

VRT: A Video Restoration Transformer

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<https://github.com/JingyunLiang/VRT>

Abstract

Video restoration (e.g., video super-resolution) aims to restore high-quality frames from low-quality frames. Different from single image restoration, video restoration generally requires to utilize temporal information from multiple adjacent but usually misaligned video frames. Existing deep methods generally tackle with this by exploiting a sliding window strategy or a recurrent architecture, which either is restricted by frame-by-frame restoration or lacks long-range modelling ability. In this paper, we propose a Video Restoration Transformer (VRT) with parallel frame prediction and long-range temporal dependency modelling abilities. More specifically, VRT is composed of multiple scales, each of which consists of two kinds of modules: temporal mutual self attention (TMSA) and parallel warping. TMSA divides the video into small clips, on which mutual attention is applied for joint motion estimation, feature alignment and feature fusion, while self attention is used for feature extraction. To enable cross-clip interactions, the video sequence is shifted for every other layer. Besides, parallel warping is used to further fuse information from neighboring frames by parallel feature warping. Experimental results on five tasks, including video super-resolution, video deblurring, video denoising, video frame interpolation and space-time video super-resolution, demonstrate that VRT outperforms the state-of-the-art methods by large margins (**up to 2.16dB**) on fourteen benchmark datasets.

1. Introduction

Video restoration, which reconstructs high-quality (HQ) frames from multiple low-quality (LQ) frames, has attracted much attention recently. Compared with image restoration, the key challenge of video restoration lies in how to make full use of neighboring highly-related but misaligned supporting frames for reconstructing reference frames.

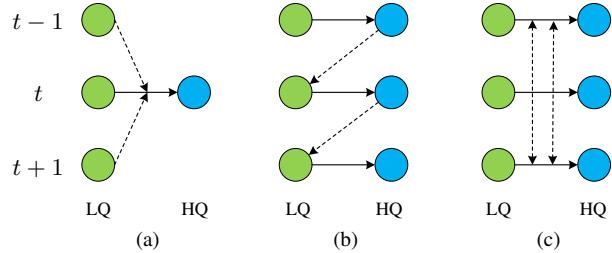


Figure 1. Illustrative comparison of sliding window-based models (1a, e.g., [44, 92, 99]), recurrent models (1b, e.g., [8, 10, 20, 27, 29]) and the proposed parallel VRT model (1c). Green and blue circles denote low-quality (LQ) input frames and high-quality (HQ) output frames, respectively. $t-1$, t and $t+1$ are frame serial numbers. Dashed lines represent information fusion among different frames.

Existing video restoration methods can be mainly divided into two categories: sliding window-based methods [5, 28, 30, 41, 44, 82, 92, 99, 123] and recurrent methods [8, 10, 20, 25, 27, 29, 31, 52, 67, 76, 80, 122]. As shown in Fig. 1a, sliding window-based methods generally input multiple frames to generate a single HQ frame and processes long video sequences in a sliding window fashion. Each input frame is processed for multiple times in inference, leading to inefficient feature utilization and increased computation cost.

Some other methods are based on a recurrent architecture. As shown in Fig. 1b, recurrent models mainly use previously reconstructed HQ frames for subsequent frame reconstruction. Due to the recurrent nature, they have three disadvantages. First, recurrent methods are limited in parallelization for efficient distributed training and inference. Second, although information is accumulated frame by frame, recurrent models are not good at long-range temporal dependency modelling. One frame may strongly affect the next adjacent frame, but its influence is quickly lost after few time steps [22, 94]. Third, they suffer from significant performance drops on few-frame videos [6].

In this paper, we propose a Video Restoration Transformer (VRT) that allows for parallel computation and long-

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range dependency modelling in video restoration. Based on a multi-scale framework, VRT divides the video sequence into non-overlapping clips and shifts it alternately to enable inter-clip interactions. Specifically, each scale of VRT has several temporal mutual self attention (TMSA) modules followed by a parallel warping module. In TMSA, mutual attention is focused on mutual alignment between neighboring two-frame clips, while self attention is used for feature extraction. At the end of each scale, we further use parallel warping to fuse neighboring frame information into the current frame. After multi-scale feature extraction, alignment and fusion, the HQ frames are individually reconstructed from their corresponding frame features.

Compared with existing video restoration frameworks, VRT has several benefits. First, as shown in Fig. 1c, VRT is trained and tested on long video sequences in parallel. In contrast, both sliding window-based and recurrent methods are often tested frame by frame. Second, VRT has the ability to model long-range temporal dependencies, utilizing information from multiple neighbouring frames during the reconstruction of each frame. By contrast, sliding window-based methods cannot be easily scaled up to long sequence modelling, while recurrent methods may forget distant information after several timestamps. Third, VRT proposes to use mutual attention for joint feature alignment and fusion. It adaptively utilizes features from supporting frames and fuses them into the reference frame, which can be regarded as implicit motion estimation and feature warping.

Our contributions can be summarized as follows:

- 1) We propose a new framework named Video Restoration Transformer (VRT) that is characterized by parallel computation and long-range dependency modelling. It jointly extracts, aligns, and fuses frame features at multiple scales.
- 2) We propose the mutual attention for mutual alignment between frames. It is a generalized “soft” version of image warping after implicit motion estimation.
- 3) VRT achieves state-of-the-art performance on video restoration, including video super-resolution, deblurring, denoising, frame interpolation and space-time video super-resolution. It outperforms state-of-the-art methods by up to 2.16dB on benchmark datasets.

