DYNAMIC SCENE VIDEO DEBLURRING USING NON-LOCAL ATTENTION

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ABSTRACT

This paper tackles the challenging problem of video deblurring. Most of the existing works depend on implicit or explicit alignment for temporal information fusion which either increase the computational cost or result in suboptimal performance due to wrong alignment. In this study, we propose a factorized spatio-temporal attention to perform non-local operations across space and time to fully utilize the available information without depending on alignment. It shows superior performance compared to existing fusion techniques while being much efficient. Extensive experiments on multiple datasets demonstrate the superiority of our method.

1 Introduction

Video deblurring, as a primary problem in the vision and graphics communities, strives to predict latent frames from a blurred sequence. The camera shake and high-speed motion in dynamic scenes often generate unwanted blur and produce blurry videos. Such videos not only deteriorate the visual quality but also hinder some high-level vision tasks such as tracking [Jin et al. 2005], Mei and Reid [2008], video stabilization [Matsushita et al. 2006], etc. As more videos are taken using hand-held and onboard video capturing devices, this problem has received great attention in the last decade. The blur in videos is usually a consequence of several interwoven factors like camera shake, object motion, depth variations, etc.

A significant number of works have been proposed [Paramanand and Rajagopalan 2011], [Nimisha et al. 2018a], [Rao et al. 2014], [Nimisha et al. 2018b], [Vasu and Rajagopalan 2017], [Paramanand and Rajagopalan 2014], [Vijay et al. 2013] where various traditional approaches were adopted for deblurring. Recent works [Purohit et al. 2019], [Purohit and Rajagopalan 2020], [Mohan et al. 2021], [2019], [Vasu et al. 2018] based on deep convolutional neural networks (CNN) have studied the benefits of replacing the image formation model with a parametric model that can be trained to emulate the non-linear relationship between blurred-sharp image pairs. Unlike single-image deblurring, video deblurring methods can utilize additional information that exists across neighboring frames. Early methods relied on motion compensation of the input frames, either explicitly [Su et al. 2017], [Mao et al. 2016], [Hyun Kim et al. 2018] or implicitly [Zhou et al. 2019], [Zhong et al.] to aggregate information at a particular location from adjacent frames. [Su et al. 2017], [Hyun Kim et al. 2018], [Chen et al. 2018] first compute optical flow between a reference frame and neighboring frames and then use the aligned observations to deblur the reference frame. [Wang et al. 2019] utilizes deformable convolution to align feature maps using learnable offsets. Implicit handling of motion using recurrent networks or 3D convolution has its own drawbacks. 3D convolution [Zhang et al. 2018] is computationally heavy and introduces a large number of parameters. For recurrent architectures, the assumption that all previous frames will be automatically aligned and fused in the hidden state remains a problem for frames with large displacement. It is not very easy to extract only the relevant information from a single combined state.

Finding the spatio-temporal relation is critical while fusing information as not all parts of the neighboring frames are equally informative for restoring the current frame due to varying factors such as occlusions, motion, etc. Fusion of incorrect information adversely affects reconstruction performance. We explore the need for non-local operations for spatio-temporal fusion. A non-local self-attention module aims at computing the correlations between all possible pixels within and across frames, which directly resonates with the current goal of spatio-temporal fusion. By nature, such a block does not require any alignment steps. [Vaswani et al. 2017] introduced self-attention based transformer network for natural language processing. [Wang et al. 2018] showed a similar non-local approach for classification and recognition. However, extending such approaches to generation tasks is non-trivial. Despite its exceptional non-local
processing capabilities, even simpler spatial self-attention can be hard to implement due to its large memory requirement for the image domain. For spatio-temporal operation in videos, it will become significantly more expensive.

In this paper, we present a factorized spatio-temporal self-attention mechanism that contains the essential properties of non-local processing in spatio-temporal domain while being much more efficient. We formulate the entire non-local operation as the composition of three lightweight operators: spatial aggregation, temporal aggregation, and pixelwise adaptive distribution. It requires significantly less memory compared to existing non-local blocks for the same spatio-temporal size while providing superior performance.

To summarize, our contributions are

- We introduce a factorized spatio-temporal attention as an effective non-local information fusion tool for video deblurring task.
- Extensive experiments and analysis are presented on several video deblurring benchmarks to show state-of-the-art accuracy and interpretability achieved by our architecture.

