Blur Interpolation Transformer for Real-World Motion from Blur

Zhihang Zhong\textsuperscript{1,2} Mingdeng Cao\textsuperscript{1} Xiang Ji\textsuperscript{1} Yinqiang Zheng\textsuperscript{1} Imari Sato\textsuperscript{1,2}
\textsuperscript{1}The University of Tokyo, Japan \textsuperscript{2}National Institute of Informatics, Japan
zhong@is.s.u-tokyo.ac.jp \{cmd,jixiang\}@g.ecc.u-tokyo.ac.jp
yqzheng@ai.u-tokyo.ac.jp imarik@nii.ac.jp

Abstract

This paper studies the challenging problem of recovering motion from blur, also known as joint deblurring and interpolation or blur temporal super-resolution. The challenges are twofold: 1) the current methods still leave considerable room for improvement in terms of visual quality even on the synthetic dataset, and 2) poor generalization to real-world data. To this end, we propose a blur interpolation transformer (BiT) to effectively unravel the underlying temporal correlation encoded in blur. Based on multi-scale residual Swin transformer blocks, we introduce dual-end temporal supervision and temporally symmetric ensembling strategies to generate effective features for time-varying motion rendering. In addition, we design a hybrid camera system to collect the first real-world dataset of one-to-many blur-sharp video pairs. Experimental results show that BiT has a significant gain over the state-of-the-art methods on the public dataset Adobe240. Besides, the proposed real-world dataset effectively helps the model generalize well to real blurry scenarios. Code and data are available at https://github.com/zzh-tech/BiT.

1. Introduction

Aside from time-lapse photography, motion blur is usually one of the most undesirable artifacts during photo shooting. Many works have been devoted to studying how to recover sharp details from the blur, and great progress has been made. Recently, starting from Jin et al.\textsuperscript{[9]}, the community has focused on the more challenging task of recovering high-frame-rate sharp videos from blurred images, which can be collectively termed joint deblurring and interpolation\textsuperscript{[37,38]} or blur temporal super-resolution\textsuperscript{[26,33–35]}. This joint task can serve various applications, such as video visual perception enhancement, slow motion generation\textsuperscript{[26]}, and fast moving object analysis\textsuperscript{[33–35]}. For brevity, we will refer to this task as blur interpolation.

Recent works\textsuperscript{[7,8,37]} demonstrate that the joint approach outperforms schemes that cascade separate deblurring and video frame interpolation methods. Most joint approaches follow the center-frame interpolation pipeline, which means that they can only generate latent frames for middle moments in a recursive manner. DeMFI\textsuperscript{[26]} breaks this constraint by combining self-induced feature-flow-based warping and pixel-flow-based warping to synthesize latent sharp frame at arbitrary time \(t\). However, even on synthetic data, the performance of current methods is still far from satisfactory for human perception. We find that the potential temporal correlation in blur has been underutilized, which allows huge space for performance improvement of the blur interpolation algorithm. In addition, blur interpolation suffers from the generalization issue because there is no real-world dataset to support model training.

The goal of this work is to resolve the above two issues. In light of the complex distribution of time-dependent reconstruction and temporal symmetry property, we propose dual-end temporal supervision (DTS) and temporally symmetric ensembling (TSE) strategies to enhance the shared temporal features of blur interpolation transformer (BiT) for time-varying motion reconstruction. In addition, a multi-scale residual Swin transformer block (MS-RSTB) is introduced to empower the model with the ability to effectively handle the blur in different scales and to fuse information from adjacent frames. Due to our design, BiT achieves state-of-the-art on the public benchmark performance even without optical flow-based warping operations. Meanwhile, to provide a real-world benchmark to the community, we further design an accurate hybrid camera system following\textsuperscript{[32,51]} to capture a dataset (RBI) containing time-aligned low-frame-rate blurred and high-frame-rate sharp video pairs. Thanks to RBI, the real data generalization problem of blur interpolation can be greatly alleviated, and a more reasonable evaluation platform becomes available. With these improvements, our model presents impressive arbitrary blur interpolation performance, and we show an example of extracting 30 frames of sharp motion from the blurred image in Fig. 1 for reference.