2. Related Work

2.1. Video Restoration

Similar to image restoration [15, 18, 19, 23, 38, 42, 47–50, 56, 63, 64, 87, 96–98, 102, 111, 114, 115, 117–121], learning-based methods, especially CNN-based methods, have become the primary workhorse for video restoration [8, 40, 55, 62, 71, 72, 93, 95, 99, 103, 104, 108–110, 123].

Framework design. From the perspective of architecture design, existing methods can be roughly divided into

two categories: sliding window-based and recurrent methods. Sliding window-based methods often takes a short sequence of frames as input and merely predict the center frame [5, 28, 30, 41, 44, 78, 82, 90–92, 99, 123]. Although some works [43] predict multiple frames, they still focus on the reconstruction of the center frame during training and testing. Recurrent framework is another popular choice [8, 10, 20, 25, 27, 29, 31, 52, 67, 76, 80, 122]. Huang *et al.* [27] propose a bidirectional recurrent convolutional neural network for SR. Sajjadi *et al.* [76] warp the previous frame prediction onto the current frame and feed it to a restoration network along with the current input frame. This idea is used by Chan *et al.* [8] for bidirectional recurrent network, and further extended as grid propagation in [10].

Temporal alignment and fusion. Since supporting frames are often highly-related but misaligned, temporal alignment plays an critical role in video restoration [8–10, 51, 92, 99, 107]. Early methods [5, 35, 51, 54, 88] use traditional flow estimation methods to estimate optical flow and warp the supporting frames towards the reference frame. To compensate occlusion and large motion, Xue *et al.* [107] utilize task-oriented flow by fine-tuning the pre-trained optical flow estimation model SpyNet [74] on different video restoration tasks. Jo *et al.* [33] use dynamic upsampling filters for implicit motion compensation. Kim *et al.* [37] propose a spatio-temporal transformer network for multi-frame optical flow estimation and warping. Tian *et al.* [92] propose TDAN that utilize deformable convolution [14] for feature alignment. Based on TDAN, Wang *et al.* [99] extend it to multi-scale alignment, while Chan *et al.* [10] incorporate optical flow as a guidance for offsets learning.

Attention mechanism. Attention mechanism has been exploited in video restoration in combination with CNN [6, 54, 84, 99]. Liu *et al.* [54] learn different weights for different temporal branches. Wang *et al.* [99] learn pixel-level attention maps for spatial and temporal feature fusion. To better incorporate temporal information, Isobe *et al.* [30] divide frames into several groups and design a temporal group attention module. Suin *et al.* [84] propose a reinforcement learning-based framework with factorized spatio-temporal attention. Cao *et al.* [6] propose to use self attention among local patches within a video.

2.2. Vision Transformer

Recently, Transformer-based models [45, 77, 94, 101] have achieved promising performance in various vision tasks, such as image recognition [7, 16, 24, 46, 57–59, 59, 86, 101] and image restoration [12, 47, 100]. Some methods have tried to use Transformer for video modelling by extending the attention mechanism to the temporal dimension [2, 4, 45, 60, 68]. However, most of them are designed for visual recognition, which are fundamentally different from restoration tasks. They are more focused

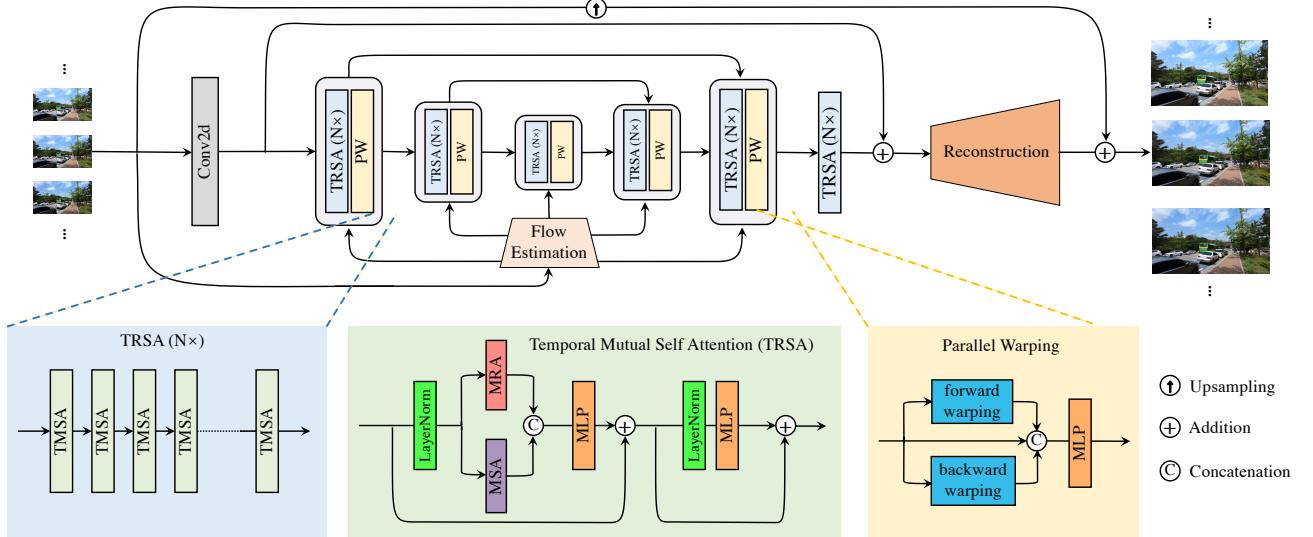


Figure 2. The framework of the proposed Video Restoration Transformer (VRT). Given T low-quality input frames, VRT reconstructs T high-quality frames in parallel. It jointly extracts features, deals with misalignment, and fuses temporal information at multiple scales. On each scale, it has two kinds of modules: temporal mutual self attention (TMSA, see Sec. 3.2) and parallel warping (see Sec. 3.3). The downsampling and upsampling operations between different scales are omitted for clarity.

on feature fusion than on alignment. Cao *et al.* [6] propose a CNN-transformer hybrid network for video super-resolution (SR) based on spatial-temporal convolutional self attention. However, it does not make full use of local information within each patch and suffers from border artifacts during testing.

