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Abstract

How to properly model the inter-frame relation within the video sequence is an important but unsolved challenge for video restoration (VR). In this work, we propose an unsupervised flow-aligned sequence-to-sequence model (S2SVR) to address this problem. On the one hand, the sequence-to-sequence model, which has proven capable of sequence modeling in the field of natural language processing, is explored for the first time in VR. Optimized serialization modeling shows potential in capturing long-range dependencies among frames. On the other hand, we equip the sequence-to-sequence model with an unsupervised optical flow estimator to maximize its potential. The flow estimator is trained with our proposed unsupervised distillation loss, which can alleviate the data discrepancy and inaccurate degraded optical flow issues of previous flow-based methods. With reliable optical flow, we can establish accurate correspondence among multiple frames, narrowing the domain difference between 1D language and 2D misaligned frames and improving the potential of the sequence-to-sequence model. S2SVR shows superior performance in multiple VR tasks, including video deblurring, video super-resolution, and compressed video quality enhancement. 

https://github.com/linjing7/VR-Baseline

1. Introduction

Video restoration (VR) aims to reconstruct high-quality (HQ) video from its degraded low-quality (LQ) counterpart, including video deblurring (Xiang et al., 2020), video super-resolution (SR) (Sajjadi et al., 2018; Chan et al., 2021), and compressed video enhancement (Guan et al., 2019). Task-driven networks often have complex structures that are elaborately designed for a specific task. These methods may be inapplicable when transferred to a new scenario or a different video restoration task (Yang et al., 2018b; Deng et al., 2020; Cao et al., 2021). Therefore, it is of great significance to explore a unified and versatile framework that can be used for multiple video restoration tasks. Early works simply extend single image restoration (Dai et al., 2015; Shahar et al., 2011; Liao et al., 2015; Cai et al., 2021) to video restoration. These image-based methods ignore inter-frame correlation, leading to limited performance. Some CNN-based methods (Wang et al., 2019; Pan et al., 2020; Deng et al., 2020) utilize information from the frames within a short temporal window. The ignorance of distant frames significantly limits the performance of these methods. Some researchers use the recurrent neural network (RNN) (Isobe et al., 2020; Yang et al., 2019; Zhong et al., 2020; Chan et al., 2021) to propagate the hidden state in the time domain to expand the temporal receptive field. However, as analyzed in (Jozefowicz et al., 2015), RNN suffers from both exploding and vanishing gradients. As a result, RNN is difficult to learn the long-term dependencies and can not be stacked into very deep models, limiting the representation capacity of restoration network. The transformer-based model (Cao et al., 2021; Lin et al., 2022a) can process a video sequence in parallel with self-attention mechanism. Nonetheless, the model complexity is quadratic to the number of tokens. For video restoration with an immense number of tokens, modeling long-range dependencies means huge computational costs and memory occupation. Thus,
the problem of modeling long-term inter-frame relations with an affordable cost remains formidable.

Based on the sequence nature of videos, our insight into this problem is to treat it as a sequence modeling task and try to solve it with the sequence-to-sequence (seq2seq) model. Seq2seq model has proven capable of sequence modeling (Sutskever et al., 2014; Chopra et al., 2016; Ott et al., 2018; Chen et al., 2018) in the field of natural language processing (NLP), showing great potential in modeling the inter-frame relation within the video sequence. Seq2seq model is devised to serially encode the input sequence into latent vectors and then dynamically decode a target sequence out of that representations. However, the migration of the seq2seq model is inevitably hindered by the domain discrepancy between NLP and VR. The video signal is composed of multiple misaligned 2D frames, while the seq2seq model can only handle continuous 1D input (e.g., language sequence, time series) canonically. So we need to establish accurate correspondences among multiple frames by performing a spatial alignment with optical flow estimator.