Our contributions can be summarized as follows: 1) We propose a novel transformer-based model, BiT, for arbitrary
2. Related works

2.1. General deblurring

The technological paradigm of general deblurring has experienced a shift from blur kernel estimation by traditional methods such as [10, 16, 31, 47] to direct sharp image regression by deep learning methods such as [24, 42, 43, 45]. Various general network architectures, including CNNs, RNNs, and GANs, have been explored in-depth for deblurring. Nah et al. [24] and Tao et al. [43] verify the effectiveness of the multi-scale (coarse-to-fine) CNNs structure for deblurring, while Zamir et al. [49] prove the efficacy of multi-stage progressive strategy for deblurring. [11, 25, 46, 51, 55] customize their RNN structures to better exploit the long-term temporal correlation of blurry video. Wang et al. [45] adopt deformable convolution [56] to align the neighboring blurry frames to boost deblurring performance. Pan et al. [27] and Son et al. [41] explicitly utilize optical flow for more accurate motion compensation. Moreover, GANs are explored by [13, 14] to deblur images with the goal of better human perception. Recently, transformer [18] has made a splash in the low-level vision tasks. Restormer [48], RVRT [19], and VDTR [4] are proposed to demonstrate the great performance of transformer structures in the general deblurring tasks.

2.2. Blur interpolation

The aim of blur interpolation goes beyond traditional deblurring, which focuses on a one-to-one mapping between blurred and sharp images. Instead, it involves utilizing the temporal information present in motion blur to reconstruct a motion sequence. There are similar tasks that utilize the partial temporal information in rolling shutter distortion to extract video clips, such as [50] and [6]. Jin et al. [9] are the first to exploit blur interpolation, extracting a sharp video clip from only one single blurry image. However, blur interpolation from single image faces the fundamental problem of directional ambiguity. Considering the freedom of each individual and uniform blurred region, the solution space of blur interpolation will be exponential. Therefore, Jin et al. propose a pairwise order-invariant loss to alleviate the fundamental directional ambiguity and help the model converge to a single solution. Then, Purohit et al. [30] utilize a motion representation, which is learned from videos by a self-supervised strategy, to further tackle the directional ambiguity. After that, Argaw et al. [2] leverage a spatial transformer network with multiple independent branches and a transformation consistency loss to simultaneously estimate the motion of middle time and other times within the exposure time. Zhong et al. [53] explicitly account for such directional ambiguity by introducing a motion guidance rep-
resentation. The motion guidelines enable their approach to produce multiple plausible solutions from the same blurred image, rather than just one as was the case before.

Taking blurry video as input [1, 8, 26, 37, 38] for blur interpolation, directional ambiguity can be largely avoided based on the motion cues of adjacent frames. Specifically, Jin et al. [8] present a cascaded scheme of deblurring-first and interpolation-later for this setting. To mitigate the accumulated errors introduced in the cascaded scheme, Shen et al. [37, 38] propose a pyramid recurrent framework to estimate the latent sharp sequence without explicitly distinguishing the deblurring stage and interpolation stage. Argaw et al. [1] implement blur interpolation by initially estimating the optical flow, and then predicting a motion sequence by warping the decoded features to the corresponding time points. Recently, Oh et al. [26] propose DeMFI framework, which combine flow-guided attentive-correlation-based feature bolstering module and recursive boosting techniques to convert lower-frame-rate blurred videos to higher-frame-rate sharp videos with state-of-the-art performance. There are also some works specialized to implement blur interpolation for fast-moving objects such as [33–35]. Given a pre-estimated background and a blurred image with a fast-moving object, they project the object representation to a latent space, and can render the object to a specified time tick within the exposure time. While Pan et al. [28] and Lin et al. [20] use an additional event camera as an aid to accomplish this task. Our approach further pushes the performance of this task on generic scenarios with dual-end temporal supervision and temporally symmetric ensembling strategies as well as a stronger backbone.