3. Video Restoration Transformer

3.1. Overall Framework

Let $I^{LQ} \in \mathbb{R}^{T \times H \times W \times C_{in}}$ be a sequence of low-quality (LQ) input frames and $I^{HQ} \in \mathbb{R}^{T \times sH \times sW \times C_{out}}$ be a sequence of high-quality (HQ) target frames. T , H , W , C_{in} and C_{out} are the frame number, height, width and input channel number and output channel number, respectively. s is the upscaling factor, which is larger than 1 (*e.g.*, for video SR) or equal to 1 (*e.g.*, for video deblurring). The proposed Video Restoration Transformer (VRT) aims to restore T HQ frames from T LQ frames in parallel for various video restoration tasks, including video SR, deblurring, denoising, *etc.* As illustrated in Fig. 2, VRT can be divided into two parts: feature extraction and reconstruction.

Feature extraction. At the beginning, we extract shallow features $I^{SF} \in \mathbb{R}^{T \times H \times W \times C}$ by a single spatial 2D convolution from the LQ sequence I^{LQ} . After that, based on [75], we propose a multi-scale network that aligns frames at different image resolutions. More specifically, when the total scale number is S , we downsample the feature for $S - 1$ times by squeezing each 2×2 neighborhood to the channel dimension and reducing the channel number to the original

number via a linear layer. Then, we upsample the feature gradually by unsqueezing the feature back to its original size. In such a way, we can extract features and deal with object or camera motions at different scales by two kinds of modules: temporal mutual self attention (TMSA, see 3.2) and parallel warping (see 3.3). Skip connections are added for features of same scales. Finally, after multi-scale feature extraction, alignment and fusion, we add several TMSA modules for further feature refinement and obtain the deep feature $I^{DF} \in \mathbb{R}^{T \times H \times W \times C}$.

Reconstruction. After feature extraction, we reconstruct the HQ frames from the addition of shallow feature I^{SF} and deep feature I^{DF} . Different frames are reconstructed independently based on their corresponding features. Besides, to ease the burden of feature learning, we employ global residual learning and only predict the residual between the bilinearly upsampled LQ sequence and the ground-truth HQ sequence. In practice, different reconstruction modules are used for different restoration tasks. For video SR, we use the sub-pixel convolution layer [79] to upsample the feature by a scale factor of s . For video deblurring, a single convolution layer is enough for reconstruction. Apart from this, the architecture designs are kept the same for all tasks.

Loss function. For fair comparison with existing methods, we use the commonly used Charbonnier loss [11] between the reconstructed HQ sequence I^{RHQ} and the ground-truth HQ sequence I^{HQ} as

$$\mathcal{L} = \sqrt{\|I^{RHQ} - I^{HQ}\|^2 + \epsilon^2}, \quad (1)$$

where ϵ is a constant that is empirically set as 10^{-3} .

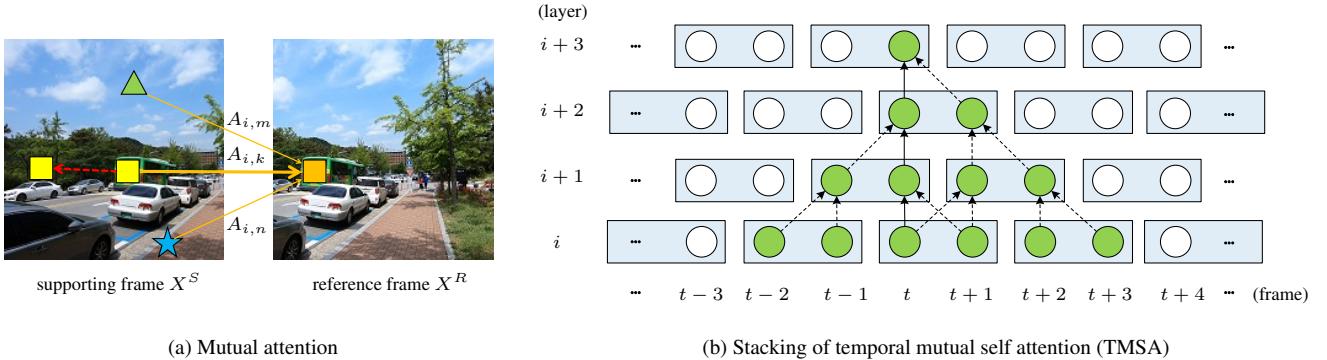


Figure 3. Illustrations for mutual attention and temporal mutual self attention (TMSA). In 3a, we let the orange square (the i -th element of the reference frame) query elements in the supporting frame and use their weighted features as a new representation for the orange square. The weights are shown around solid arrows (we only show three examples for clarity). When $A_{i,k} \rightarrow 1$ and the rest $A_{i,j} \rightarrow 0(j \neq k)$, the mutual attention equals to warping the yellow square to the position of the orange square (illustrated as a dashed arrow). 3b shows a stack of temporal mutual self attention (TMSA) layers. The sequence is partitioned into 2-frame clips at each layer and shifted for every other layer to enable cross-clip interactions. Dashed lines represent information fusion among different frames.