Previous flow-based (Wedel et al., 2009; Sun et al., 2018; Teed & Deng, 2020) methods perform spatial alignment with a pretrained optical flow network. (Chan et al., 2021) prove that feature alignment, i.e., estimating optical flow from the LQ videos and using it to warp the hidden state, can yield a better restoration result than image alignment. However, these flow-based methods may be suboptimal and suffer from the following issues: Firstly, the data discrepancy between synthetic flow dataset and real-world video affects the performance of the pretrained optical flow module in VR. Secondly, the optical flow estimated from the LQ input video (LQ flow) may be unreliable since the video degradation may seriously distort video contents and break pixel-wise correspondences between frames (Zheng et al., 2021). As shown in Fig. 1, the LQ flows lose some motion details, and the frames aligned by the LQ flows (LQ-aligned frames) contain blurry edges. In contrast, the HQ flow is more detailed, and the HQ-aligned frames contain sharper semantics. Besides, for feature alignment, the motion information estimated from the LQ video may be inconsistent with that of the hidden state, which is expected to be spatially aligned with the HQ video. So some artifacts will be brought when the LQ flow is used for feature alignment.

We attempt to address the data discrepancy and inaccurate LQ flow issues with unsupervised distillation optical flow loss. To be specific, we train an optical flow estimator on the VR dataset with unsupervised loss. The data discrepancy naturally disappear since the training and testing dataset both come from the real-world VR dataset. Furthermore, a novel data distillation loss is designed to generate more accurate LQ flows, in which the optical flows estimated from the HQ video serve as the pseudo-labels of the LQ flows. This loss encourages the LQ flows to imitate the HQ flows, which are more accurate and spatial consistent with the motion information of the hidden state.

Therefore, the unsupervised flow-aligned sequence-to-sequence model is proposed for video restoration tasks (S2SVR). We migrate and improve the seq2seq model from NLP to VR task, and maximize the potential of the seq2seq model with an unsupervised optical flow estimator. In a nutshell, our contributions can be summarized as follows:

- This is the first VR work to explore the sequence-to-sequence model, which comes from NLP and is intrinsically suitable for video sequence modeling.
- The proposed unsupervised distillation optical flow loss alleviates the data discrepancy and inaccurate LQ flow issues of previous flow-based methods, narrowing the domain difference between NLP and VR.
- Extensive experiments show that our method achieves state-of-the-art performance in three typical video restoration tasks, including video deblurring, video super-resolution, and compressed video enhancement.

2. Related Work

2.1. Video Restoration

Early work (Takeda et al., 2009; Shahar et al., 2011; Dai et al., 2015) adopt an image restoration model for video restoration and do not take advantage of information in the neighbouring frames. The ignorance of the inter-frame correlation severely limits the restoration result. Some CNN-based methods (Deng et al., 2020; Tian et al., 2020) employ deformable convolution to perform feature-level alignment. The RNN-based methods design the recurrent structure and attempt to model the long-term dependencies by propagating the hidden state (Isobe et al., 2020; Yang et al., 2019; Zhong et al., 2020). (Chan et al., 2021) prove that the combination of bidirectional propagation and optical flow estimation can achieve ideal results. (Deng et al., 2021) propose a recurrent model with separable-patch architecture and multi-scale integration scheme for fast and accurate video deblurring. However, the RNN-based methods inevitably suffer from the vanishing gradient problem and have difficulty in capturing the long-range temporal dependencies. Recently, the emerging Transformer model has been applied in image and video restoration tasks (Cai et al., 2022a; Liang et al., 2022; Lin et al., 2022b; Cao et al., 2021; Cai et al., 2022b). Nonetheless, the token-based self-attention module has enormous computational and memory cost in restoring long video sequence. Thus, the problem of effectively modeling long-range temporal dependencies within the video sequence remains formidable.