2.3. Deblurring dataset

In the early stage, the research community applied various blur kernels to synthesize blurred images with uniform motion, such as [15, 17, 36, 39]. A blurred image $I_b$ can be described as the convolution between a sharp image $I_s$ and a blurred kernel $K$ with optional Gaussian noise $N$:

$$I_b = K * I_s + N.$$  \hspace{1cm} (1)

Then, to deal with more realistic situation with spatially varying blur, researchers adopt a scheme of averaging consecutive frames of a high-frame-rate sharp video to synthesize blurred and sharp image/video pairs. Based on this basic pipeline, Su et al. [42] synthesize a dataset named DVD and additionally interpolates between sharp frames using optical flow to reduce ghosting artifacts in the synthesized blurry video. While Nah et al. [24] synthesize a dataset named GOPRO by applying an inverse gamma correction before averaging to reduce the effect of non-linear transformations. Later, Nah et al. [23] combine the strengths of DVD and GOPRO to create a larger and more diverse synthetic deblurring dataset dubbed REDS. Regarding the more challenging blur interpolation task, previous works like [1, 8, 26, 37, 38] also use discrete frames to create datasets of one-to-many blur-sharp pairs.

Models trained on synthetic data suffer from the persistent problem of being difficult to generalize to real-world data. Thus, many researchers have started to use hybrid camera systems to collect real-world datasets for low-level vision tasks [5, 32, 51, 54]. Rim et al. [32] and Zhong et al. [51, 54] build hybrid camera systems based on beam-splitter to collect real image deblurring dataset (RealBlur) and real video deblurring datasets (BSD and BS-RSCD), respectively. Inspired by the success of real-world datasets, we customize a hybrid system to collect a real dataset (RBI) of time-aligned low-frame-rate and high-frame-rate blur-sharp video pairs. We believe RBI can benefit the community to better benchmark blur interpolation algorithms.

3. Blur interpolation transformer

The overview architecture of our blur interpolating transformer (BiT) is shown in Fig. 2 (a). BiT focuses on interpolating a sharp motion $I_{t}$ for a blurred image given an arbitrary $t$ during the exposure time. Regarding the directional ambiguity in this problem, considering that modern cameras have short exposure times and that the relative speed between camera and scene is not very fast, we follow the implicit assumption of previous works [8, 26, 38, 53] that there is no ambiguity when the input is video. Thus, we also use neighboring frames as auxiliary inputs to get rid of this issue. The inference process of the target model $F$ can be described as follows:

$$\hat{I}_b = F (I_b, t),$$  \hspace{1cm} (2)

where $I_b = \{I_{b}^{pre}, I_{b}^{cur}, I_{b}^{nxt}\}$, denoting the input set of previous, current, and next blurred images. $t$ represents a specific time point during exposure $I_{b}^{cur}$ with a normalized value range of $t \in [0, 1]$. Apart from the lightweight reconstruction layer $F_R$, the model is divided into two stages, including a shared temporal feature extraction stage $F_N$ and an arbitrary motion rendering stage $F_M$. $F_N$ consists of a shared down-sampling convolutional block for shallow feature extraction and followed by $N$ blocks of multi-scale residual Swin transformer blocks (MS-RSTB). The $F_M$ consists of $t$ encoding module and $M$ MS-RSTBs. Then, the inference process Eq. 2 can be reformulated as:

$$\hat{I}_b = F_R (F_M (F_N (I_b), t)).$$  \hspace{1cm} (3)

The fact that only the latter part $F_M$ needs to be repeated when performing multiple time inferences can optimize the network multiplexing efficiency. Extracting well-formed shared temporal features is the key to achieving arbitrary motion rendering under discrete-time supervision. We then present the module and training strategies introduced for
improving the performance of arbitrary motion rendering from blur, one by one.