3.2. Temporal Mutual Self Attention

In this section, based on the attention mechanism [45, 94, 101], we first introduce the mutual attention and then propose the temporal mutual self attention (TMSA).

Mutual attention. Given a reference frame feature $X^R \in \mathbb{R}^{N \times C}$ and a supporting frame feature $X^S \in \mathbb{R}^{N \times C}$, where N is the number of feature elements and C is the channel number, we compute the *query* Q^R , *key* K^S and *value* V^S from X^R and X^S by linear projections as

$$Q^R = X^R P^Q, \quad K^S = X^S P^K, \quad V^S = X^S P^V, \quad (2)$$

where $P^Q, P^K, P^V \in \mathbb{R}^{C \times D}$ are projection matrices. D is the channel number of projected features. Then, we use Q^R to query K^S in order to generate the attention map $A = \text{SoftMax}(Q^R(K^S)^T / \sqrt{D}) \in \mathbb{R}^{N \times N}$, which is then used for weighted sum of V^S . This is formulated as

$$\text{MA}(Q^R, K^S, V^S) = \text{SoftMax}(Q^R(K^S)^T / \sqrt{D}) V^S, \quad (3)$$

where SoftMax means the row softmax operation.

Since Q^R and K^S come from X^R and X^S , respectively, A reflects the correlation between elements in the reference image and the supporting image. For clarity, we rewrite Eq. (3) for the i -th element of the reference image as

$$Y_{i,:}^R = \sum_{j=1}^N A_{i,j} V_{j,:}^S, \quad (4)$$

where $Y_{i,:}^R$ refers to the new feature of the i -th element in the reference frame. As shown in Fig. 3a, when $K_{k,:}^S$ (e.g., the yellow square from the supporting frame) is the most similar element to $Q_{i,:}^R$ (e.g., the orange square from the reference frame), $A_{i,k} > A_{i,j}$ holds for all $j \neq k$ ($j \leq N$).

When all $K_{j,:}^S$ ($j \neq k$) are very dissimilar to Q_i^R , we have

$$\begin{cases} A_{i,k} \rightarrow 1, \\ A_{i,j} \rightarrow 0, \end{cases} \quad \text{for } j \neq k, j \leq N. \quad (5)$$

In this extreme case, by combining Eq. (4) and (5), we have $Y_{i,:}^R = V_{k,:}^S$, which moves the k -th element in the supporting frame to the position of the i -th element in the reference frame (see the dashed red line in Fig. 3a). This equals to image warping given an optical flow vector. When $A_{i,k} \rightarrow 1$ does not hold, Eq. (4) can be regarded as a “soft” version of image warping. In practice, the reference frame and supporting frame can be exchanged, allowing mutual alignment between two frames. Besides, similar to multi-head self attention, we can also perform the attention for h times and concatenate the results as multi-head mutual attention (MMA).

Particularly, mutual attention has several benefits over the combination of explicit motion estimation and image warping. First, mutual attention can adaptively preserve information from the supporting frame than image warping, which only focuses on the target pixel. It also avoids black hole artifacts when there is no matched positions. Second, mutual attention does not have the inductive biases of locality, which is inherent to most CNN-based motion estimation methods [17, 69, 74, 85] and may lead to performance drop when two neighboring objects move towards different directions. Third, mutual attention equals to conducting motion estimation and warping on image features in a joint way. In contrast, optical flows are often estimated on the input RGB image and then used for warping on features [8, 10]. Besides, flow estimation on RGB images is often not robust to lighting variation, occlusion and blur [107].

Temporal mutual self attention (TMSA). Mutual attention is proposed for joint feature alignment between two

frames. To extract and preserve feature from the current frame, we use mutual attention together with self attention. Let $X \in \mathbb{R}^{2 \times N \times C}$ represent two frames, which can be split into $X_1 \in \mathbb{R}^{1 \times N \times C}$ and $X_2 \in \mathbb{R}^{1 \times N \times C}$. We use multi-head mutual attention (MMA) on X_1 and X_2 for two times: warping X_1 towards X_2 and warping X_2 towards X_1 . The warped features are combined and then concatenated with the result of multi-head self attention (MSA), followed by a multi-layer perceptron (MLP) for the purpose of dimension reduction. After that, another MLP is added for further feature transformation. Two LayerNorm (LN) layers and two residual connections are also used as shown in the green box of Fig. 2. The whole process formulated as follows

$$\begin{aligned} X_1, X_2 &= \text{Split}_0(\text{LN}(X)) \\ Y_1, Y_2 &= \text{MMA}(X_1, X_2), \text{MMA}(X_2, X_1) \\ Y_3 &= \text{MSA}([X_1, X_2]) \\ X &= \text{MLP}(\text{Concat}_2(\text{Concat}_0(Y_1, Y_2), Y_3)) + X \\ X &= \text{MLP}(\text{LN}(X)) + X \end{aligned} \quad (6)$$

where the subscripts of Split and Concat refer to the specified dimensions. However, due to the design of mutual attention, Eq. (6) can only deal with two frames at a time.