2.2. Sequence-to-Sequence Learning

Seq2seq model is first proposed by (Sutskever et al., 2014) for the machine translation task in which a long short-term...
memory (LSTM) encodes the input sequence into a latent representation and then another LSTM decodes the target sequence out of that representation. The model is intrinsically suitable for long-range coding tasks. Various variants of the seq2seq model have been applied to many sequence modeling tasks, such as speech recognition (Venugopalan et al., 2015), time series analysis (Kuznetsov & Mariet, 2019; He et al., 2021), and text summarization (Shi et al., 2021). Due to the fundamental difference between video and language, the potential of this serialized encoding-decoding structure in assisting continuous-frame VR is unexplored.

2.3. Optical Flow Estimation

With the development of deep learning, some optical flow estimation networks (Sun et al., 2018; Teed & Deng, 2020) trained on synthetic datasets have achieved better results than non-learning methods (Mémin & Pérez, 1998; Wedel et al., 2009). The domain difference between synthetic optical flow and real-world optical flow datasets leads to limited model performance. (Wang et al., 2018a) suggest using an unsupervised optical flow estimator to circumvent the need for labels. (Wang et al., 2018b) improve the performance of unsupervised optical methods by proposing a new warping module to facilitate large motion learning and model occlusion explicitly. (Shi et al., 2017) train a task-oriented flow module jointly with the video enhancement module in the supervision of $L_1$ loss. But the jointly-trained flow module becomes unsuitable when cooperating with other video processing modules. Besides, they have not solved the problem that it’s difficult to estimate accurate motion information from the severely degraded input frames. Based on the LQ-HQ paired characteristics of VR tasks, we propose a data distillation loss to improve the quality of the LQ flows.

3. Method

In this section, we present our S2SVR model. We first introduce the overall framework of the seq2seq model. Then, we explain the unsupervised distillation optical flow method, which narrow the domain discrepancy between NLP and VR and improve the potential of the seq2seq model in VR.

3.1. Sequence-to-Sequence Learning

To promise that the scalable seq2seq architectures and their efficient implementations can be preserved, S2SVR follows the seq2seq framework from NLP as closely as possible. As shown in Fig. 2, S2SVR is composed of four components: encoder, decoder, local attention, and optical flow estimator.

For notation, we use capital letters to represent sequences, (e.g., $X, Y$), lower case to denote individual frames in a sequence, (e.g., $x_1, x_2$). Let $X = \{x_1, x_2, \ldots, x_N\}$ represent the input low-quality video sequence and $Y = \{y_1, y_2, \ldots, y_N\}$ be the corresponding high-quality video sequence, where $N$ is the length of the sequence. The goal of our S2SVR is to estimate the conditional probability of the target sequence respective to the input sequence $P(Y|X)$.

**Encoder.** Firstly, the encoder read sequentially each $x_i \in X$ and transforms the source sequence into a list of latent vectors $Z = \{z_1, z_2, \ldots, z_N\}$:

$$z_i = F_e(z_{i-1}, x_i),$$

where $z_i$ denotes the latent vector at time step $i$, and $F_e$ denotes the function of the encoder, which in our implementation is a residual stacked ConvGRU (ResConvGRU). The ResConvGRU will be introduced in the next subsection.

**Decoder.** Next, the decoder sequentially produces the out-
put video based on the encoded vectors. Specifically, using the chain rule, the conditional probability $P(Y|X)$ can be decomposed as:

$$P(Y|X) = P(y_1, y_2, \ldots, y_N|z_1, z_2, \ldots, z_N)$$

$$= \prod_{t=1}^{N} P(y_t|y_1, \ldots, y_{t-1}; z_1, \ldots, z_N). \quad (2)$$

We serially generate the subsequent output based on the source sequence encoding and the decoded sequence so far:

$$y_t = F_d(y_1, y_2, \ldots, y_{t-1}; z_1, z_2, \ldots, z_N). \quad (3)$$

$F_d$ represents the decoder, which is composed of a ResConvGRU and a feed-forward network. ResConvGRU generates a hidden state $s_i$, and then $s_i$ passes through the feed-forward network to produce the output frame:

$$s_i = F_r(s_{i-1}, y_{i-1}, c_i),$$

$$y_i = F_f(s_i), \quad (4)$$

where $F_r$ is the ResConvGRU and $F_f$ denotes the feed-forward network. $s_i, y_i$ refer to the hidden state of ResConvGRU and output frame at $i^{th}$ time step, respectively. And $c_i$ is a context vector generated by the local attention module based on the latent vectors $Z = \{z_1, z_2, \ldots, z_N\}$.