Multi-scale residual Swin transformer block. Inspired by the powerful modelling ability of residual Swin transformer block (RSTB) [18] for image restoration task, a new and efficient backbone block is constructed by introducing the classic coarse-to-fine multi-scale structure. The proposed MS-RSTB reuses one RSTB to process interpolated features at different scales, and then a convolutional layer is used to fuse the features to the same shape as the input features, as illustrated in Fig. 2 (b). The original input feature of shape $R^{C \times H \times W}$ is interpolated to the shape $R^{C \times H/r^{s-1} \times W/r^{s-1}}$ regarding to the scale level $s \in \{1, \cdots, S\}$ and the rescale ratio $r$. The computational complexity of MS-RSTB is increased as follows:

$$\Omega(\text{MS-RSTB}) \approx \frac{1 - (1/r)^2S}{1 - (1/r)^2} \Omega(\text{RSTB}),$$

where we set $S = 3$ and $r = 2$ so that there is an additional computational cost less than $1/3$. Since the window size of RSTB is fixed, the multi-scale features allow the self-attentive mechanism to be applied from global to local. This facilitates the handling of different scales of blur and the fusion of informative features from adjacent frames without prior knowledge of the range of motion.

Dual-end temporal supervision. A key observation for time-varying motion rendering from blur is that the difficulty increases from the middle moment to both sides with greater temporal difference. One insight is that if, without any temporal cues, the model is able to extract qualified features to render the most extreme moments of motion, such learned features are well-formed in respect to the varying $t$ to better render motions at other moments. Thus, we propose a simple yet effective learning strategy, called dual-end temporal supervision (DTS), to underpin and spread the shared temporal features. Specifically, the shared temporal features, i.e., the yellow cube in Fig. 2 (a), are forced to restore the motions of the two end time points using an additional lightweight reconstruction layer $F^D_R$ without any $t$ encoding:

$$\{ \hat{I}^t_s \mid t = 0, 1 \} = F^D_R(\mathcal{F}_X(I_b)).$$

Note that this extra reconstruction layer will be discarded in the test mode. DTS acts as anchors for the boundaries, mak-
Temporally symmetric ensembling. Another insight into the arbitrary time motion rendering from blur arises from the consistency of the results from temporally forward and reverse inputs. Intuitively, the rendered motion at $t$ of $I_b$ can also be represented as the rendered motion at $1-t$ of the temporally inverse blurred inputs $I_b^{\text{inv}} = \{I_b^{\text{next}}, I_b^{\text{curr}}, I_b^{\text{prev}}\}$. Thus, given a pre-trained BiT, we can further enhance it by fusing forward and inverse complementary features, named temporally symmetric ensembling (TSE). As shown in Fig. 2 (c), during the fine-tuning process, the last reconstruction layer is replaced by a new layer $F_T^R$ that can accept twice the number of input channels. The inference process with TSE strategy is as follows:

$$\hat{I}_t = F_T^R (F_M (F_N (I_b), t), F_M (F_N (I_b^{\text{inv}}), 1-t)).$$

(6)

Thanks to the proposed MS-RSTB and the designed temporal optimization strategies, taking the L1 loss to supervise reconstruction results is sufficient to ensure an excellent performance of the model. The total loss terms are as follows:

$$\mathcal{L} = \mathcal{L}_1 (\hat{I}_t, I_t) + \lambda \left( \mathcal{L}_1 (\hat{I}_0, I_0) + \mathcal{L}_1 (\hat{I}_1, I_1) \right).$$

(7)

In the training phase, $t$ is only randomly sampled from the available discrete time points of the corresponding dataset. However, in the test phase, $t$ can take any continuous value between 0 and 1. As for the $t$ encoding, we expand the spatial size of $t$ to the same size as the shared features. Then, we merge it into the channel dimension of the shared features, followed by a linear layer for feature fusion. Empirically, we find that such simple encoding can provide good performance, slightly better than the widely used frequency encoding such as [22].