One naive way to extend Eq. (6) for T frames is to deal with frame-to-frame pairs exhaustively, resulting in the computational complexity of $\mathcal{O}(T^2)$. Inspired by the shifted window mechanism [59, 60], we propose the temporal mutual self attention (TMSA) to remedy the problem. TMSA first partitions the video sequence into non-overlapping 2-frame clips and then applies Eq. (6) to them in parallel. Next, as shown in Fig. 3b, it shifts the sequence temporally by 1 frame for every other layer to enable cross-clip connections, reducing the computational complexity to $\mathcal{O}(T)$. The temporal receptive field size is increased when multiple TMSA modules are stacked together. Specifically, at layer i ($i \geq 2$), one frame can utilize information from up to $2(i - 1)$ frames.

Discussion. Video restoration tasks often need to process high-resolution frames. Since the complexity of attention is quadratic to the number of elements within the attention window, global attention on the full image is often impractical. Therefore, following [47, 59], we partition each frame spatially into non-overlapping $M \times M$ local windows, resulting in $\frac{HW}{M^2}$ windows. Shifted window mechanism (with the shift of $\lfloor \frac{M}{2} \rfloor \times \lfloor \frac{M}{2} \rfloor$ pixels) is also used spatially to enable cross-window connections. Besides, although stacking multiple TMSA modules allows for long-distance temporal modelling, distant frames are not directly connected. As will show in the ablation study, using only a small temporal window size cannot fully exploit the potential of the model. Therefore, we use larger temporal window size for the last quarter of TMSA modules to enable direct interactions between distant frames.

3.3. Parallel Warping

Due to spatial window partitioning, the mutual attention mechanism may not be able to deal with large motions well. Hence, as shown in the orange box of Fig. 2, we use feature warping at the end of each network stage to handle large motions. For any frame feature X_t , we calculate the optical flows of its neighbouring frame features X_{t-1} and X_{t+1} , and warp them towards the frame X_t as \hat{X}_{t-1} and \hat{X}_{t+1} (*i.e.*, backward and forward warping). Then, we concatenate them with the original feature and use an MLP for feature fusion and dimension reduction. Specifically, following [10], we predict the residual flow by a flow estimation model and use deformable convolution [14] for deformable alignment. More details are provided in the supplementary.

4. Experiments

4.1. Experimental Setup

For video SR, we use 4 scales for VRT. On each scale, we stack 8 TMSA modules, the last two of which use a temporal window size of 8. The spatial window size $M \times M$, head size h , and channel size C are set to 8×8 , 6 and 120, respectively. After 7 multi-scale feature extraction stages, we add 24 TMSA modules (only with self attention) for further feature extraction before reconstruction. More details are provided in the supplementary.

4.2. Video Super-Resolution

As shown in Table 1, we compare VRT with the state-of-the-art image and video SR methods. VRT achieves best performance for both bicubic (BI) and blur-downsampling (BD) degradations. Specifically, when trained on the REDS [65] dataset with short sequences, VRT outperforms VSRT by up to 0.57dB in PSNR. Compared with another representative sliding window-based model EDVR, VRT has an improvement of 0.50~1.57dB on different datasets, showing its good ability to fuse information from multiple frames. Note that VRT outputs all frames simultaneously rather than predicting them frame by frame as EDVR does. On the Vimeo-90K [107] dataset, VRT surpasses BasicVSR++ by up to 0.38dB, although BasicVSR++ and other recurrent models may mirror the 7-frame video for training and testing. When VRT is trained on longer sequences, it shows good potential in temporal modelling and further increases the PSNR by 0.52dB. As indicated in [6], recurrent models often suffer from significant performance drops on short sequences. In contrast, VRT performs well on both short and long sequences. We note that VRT is slightly lower than the 32-frame model BasicVSR++. This is expected since VRT is only trained on 16 frames.

We also provide comparison on parameter number and runtime in Table 1. As a parallel model, VRT needs to restore all frames at the same time, which leads to relatively

Table 1. Quantitative comparison (average PSNR/SSIM) with state-of-the-art methods for **video super-resolution** ($\times 4$) on **REDS4** [65], **Vimeo-90K-T** [107], **Vid4** [53] and **UDM10** [110]. Best and second best results are in red and blue colors, respectively. † We currently do not have enough GPU memory to train the fully parallel model VRT on 30 frames.