**Local Attention.** As shown in Fig. 2(a), the attention module generates a context vector $c_i$ for each time step, allowing the decoder to extract information from different parts of the input sequence. Specifically, we represent the context vector $c_i$ as a weighted sum of a subset of the latent vectors:

$$c_i = \sum_{j=i-r}^{i+r} \alpha_{ij} z_j, \quad (5)$$

where $r$ is the the subset radius and the weight $\alpha_{ij}$ is:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=i-r}^{i+r} \exp(e_{ik})}. \quad (6)$$

$e_{ij} = F_g(s_{i-1}, z_j)$ is an attention model scoring the correspondence between the $i^{th}$ input and the $j^{th}$ output based on $s_{i-1}$ and $z_j$. Similar to (Shahar et al., 2011), a two-layer feed-forward network is adopted as the attention model:

$$e_{ij} = V_a \cdot \tanh(W_a[s_{i-1}, z_j]), \quad (7)$$

where $V_a$ and $W_a$ denote the first and second convolution layers of the feed-forward network, respectively. And $\lfloor \cdot, \cdot \rfloor$ refers to concatenation along the channel dimension.

**Motion Compensation.** To improve the performance of the seq2seq model in VR, we need to establish accurate spatial correspondences among multiple frames. Similar to previous methods (Isobe et al., 2020; Yang et al., 2019; Zhong et al., 2020; Chan et al., 2021), we adopt an optical flow estimator for motion compensation. Specifically, as shown in Fig. 2(b), we employ a flow estimator to predict the motion between two consecutive frames. Then we warp the hidden state of ResConvGRU at last time step $s_{t-1}$, making it spatially aligned with the input at the current step:

$$o_t = F_o(x_t, x_{t-1}),$$

$$s_{t-1} = F_w(s_{t-1}, o_t), \quad (8)$$

where $F_o$ and $F_w$ respectively refer to the optical flow estimator and spatial warping module. $o_t$ is the optical flow field between the adjacent input frames $x_t$ and $x_{t-1}$.

### 3.2. Residual Stacked ConvGRU

We use a deep-stacked ConvGRU for both the encoder and the decoder. Considering the video characteristics, as shown in Fig. 2(c), we make two modifications to the original ConvGRU. Firstly, to improve the image processing ability, several residual blocks are concatenated after the ConvGRU. Besides, motivated by the idea of modeling the difference between an intermediate layer’s output and the target, we introduce residual among the layers in a stack. We define the ConvGRU and residual blocks as $F_g(\cdot)$ and $F_b(\cdot)$:

$$z_t^l = z_t^{l-1} + F_b(F_g(z_{t-1}^l, z_t^{l-1})), \quad (9)$$

where $z_t^l$ denote the hidden state of $l^{th}$ ConvGRU at time step $t$. In this way, the vanishing gradient problem can be addressed, allowing us to model the long-term temporal dependencies. More details are provided in the appendix.

### 3.3. Unsupervised Optical Flow Estimator

As analyzed in Sec. 1, previous flow-based motion compensation methods suffer from the data discrepancy between synthesized and real-world datasets, as well as inaccurate LQ flows. To solve these problems, we propose an unsupervised scheme equipped with a novel distillation loss to train the flow estimator on the VR dataset as shown in Fig. 3.