4. Real-world blur interpolation dataset

Limitation of synthetic dataset. First, let us briefly review the synthetic pipeline of previous works. Taking Adobe240 from [37, 38] as an example, a sliding window with size of $M$ frames is used to average the sharp images. The blurred image can be generated as follows:

$$I_b = \frac{1}{M} \sum_{m=1}^{M} (I_m^s),$$

(8)

where $M = 11$. The samples of Adobe240 are illustrated in Fig. 3 (a). We can observe the unnatural spikes or steps in the blur trajectory due to the discrete averaging process. Therefore, synthetic datasets like Adobe240 may not reflect the actual difficulty of the blur interpolation task. In addition, the gap between synthetic blur and real blur may lead to generalization problems for models trained on synthetic datasets.

Hybrid camera system. Building a real-world dataset for the blur interpolation task becomes an urgent need. Blur should occur naturally in the form of signal accumulation, as follows:

$$I_b = \int_0^\tau S(t) dt,$$

(9)

where $\tau$ denotes the exposure time, and $S(t)$ denotes the signal captured by the camera sensor at time $t$. To this end, we design a hybrid camera system as illustrated in Fig. 3 (b). Specifically, two BITRAN CS-700C cameras are physically aligned to the beam-splitter by laser calibration. During shooting, the light is split in half and goes into the camera with high and low frame rate modes. The low-frame-rate camera adopts long exposure scheme to capture the blurred video. Besides, a ND filter with about 10% transmittance is installed before the low-frame-rate camera to ensure photometric balance between the blurred frames and the corresponding sharp frames from the high-frame-rate camera.
**RBI dataset.** We use this customized hybrid camera system to collect 55 video pairs as real-world blur interpolation (RBI) dataset. The frame-rate of blurred video and the corresponding sharp video are 25 fps and 500 fps, respectively. The exposure time of blurred image is 18 ms, while the exposure time of sharp image is nearly 2 ms. This means that there are 9 sharp frames corresponding to one blurred frame, and 11 sharp frames exist in the readout deadtime between adjacent blurred frames. The image size is 640 × 480. We shoot videos of normal urban scenes with various motion modes, including ego-motion, object motion, and both. In addition to blur interpolation, RBI can serve as a dataset to measure the performance of blur synthesis algorithms, such as [3].

**5. Experiments**

We optimize the loss using AdamW [21] in the PyTorch framework [29]. λ is empirically set as 0.5. In both the initial training or fine-tuning phase, the learning rate is scheduled by the cosine scheduler from $1 \times 10^{-4}$ to $1 \times 10^{-6}$. Common data augmentation operations, including flipping, rotation, and cropping of size $256 \times 256$, are used. We set $M = 3$ and $N = 3$ as the default BiT settings for $F_N$ and

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**Figure 4.** Qualitative comparisons on Adobe240 dataset and real-world dataset RBI.

**Figure 5.** Cross-validation between synthetic dataset Adobe240 [38] and real-world dataset RBI. BiT++(Adobe240) and BiT++(RBI) represent the model trained on Adobe240 and RBI. The model trained on synthetic data will cause artifacts when tested on real data.
Table 1. Comparison with the state-of-the-arts on synthetic dataset Adobe240 and our real-world dataset RBI. Red denotes the best performance, and blue denotes the second best performance. Runtime is calculated uniformly using images from the Adobe240 dataset with size of 640 × 352 on a single RTX2080 Ti GPU.

|               | Adobe240 | RBI        | Runtime          |
|---------------|----------|------------|------------------|
|               | PSNR ↑   | SSIM ↑     | 1x [s] ↓         |
|               | PSNR ↑   | SSIM ↑     | 60x [s] ↓        |
|               | Params [M] ↓ |
| EDVR [45]+XVFI [40] | 33.19 | 0.934 | 28.17 | 0.847 | 0.294 | 17.64 | 29.2 |
| Jin et al. [8]   | 32.47 | 0.924 | 27.73 | 0.853 | 0.250 | 15.00 | 10.8 |
| RPF4 [38]       | 33.32 | 0.935 | 28.55 | 0.872 | 0.746 | 44.76 | 11.4 |
| DeMFI [26]      | 34.34 | 0.945 | 29.03 | 0.895 | 0.513 | 10.80 | 7.41 |
| BiT             | 34.34 | 0.948 | 29.90 | 0.900 | 0.203 | 5.76  | 11.3 |
| BiT++           | 34.97 | 0.954 | 30.45 | 0.908 | 0.395 | 11.64 | 11.3 |