Method	Training Frames (REDS/ Vimeo-90K)	Params (M)	Runtime (ms)	BI degradation			BD degradation		
				REDS4 [65] (RGB channel)	Vimeo-90K-T [107] (Y channel)	Vid4 [53] (Y channel)	UDM10 [110] (Y channel)	Vimeo-90K-T [107] (Y channel)	Vid4 [53] (Y channel)
Bicubic	-	-	-	26.14/0.7292	31.32/0.8684	23.78/0.6347	28.47/0.8253	31.30/0.8687	21.80/0.5246
SwinIR [47]	-	11.9	-	29.05/0.8269	35.67/0.9287	25.68/0.7491	35.42/0.9380	34.12/0.9167	25.25/0.7262
SwinIR-ft [47]	1/1	11.9	-	29.24/0.8319	35.89/0.9301	25.69/0.7488	36.76/0.9467	35.70/0.9293	25.62/0.7498
TOFlow [107]	5/7	-	-	27.98/0.7990	33.08/0.9054	25.89/0.7651	36.26/0.9438	34.62/0.9212	25.85/0.7659
FRVSR [76]	10/7	5.1	137	-	-	-	37.09/0.9522	35.64/0.9319	26.69/0.8103
DUF [33]	7/7	5.8	974	28.63/0.8251	-	27.33/0.8319	38.48/0.9605	36.87/0.9447	27.38/0.8329
PFNL [110]	7/7	3.0	295	29.63/0.8502	36.14/0.9363	26.73/0.8029	38.74/0.9627	-	27.16/0.8355
RBPN [25]	7/7	12.2	1507	30.09/0.8590	37.07/0.9435	27.12/0.8180	38.66/0.9596	37.20/0.9458	27.17/0.8205
MuCAN [44]	5/7	-	-	30.88/0.8750	37.32/0.9465	-	-	-	-
RLSP [20]	-/7	4.2	49	-	-	-	38.48/0.9606	36.49/0.9403	27.48/0.8388
TGA [30]	-/7	5.8	384	-	-	-	38.74/0.9627	37.59/0.9516	27.63/0.8423
RSDN [29]	-/7	6.2	94	-	-	-	39.35/0.9653	37.23/0.9471	27.92/0.8505
RRN [31]	-/7	3.4	45	-	-	-	38.96/0.9644	-	27.69/0.8488
FDAN [52]	-/7	9.0	-	-	-	-	39.91/0.9686	37.75/0.9522	27.88/0.8508
EDVR [99]	5/7	20.6	378	31.09/0.8800	37.61/0.9489	27.35/0.8264	39.89/0.9686	37.81/0.9523	27.85/0.8503
GOVSR [109]	-/7	7.1	81	-	-	-	40.14/0.9713	37.63/0.9503	28.41/0.8724
VSRT [6]	5/7	32.6	-	31.19/0.8815	37.71/0.9494	27.36/0.8258	-	-	-
VRT (ours)	6/-	30.7	236	31.60/0.8888	-	-	-	-	-
BasicVSR [8]	15/14	6.3	63	31.42/0.8909	37.18/0.9450	27.24/0.8251	39.96/0.9694	37.53/0.9498	27.96/0.8553
IconVSR [8]	15/14	8.7	70	31.67/0.8948	37.47/0.9476	27.39/0.8279	40.03/0.9694	37.84/0.9524	28.04/0.8570
BasicVSR++ [10]	30/14	7.3	77	32.39/0.9069 †	37.79/0.9500	27.79/0.8400	40.72/0.9722	38.21/0.9550	29.04/0.8753
VRT (ours)	16/7	35.6	243	32.19/0.9006	38.20/0.9530	27.93/0.8425	41.05/0.9737	38.72/0.9584	29.42/0.8795



Figure 4. Visual comparison of **video super-resolution** ($\times 4$) methods.

larger model size and longer runtime per frame compared with recurrent models. However, VRT has the potential for distributed deployment, which is hard for recurrent models that restore a video clip recursively by design.

Visual results of different methods are shown in Fig. 4.

As one can see, in accordance with its significant quantitative improvements, VRT can generate visually pleasing images with sharp edges and fine details, such as horizontal strip patterns of buildings. By contrast, its competitors suffer from either distorted textures or lost details.

Table 2. Quantitative comparison (average RGB channel PSNR/SSIM) with state-of-the-art methods for **video deblurring** on **DVD** [82]. Following [41, 71], all restored frames instead of randomly selected 30 frames from each test set [82] are used in evaluation. Best and second best results are in red and blue colors, respectively.

Method	DeepDeblur [66]	SRN [89]	DBN [82]	DBLRNet [116]	STFAN [123]	STTN [37]	SFE [104]	EDVR [99]	TSP [71]	PVDNet [80]	GSTA [84]	ARVo [41]	VRT (ours)
PSNR	29.85	30.53	30.01	30.08	31.24	31.61	31.71	31.82	32.13	32.31	32.53	32.80	34.27 (+1.47)
SSIM	0.8800	0.8940	0.8877	0.8845	0.9340	0.9160	0.9160	0.9160	0.9268	0.9260	0.9468	0.9352	0.9651 (+0.03)

Table 3. Quantitative comparison (average RGB channel PSNR/SSIM) with state-of-the-art methods for **video deblurring** on **GoPro** [66]. Best and second best results are in red and blue colors, respectively.

Method	DeepDeblur [66]	SRN [89]	DMPHN [113]	SAPHN [83]	MPRNet [112]	SFE [104]	IFI-RNN [67]	ESTRNN [122]	EDVR [99]	TSP [71]	PVDNet [80]	GSTA [84]	VRT (ours)
PSNR	29.23	30.26	31.20	31.85	32.66	31.01	31.05	31.07	31.54	31.67	31.98	32.10	34.81 (+2.15)
SSIM	0.9162	0.9342	0.9400	0.9480	0.9590	0.9130	0.9110	0.9023	0.9260	0.9279	0.9280	0.9600	0.9724 (+0.01)



Figure 5. Visual comparison of **video deblurring** methods. Part of compared images are derived from [41, 112].

Table 4. Quantitative comparison (average RGB channel PSNR/SSIM) with state-of-the-art methods for **video deblurring** on **REDS** [65]. Best and second best results are in red and blue colors, respectively.