Let $X$ denotes a LQ input video, and $Y$ is the corresponding HQ video. Our goal is to train a flow network $F_o$ that can estimate accurate motion information from the LQ videos (HQ
videos are unavailable during inference) by predicting the optical flow $F_{12}^x$ for two consecutive LQ frames $\{x_1, x_2\}$:

$$F_{12}^x = F_o(x_1, x_2).$$

The unsupervised scheme is summarized in Algorithm 1 to better understand the proposed unsupervised optical flow estimation method. Firstly, we train a teacher flow estimation network parameterized by $\theta_t$ on the HQ videos with photometric loss and smooth loss. After convergence, we use the pretrained teacher estimator to generate pseudo-labels and train a student flow network parameterized by $\theta_o$ on the LQ video. In the following, we explain the proposed unsupervised optical flow training scheme step by step.

**Step 1.** We train an optical flow estimator $F_t$ with photometric loss and smooth loss on the HQ video $Y$. This optical flow estimator $F_t$ will be frozen and serves as a teacher network in the next step. The photometric loss (Yu et al., 2016) is based on the assumption that the same object in two consecutive frames must have similar intensities:

$$L_{ph}(F_{12}^y) = \sum_p \rho(y_1(p), y_2(p + F_{12}^y(p))) \cdot O^y(p),$$

where $p$ is the coordinate and $O^y$ is the occlusion mask to discard the loss on the occurred region generated by the bidirectional checking (Wang et al., 2018b), $\rho(\cdot)$ is the $\ell_1$ loss, and $F_{12}^y$ is the optical flow field for two consecutive frames in the HQ videos $Y$:

$$F_{12}^y = F_t(y_1, y_2).$$

Further, we adopt a one-order smooth loss (Godard et al., 2017) to encourage colinearity of neighboring flows:

$$L_{sm}(F_{12}^y) = \sum_{d \in x, y} \sum_p |\partial_y F_{12}^y(p)| e^{-|\partial_y y_1(p)|}$$

And then we formulate the loss used in the first step as:

$$L = \omega_{ph} \cdot L_{ph}(F_{12}^y) + \omega_{sm} \cdot L_{sm}(F_{12}^y).$$

We respectively set the weights $\omega_{ph}$ and $\omega_{sm}$ to 0.15 and 50.

**Step 2.** Now we have trained a teacher optical flow estimator $F_t$ which can predict the accurate optical flow $F_{12}^y$ for two consecutive HQ frames $\{y_1, y_2\} \in Y$:

$$F_{12}^y = F_t(y_1, y_2).$$

Based on the assumption that the HQ flow is more accurate for motion compensation, we use $F_{12}^y$ as the pseudo-labels of the LQ flows $F_{12}^x$ and and propose the distillation loss:

$$L_{dis}(F_{12}^x, F_{12}^y) = \sum_p |F_{12}^y(p) - F_u(F_{12}^x(p))|,$$

where $F_u$ is a upsample operation to ensure that $F_{12}^x$ has the same size as $F_{12}^y$ in video super-resolution task. Along with the photometric loss and smoothness regularization, we train the student flow estimator $F_o$ on the LQ dataset:

$$L = \omega_{ph} L_{ph}(F_{12}^x) + \omega_{sm} L_{sm}(F_{12}^x) + \omega_{dis} L_{dis}(F_{12}^x, F_{12}^y).$$

We set the weights to $\{\omega_{ph} = 0.15, \omega_{sm} = 50, \omega_{dis} = 0.1\}$. The student network will be later used as our optical flow estimator for motion compensation as in Eq. (8). In implementation, we adopt a lightweight flow model pwclite (Liu et al., 2020) as our optical flow network.

### 4. Experiments

#### 4.1. Implementation Details

**Datasets.** For video SR, the benchmark datasets consist of REDS4 (Nah et al., 2019a) and Vimeo-90K-T (Xue et al., 2019). For video deblurring, we use the Gopro dataset (Nah et al., 2017), where 22 videos are used for training and 11 videos for testing. For compressed video enhancement, our models are trained with the MFQEv2 dataset (Guan et al., 2019) including 108 lossless videos. We adopt the dataset from ITU-T (Ohm et al., 2012) containing 18 videos for evaluation. We compress videos by HEVC reference software HM16.5 under Low Delay P (LDP) configuration (Guan et al., 2019; Deng et al., 2020). Evaluation metrics include PSNR and SSIM (Wang et al., 2004).