Figure 6. Ablation studies for temporal strategies. (a) shows time-varying performance. (b) is CKA analysis of shared temporal features. This visualization is created based on the test data of RBI.

$F_M$. The number of heads and channel size of self-attention is set to 6 and 174. Regarding the partitioning of the dataset, Adobe240 is the same as previous work [37, 38]; while 50 videos of RBI are used for training and the remaining 5 videos are used for testing. We train BiT on Adobe240 with a batch size of 32 for 800 epochs, and finetune it with TSE strategy for another 400 epochs, on 8 NVIDIA Tesla V100 GPUs. Since the size of RBI is smaller than Adobe240, we double the number of epochs and reduce the batch to 8 to get more iterations for training. Regarding the other models, we retrain them on each dataset for a fair comparison. In addition to this section, we encourage readers to refer to the appendices for more details regarding the proposed RBI dataset, as well as supplementary ablation studies and experiments.

Quantitative and qualitative results. We compare our method with previous state-of-the-arts including Jin et al. [8], RPF4 [38], DeMFI [26], and a cascaded method consists of deblurring model EDVR [45] and interpolation model XVFI [40]. Since the Adobe240 dataset has no readout deadline, we follow the 2x temporal super-resolution setting of this dataset to compare with other methods. While on the RBI dataset, we compare the middle deblurred images, because in the real case, there is a readout deadline.

Quantitative results are shown in Table 1. We name our model with the TSE strategy as BiT++ and the one without is BiT. BiT++ can outperform the prior art on Adobe240 and on RBI by a large margin. Besides, the more time points are derived from the same input, the faster our model becomes. BiT achieves 60 inferences in 5.76 seconds, while maintaining favorable performance. Qualitative results are shown in Fig. 4. We can see that the predictions of BiT and BiT++ are closer to the groundtruth with clearer details on both Adobe240 and RBI. We further utilize RAFT [44] to estimate the optical flow between two adjacent predicted frames on Adobe240, as illustrated in Fig. 4 (a). The optical flow of our results is also closer to the groundtruth, which indicates better motion consistency.

Dataset cross-evaluation. To demonstrate the need for a real dataset, we conduct experiments on cross-evaluation between the synthetic dataset Adobe240 and the real-world dataset RBI. First, we show the results of RBI samples predicted by independent BiT++ models trained on Adobe240 and RBI in Fig. 5 (a). We can observe severe artifacts in the results of the model trained on Adobe240. Conversely, testing on synthetic data shown in Fig. 5 (b), we find that
Table 2. **Ablation studies.** BiT w/o MS denotes BiT using single-scale RSTB module. BiT w/o DTS denotes BiT without dual-end temporal supervision. BiT+ denotes BiT that has the same training epochs as BiT++.

|               | Adobe240 | RBI      |
|---------------|----------|----------|
|               | PSNR ↑   | SSIM ↑   |
| BiT w/o MS    | 33.96    | 0.944    |
| BiT w/o DTS   | 34.10    | 0.946    |
| BiT           | 34.34    | 0.948    |
| BiT+          | 34.52    | 0.946    |
| BiT++         | 34.97    | 0.954    |

|               | PSNR ↑   | SSIM ↑   | 5720 Runtime [s] ↓ |
|---------------|----------|----------|--------------------|
| BiT w/o MS    | 29.40    | 0.893    | 11.34              |
| BiT w/o DTS   | 29.44    | 0.894    | 9.36               |
| BiT           | 29.90    | 0.900    | 7.98               |
| BiT+          | 29.99    | 0.901    | 5.76               |
| BiT++         | 30.45    | 0.908    | 4.02               |