Method	DeepDeblur [66]	SRN [89]	DBN [82]	EDVR [99]	VRT (ours)
PSNR	26.16	26.98	26.55	34.80	36.79 (+1.99)
SSIM	0.8249	0.8141	0.8066	0.9487	0.9648 (+0.02)

4.3. Video Deblurring

We conduct experiments on three different datasets for fair comparison with existing methods. Table 2 shows the results on the DVD [82] dataset. It is clear that VRT achieves the best performance, outperforming the second best method ARVo by a remarkable improvement of 1.47dB and 0.0299 in terms of PSNR and SSIM. Related to the attention mechanism, GSTA designs a gated spatio-temporal attention mechanism, while ARVo calculates the corre-

lation between pixel pairs for correspondence learning. However, both of them are based on CNN, achieving significantly worse performance compared with the Transformer-based VRT. We also compare VRT on the GoPro [66] and REDS [65] datasets. VRT shows its superiority over other methods with significant PSNR gains of 2.15dB and 1.99dB. The total number of parameters of VRT is 18.3M, which is slightly smaller than EDVR (23.6M) and PVDNet (23.5M). The runtime is 2.2s per frame on 1280×720 blurred videos. Notably, during evaluation, we do not use any pre-processing techniques such as sequence truncation and image alignment [71, 80].

Fig. 5 shows the visual comparison of different methods. VRT is effective in removing motion blurs and restoring faithful details, such as the pole in the first example and characters in the second one. In comparison, other approaches fail to remove blurs completely and do not produce sharp edges.

Table 5. Quantitative comparison (average RGB channel PSNR) with state-of-the-art methods for **video denoising** on **DAVIS** [36] and **Set8** [90]. σ is the additive white Gaussian noise level. Best and second best results are in red and blue colors, respectively.

Dataset	σ	VLNB [1]	DVDnet [90]	FastDVDnet [91]	PaCNet [93]	VRT (ours)
DAVIS	10	38.85	38.13	38.71	39.97	40.82 (+0.85)
	20	35.68	35.70	35.77	36.82	38.15 (+1.33)
	30	33.73	34.08	34.04	34.79	36.52 (+1.73)
	40	32.32	32.86	32.82	33.34	35.32 (+1.98)
	50	31.13	31.85	31.86	32.20	34.36 (+2.16)
Set8	10	37.26	36.08	36.44	37.06	37.88 (+0.82)
	20	33.72	33.49	33.43	33.94	35.02 (+1.08)
	30	31.74	31.79	31.68	32.05	33.35 (+1.30)
	40	30.39	30.55	30.46	30.70	32.15 (+1.45)
	50	29.24	29.56	29.53	29.66	31.22 (+1.56)

Table 6. Quantitative comparison (average RGB channel PSNR) with state-of-the-art methods for **video frame interpolation** (single frame interpolation, $\times 2$) on **Vimeo-90K-T** [107], **UCF101** [81] and **DAVIS** [36]. R, D and F means that the model uses RGB images, depth maps and optical flows, respectively.

Method	Inputs	Vimeo-90K-T [107]	UCF101 [81]	DAVIS [36]
DAIN [3]	R+D+F	33.35/0.945	31.64/0.957	26.12/0.870
QVI [106]	R+F	35.15/0.971	32.89/0.970	27.17/0.874
DVF [61]	R	27.27/0.893	28.72/0.937	22.13/0.800
SepConv [70]	R	33.60/0.944	31.97/0.943	26.21/0.857
CAIN [13]	R	33.93/0.964	32.28/0.965	26.46/0.856
SuperSloMo [32]	R	32.90/0.957	32.33/0.960	25.65/0.857
BMBC [73]	R	34.76/0.965	32.61/0.955	26.42/0.868
AdaCoF [39]	R	35.40/0.971	32.71/0.969	26.49/0.866
FLAVR [34]	R	36.25/0.975	33.31/0.971	27.43/0.874
VRT (ours)	R	36.53/0.977	33.30/0.970	27.88/0.889

4.4. Video Denoising

We also conduct experiments on video denoising to show the effectiveness of VRT. Following [90, 91], we train one non-blind model for noise level $\sigma \in [0, 50]$ on the DAVIS [36] dataset and test it on different noise levels. Table 5 shows the superiority of VRT on two benchmark datasets over existing methods. Even though PaCNet [93] trains different models separately for different noise levels, VRT still improves the PSNR by 0.82~2.16dB.

4.5. Video Frame Interpolation

To show the generalizability of our framework, we conduct experiments on video frame interpolation. Following [34, 106], we train the model on Vimeo-90K [107] for single frame interpolation and test it on quintuples generated from Vimeo-90K-T [107], UCF101 [81] and DAVIS [36]. As shown in Table 6, VRT achieves best or competitive performance on all datasets compared with its competitors, including those using depth maps or optical flows. As for the model size, VRT only has 9.9M parameters, which is much smaller than the recent best model FLAVR (42.4M).

Table 7. Quantitative comparison (average Y channel PSNR) with state-of-the-art methods for **space-time video super-resolution** (time: $\times 2$, space: $\times 4$) on **Vid4** [53] and **Vimeo-90K-T** [107]. [32], [70] and [3] are frame interpolation methods SuperSloMo, SepConv and DAIN, respectively. Note that the proposed VRT is not trained on this task.