**Settings.** Models are trained with nature videos and their degraded counterparts. During unsupervised optical flow training, the learning rate is set to $1 \times 10^{-4}$. And during restoration training, the initial learning rate of the flow esti-
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Figure 4. Visual comparison of video 4 × SR results on the REDS4 (Nah et al., 2019a) dataset. Please zoom in for a better comparison.

Table 1. Quantitative comparison (PSNR/SSIM) on the video SR dataset REDS4 and Vimeo-90K-T. Bold and underlined text indicate the best and the second-best performance, respectively.

| Methods      | Params | REDS4  | Vimeo-90K-T |
|--------------|--------|--------|-------------|
| Bicubic      | -      | 26.14  | 31.32       |
| TOFlow       | -      | 27.98  | 33.08       |
| DUF          | 5.8 M  | 28.63  | 37.07       |
| RBPNN        | 12.2 M | 30.09  | 37.09       |
| EDVR-M       | 3.3 M  | 30.53  | 37.09       |
| EDVR         | 20.6 M | 31.09  | 37.61       |
| PFNL         | 3.0 M  | 29.63  | 36.14       |
| MuCAN        | -      | 30.88  | 37.32       |
| BasicVSR     | 6.3 M  | 31.42  | 37.18       |
| IconVSR      | 8.7 M  | 31.67  | 37.47       |
| S2SVR (Ours) | 13.4 M | 31.96  | **37.71**   |

Table 2. Video deblurring performance comparison and model parameter analysis on the GOPRO dataset (Nah et al., 2017).

| Methods      | Params | PSNR (dB) | SSIM  |
|--------------|--------|-----------|-------|
| Tao et al.   | -      | 30.29     | 0.9014|
| Su et al.    | 15.30 M| 27.31     | 0.8255|
| Kim et al.   | -      | 26.82     | 0.8245|
| Nah et al.   | -      | 29.97     | 0.8947|
| EDVR         | 23.6 M | 26.83     | 0.8426|
| STFAN        | 5.73 M | 28.59     | 0.8608|
| TSP          | 16.19 M| 31.67     | **0.9279**|
| UHDVD        | -      | 31.33     | 0.9210|
| S2SVR (Ours) | 8.44 M | **31.81** | 0.9231|

4.2. Video Super-Resolution

Quantitative Comparison. We compare our method with previous methods: TOFlow (Xue et al., 2019), DUF (Jo et al., 2018), RBPNN (Haris et al., 2019), EDVR-M (Wang et al., 2019), EDVR (Wang et al., 2019), PFNL (Yi et al., 2019), MuCAN (Li et al., 2020), BasicVSR (Chan et al., 2021), IconVSR (Chan et al., 2021), and VSR-Transformer (Cao et al., 2021). As shown in Tab. 1, it is clear that our method outperforms all other models by a large margin on the REDS4 dataset. Specifically, our S2SVR model achieves 0.29dB gain over the suboptimal model and 0.77dB over the VSR-Transformer model in PSNR. For Vimeo-90K-T, our performance is slightly lower than VSR-Transformer, but S2SVR only requires 41% parameters compared with the latter. It shows that we only need half the parameters to obtain comparable performance to transformer-based models. Note that Vimeo-90K-T contains sequences with seven frames. So it also indicates that our method performs better in restoring long sequences. Serialized modeling of seq2seq models and accurate optical flow estimation facilitates the capture of long-range inter-frame dependencies.

Visual Comparison. From the comparison with other methods in Fig. 4, our S2SVR network has shown great advantages in the restoration of textures and structural details, such as license plate numbers, pane lines, and hairs. Our results are more reliable and detailed, while the other methods suffer from excessive smoothing and content distortion.

