Information Mining Block (CHIMB) and the Cross-View Interaction Module (CVIM). CHIMB is developed to simulate and recover intra-view information across different levels, employing large-kernel convolutional attention and channel attention mechanisms. Meanwhile, CVIM utilizes a cross-view attention mechanism to effectively consolidate similar information from different views. These two modules facilitate CVHSSR to better aggregate cross-view information for higher performance.

In order to improve the SR performance of the model more efficiently with a limited number of parameters and MACs, the number of channels and the number of the CHIMB and CVIM modules are tuned. The final number of parameters is 999.54 K.

Training Settings. The training of the proposed model consists three phases. In the first phase, only 700 stereo image pairs were used as the training set. The proposed model was trained for 200K iterations with an MSE loss and a frequency Charbonnier loss. The Lion optimizer was employed in this phase. The batch size was set to 18 and the patch size was set to 64×64. The learning rate was initialized as 1×10^{-4} and updated using a cosine annealing strategy. The minimum learning rate was set to 1×10^{-8}. Data augmentation was performed through RGB channel shuffing and horizontal/vertical flipping. In the second phase, the resultant model was used for initialization and all 800 stereo image pairs were included for training. The model was fur-

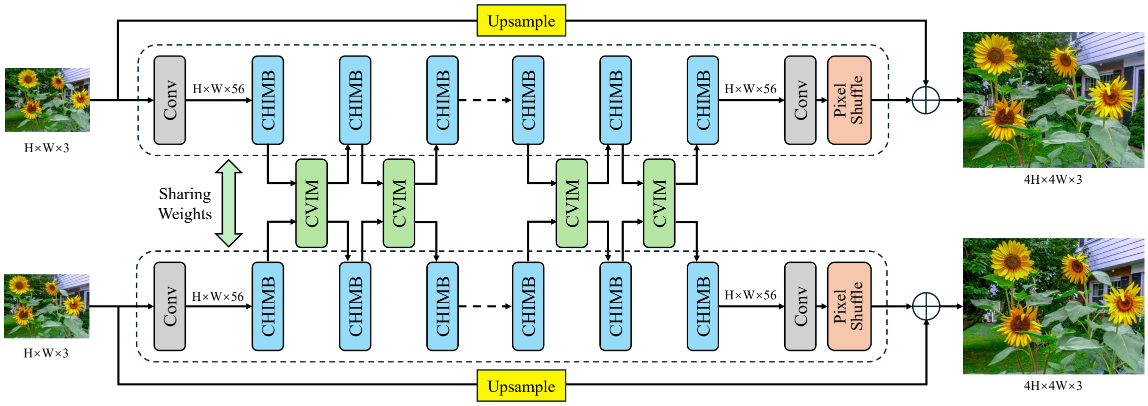

Figure 5. BUPTMM: The structure of the proposed Efficient CVHSSR.

ther trained for 100K iterations, with the same settings as the first phase. In the third phase, the resultant model is further trained for 100K iterations. The batch size was set to 16 and the learning rate was updated to 2×10^{-6} for further training.

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