VFI+VSR Methods	Vid4 [53]	Vimeo-Fast [107]	Vimeo-Medium [107]	Vimeo-Slow [107]
[32]+Bicubic	22.84/0.5772	31.88/0.8793	29.94/0.8477	28.37/0.8102
[32]+RCAN [119]	23.80/0.6397	34.52/0.9076	32.50/0.8884	30.69/0.8624
[32]+RBPN [25]	23.76/0.6362	34.73/0.9108	32.79/0.8930	30.48/0.8584
[32]+EDVR [99]	24.40/0.6706	35.05/0.9136	33.85/0.8967	30.99/0.8673
[70]+Bicubic	23.51/0.6273	32.27/0.8890	30.61/0.8633	29.04/0.8290
[70]+RCAN [119]	24.92/0.7236	34.97/0.9195	33.59/0.9125	32.13/0.8967
[70]+RBPN [25]	26.08/0.7751	35.07/0.9238	34.09/0.9229	32.77/0.9090
[70]+EDVR [99]	25.93/0.7792	35.23/0.9252	34.22/0.9240	32.96/0.9112
[3]+Bicubic	23.55/0.6268	32.41/0.8910	30.67/0.8636	29.06/0.8289
[3]+RCAN [119]	25.03/0.7261	35.27/0.9242	33.82/0.9146	32.26/0.8974
[3]+RBPN [25]	25.96/0.7784	35.55/0.9300	34.45/0.9262	32.92/0.9097
[3]+EDVR [99]	26.12/0.7836	35.81/0.9323	34.66/0.9281	33.11/0.9119
ZSM [103]	26.31/0.7976	36.81/0.9415	35.41/0.9361	33.36/0.9138
STARnet [26]	26.06/0.8046	36.19/0.9368	34.86/0.9356	33.10/0.9164
TMNet [105]	26.43/0.8016	37.04/0.9435	35.60/0.9380	33.51/0.9159
RSTT [21]	26.43/0.7994	36.80/0.9403	35.66/0.9381	33.50/0.9147
VRT (VFI+VSR)	26.59/0.8014	36.56/0.9372	35.28/0.9343	33.75/0.9204
VRT (VSR+VFI)	27.46/0.8392	36.98/0.9439	36.01/0.9434	34.01/0.9236

4.6. Space-Time Video Super-Resolution

With the pretrained models on video SR (VSR) and video frame interpolation (VFI), we directly test VRT on space-time video super-resolution by cascading VRT models in two ways: VFI followed by VSR, or VSR followed by VFI. As shown in Table 7, compared with existing methods, VRT provides a strong baseline for space-time video super-resolution, even though it serves as a two-stage model and is not specifically trained for this task. In particular, it improves the PSNR by 1.03dB on the Vid4 dataset.

4.7. Ablation Study

For ablation study, we set up a small version of VRT as the baseline model by halving the layer and channel numbers. All models are trained on Vimeo-90K [107] for bicubic video SR ($\times 4$) and tested it on Vid4 [53].

Impact of multi-scale architecture & parallel warping. Table 8 shows the ablation study on the multi-scale architecture and parallel warping. When the number of model scales is reduced, the performance drops gradually, even though the computation burden becomes heavier. This is expected because multi-scale processing can help the model utilize information from a larger area and deal with large motions between frames. Besides, parallel warping also helps, bringing an improvement of 0.17dB.

Impact of temporal mutual self attention. To test the effectiveness of mutual and self attention in TMSA, we conduct ablation study in Table 9. When we replace mutual attention with self attention (*i.e.*, two self attentions) or only use one self attention, the performance drops by 0.11~0.17dB. One possible reason is that the model may be more focused on the reference frame rather than on the supporting frame during the computation of attention maps.

Table 8. Ablation study on multi-scale architecture and parallel warping. Given an input of spatial size 64×64 , the corresponding feature sizes of each scale are shown in brackets. When some scales are removed, we add more layers to the rest scales to keep similar model size.

1 (64×64)	2 (32×32)	3 (16×16)	4 (8×8)	Parallel warping	PSNR
✓				✓	27.13
✓	✓			✓	27.20
✓	✓	✓		✓	27.25
✓	✓	✓	✓		27.11
✓	✓	✓	✓	✓	27.28

Table 9. Ablation study on temporal mutual self attention.

Attention 1	Self Attn.	-	Mutual Attn.	Mutual Attn.
Attention 2	Self Attn.	Self Attn.	-	Self Attn.
PSNR	27.17	27.11	26.92	27.28

Table 10. Ablation study on attention window size (frame \times height \times width).

Window Size	$1 \times 8 \times 8$	$2 \times 8 \times 8$	$4 \times 8 \times 8$	$8 \times 8 \times 8$
PSNR	27.10	27.13	27.18	27.28

In contrast, using the mutual attention can help the model to explicitly attend to the supporting frame and benefit from feature fusion. In addition, we can find that only using mutual attention is not enough. This is because mutual attention cannot preserve information of reference frames.

Impact of attention window size. We conduct ablation study in Table 10 to investigate the impact of attention window size in the last few TMSAs of each scale. When the temporal window size increases from 1 to 2, the performance only improves slightly, possibly due to the fact that previous TMSA layers can already make good use of neighboring two-frame information. When the size is increased to 8, we can see an obvious improvement of 0.18dB. As a result, we use the window size of $8 \times 8 \times 8$ for those layers.

5. Conclusion

In this paper, we proposed the Video Restoration Transformer (VRT) for video restoration. Based on a multi-scale framework, it jointly extracts, aligns, and fuses information from different frames at multiple resolutions by two kinds of modules: multiple temporal mutual self attention (TMSA) and parallel warping. More specifically, TMSA is composed of mutual and self attention. Mutual attention allows joint implicit flow estimation and feature warping, while self attention is responsible for feature extraction. Parallel warping is also used to further enhance feature alignment and fusion. Extensive experiments on various benchmark datasets show that VRT leads to significant performance gains (up to 2.16dB) for video restoration, including video super-resolution, video deblurring, video denoising, video frame interpolation and space-time video super-resolution.

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