4.3. Video Deblurring

Quantitative Comparison. We compare our method against state-of-the-art algorithms, including Tao et al. (Tao et al., 2018), Su et al. (Su et al., 2017), Kim et al.
We experiment with five different video resolutions: A (2,560×1,600), B (1,920×1,080), C (832×480), D (480×240), E (1,280×720).

We also report the size of the model. For example, S2SVR (Ours) has 8.44M parameters. Compared to other methods, our model achieves a performance gain of 0.14dB on the dataset with a lightweight structure. We also report the size of the model in Tab. 2. As the largest model, EDVR’s parameter is up to 23M, but its performance is unsatisfactory. Our S2SVR network contains 8.44M parameters. Compared with the TSP (Pan et al., 2020), our model achieves a higher PSNR performance with only one-half of its size.

Visual Comparison. From the comparison results in Fig. 5, it can be seen that our method can restore the original structure as much as possible from the severely degraded scene. Digital restoration of blurred scenes is difficult. It can be seen that no other method except ours can guarantee the satisfying visual results.

4.4. Compressed Video Enhancement

Quantitative Comparison. We evaluate the performance of compressed video enhancement by ΔPSNR and ΔSSIM, which measure the PSNR and SSIM improvement after the degraded video is restored.
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Figure 6. Visual comparison on Video BasketballPass at QP = 37.

(a) Without Motion Compensation

(b) With Motion Compensation

Figure 7. Visualization with and without motion compensation.

5. Ablation Study

Unsupervised Optical Flow Estimator. To demonstrate the effectiveness of the unsupervised training scheme, we retrain our optical flow network pwclite in a supervised manner with the optical flow dataset FlyingChairs (Dosovitskiy et al., 2015). We also adopt pre-trained RAFT (Teed & Deng, 2020), the SOTA supervised optical flow network, as our optical flow estimator. As shown in Tab. 4, the pwclite trained with our unsupervised distillation loss can outperform the supervised counterpart by 0.17 dB. It indicates that the flow estimator trained in our unsupervised scheme fits the VR tasks well. Notably, it achieves a better result than the state-of-the-art supervised method RAFT by 0.08dB.

| Method | RAFT | Pwclite |
|--------|------|---------|
| Sup.   | 31.88 | 31.79 |
| Unsup. | 31.79 | 31.62 |

Table 5. Quantitative comparison on sequences of different length.

Motion Compensation Visualization. We visualize the feature saliency maps with (W/I) and without (W/O) motion compensation in Fig. 7. Obviously, the video frame will lose lots of motion details and texture edges without motion compensation. It is caused by the misalignment among multiple frames, which limits the potential of the seq2seq model in VR. In contrast, with motion compensation, the feature map is much sharper and preserves more movement details, which benefits from our accurate optical flow estimation. Motion compensation narrows the domain difference between NLP and VR, facilitating information aggregation.

Long Sequence Reconstruction. To validate the effectiveness of our S2SVR in capturing long-range temporal dependencies, we separate a video in REDS4 dataset into 4 segments with different lengths, including 5, 15, 30, and 50 frames, respectively. And we use S2SVR, EDVR, and EDVR-M to restore these sequences independently. Our method performs the best among the three methods in Tab. 5. And the longer the sequence is, the more superior our S2SVR shows. It suggests that our method has an excellent performance in modeling long-range dependencies.

6. Conclusions

In this paper, we propose an unsupervised flow-aligned seq2seq model for multiple video restoration tasks. Our work aims at solving the challenges of properly modeling the inter-frame relation within the video sequence. The sequence-to-sequence learning is explored for the first time in VR to capture long-term temporal dependencies at a low cost. What’s more, we design an unsupervised optical method equipped with a novel distillation loss to improve the performance of the seq2seq model in VR. Extensive experiments show that the proposed method achieves comparable performance in video deblurring, video super-resolution, and compressed video quality enhancement tasks with moderate model size, especially in long sequence VR.

Acknowledgements: This work is partially supported by the NSFC fund (61831014), the Shenzhen Science and Technology Project under Grant (CJGJZD20200617102601004, JSGG20210802153150005).
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