Table 3. **Effect of # of MS-RSTB.** The performance is evaluated on Adobe240 using BiT.

|               | N, M = 0, 6 | N, M = 1, 5 | N, M = 2, 4 | N, M = 3, 3 | N, M = 4, 2 | N, M = 5, 1 | N, M = 6, 0 |
|---------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| PSNR ↑        | 34.08       | 34.09       | 34.18       | **34.34**   | 34.30       | 34.05       | 27.13       |
| SSIM ↑        | **0.947**   | 0.942       | 0.943       | **0.948**   | **0.948**   | 0.944       | 0.832       |
| 60x Runtime [s] ↓ | 11.34       | 9.36        | 7.98        | 5.76        | 4.02        | 2.16        | **0.36**    |

the model trained on RBI does not introduce artifacts, even if it could not remove the synthetic blur. This experiment demonstrates the risks of training a model on a synthetic dataset for the blur interpolation task, which is consistent with the findings of previous work [52].

**Ablation studies.** In order to verify the validity of the proposed new module and strategies, we perform relevant ablation experiments. We show the results of BiT with only single-scale RSTB (denoted as BiT w/o MS), BiT without DTS (denoted as BiT w/o DTS), and BiT with the same total training epochs as BiT++ (denoted as BiT+) in Table 2. The MS-RSTB, DTS, and TSE can bring 0.38dB, 0.24dB, and 0.45dB gain on Adobe240, as well as 0.50dB, 0.46dB, and 0.46dB gain on RBI, respectively. We also present the curves of time-varying performance of ablated models on RBI, as illustrated in Fig.6 (a). The full model BiT++ improves the performance of all time points within the exposure time.

To further explain the benefits from our temporal feature enhancement strategies, we use the central kernel alignment (CKA) [12] to measure the channel-wise similarity of the extracted shared temporal features, as shown in Fig. 6 (b). The modified CKA calculation process is as follows:

$$
	ext{CKA}(i,j) = \frac{\text{HSIC}(G(F_i), G(F_j))}{\sqrt{\text{HSIC}(G(F_i), G(F_i))\text{HSIC}(G(F_j), G(F_j))}}
$$

where $i$ and $j$ are the channel indices of extracted shared temporal feature $F \in \mathbb{R}^{C \times H \times D}$. HSIC and $G$ are the functions to calculate the Hilbert-Schmidt independence criterion and Gram matrices, respectively. We find that after applying the temporal feature enhancement strategy including DTS and TSE, the shared features show a significant functional stratification in the channel dimension. In particular, the channel features of BiT++ are clustered into three rectangular blocks. We speculate that the first and third feature blocks aggregate common features shared by different time inferences, while the middle feature block aggregates more differentiated features ready to be retrieved accordingly based on the given time query.

Finally, we investigate the optimal distribution of MS-RSTB in Table 3 with a constant total number of 6. By sharing MS-RSTBs before shared temporal features at different inference points, temporal feature computation for multiple time points requires only a single computation of the $N$ MS-RSTB blocks, enabling faster inference with larger values of $N$. Our analysis indicates that increasing $N$ to 4 or 5 offers a substantial speedup with a negligible decline in performance compared to the default $N = 3$ setting.

6. Conclusion, limitation, and future work

We propose a novel and efficient model, BiT, to realize arbitrary time blur interpolation with state-of-the-art performance. In addition, we present a real-world dataset RBI that enables the first real-world benchmark for blur interpolation task. However, current limited discrete supervision may not be sufficient to cope with very fast motions. Besides, to better cope with different real-world situations, our dataset needs to be expanded to include video pairs with different devices and different exposure parameters. We believe that the reversed process, i.e., learning to synthesize real blur using successive sharp frames from RBI, is also an interesting and valuable direction for the future.

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