2 Related Works

Early video or multiframe deblurring methods [Cho et al. 2012, Matsushita et al. 2006] usually assume that there exist sharp contents and interpolate them to help the restoration of latent frames. The main success of these methods is due to the use of sharp contents from adjacent frames. Wulff and Black [2014] develop a novel layered model of scenes in motion and restore latent frames layer by layer. Recently, several end-to-end CNN methods [Su et al. 2017, Hyun Kim et al. 2017] have been proposed for video deblurring. To improve the generalization ability, Chen et al. [2018] propose an optical flow based reblurring step to reconstruct the blurry input, which is employed to fine-tune deblurring network via self-supervised learning. Zhang et al. [2018] employ 3D convolutions to help latent frame restoration. Hyun Kim and Mu Lee [2015] treat optical flow as a line-shaped approximation of blur kernels, which optimize optical flow and blur kernels iteratively. Wieschollek et al. [2017] recurrently use the features from the previous frame in multiple scales based on a recurrent network. Hyun Kim et al. [2017] develop a spatial-temporal recurrent network with a dynamic temporal blending layer, where they concatenated feature of the current frame and the previous frame and pass through a recurrent network. Zhou et al. [2019] fed the previous deblurred frame along with the current blurry frame through their network in a progressive manner and modeled frame alignment and non-uniform blur removal as element-wise filter adaptive convolution processes. Wang et al. [2019] develop pyramid, cascading, and deformable convolution to achieve better alignment performance. They have used a simpler temporal and spatial attention strategies. First, they align the neighboring frames, and then at each pixel location, they aggregate the information using convolution. For spatial attention, they have used simple mask multiplication. In comparison, we resort to more effective non-local processing [Buades et al. 2005, Wang et al. 2018] using the proposed spatio-temporal attention module where each pixel in the current frame can gather complementary information from all other pixels in all the frames.

3 Method

An overview of our network is shown in Fig. [1] We use a hierchical encoder-decoder architecture comprising of densely connected modules as the backbone of our restoration network. We use spatio-temporal self-attention blocks to fuse features of the current frame and the neighboring frames.
Non-local means [Buades et al., 2005] is a classical filtering algorithm that allows distant pixels to contribute to the filtered response at a location based on patch appearance similarity. This non-local filtering idea was later developed into block-matching algorithm, which was used with neural networks for image denoising [Lefkimmiatis, 2017]. A similar technique was shown to be successful in the natural language processing domain [Vaswani et al., 2017]. The main building block of [Vaswani et al., 2017] is a self-attention module that computes the response at a position in a sequence (e.g., a sentence) by attending to all positions and taking their weighted average in an embedding space. [Wang et al., 2018] proposed a generic non-local operation in deep neural networks to calculate the relation between all possible positions. Given an input feature map of size $T \times H \times W$ (omitting the channel dimension for brevity), the goal of non-local block is to compute the relation $THW \times THW$. But, the tensor of size $THW \times THW$ is huge for videos and to reduce the computational overhead, Wang et al. [2018] typically used $T = 4, H = W = 7$.

For a restoration task like video deblurring, large downsampling will deteriorate pixel-level accuracy. Some works like Ramachandran et al. [2019] use non-local operations in small blocks inside an image, which hinders its expressibility. Instead, we propose a factorized spatio-temporal self-attention module. Our design is intuitively motivated by examining the flow of information in [Hu et al., 2018, Cao et al., 2019, Li et al., 2019] etc, which deploy a squeeze-based aggregation operation in their approach. We gather global information from spatial and temporal domain by performing squeezing operation, and then adaptively distribute it to each pixel of the current frame. We construct three lightweight operations, including spatial squeezing, temporal squeezing, and pixelwise adaptive distribution. For simplicity, we assume batch and channel dimensions to be 1 in the following sections, but it can have any standard values. Given an input tensor $x \in \mathbb{R}^{T \times 1 \times HW}$, we calculate a set of spatial attention maps as

$$A_s = \text{softmax}_{HW}(f_s(x))$$

where $A_s \in \mathbb{R}^{T \times M \times HW}$. $f_s$ is convolutional operation, $\text{softmax}_{HW}$ is softmax along $HW$ and $M$ is the number of attention maps per frame. Next, we elementwise multiply each frame with each of these $M$ attention maps. Let, $A^m_s \in \mathbb{R}^{T \times HW}$ denote the $m^{th}$ attention map. Non-local spatial feature is aggregated for each of the frames using the $m^{th}$ attention map as

$$G^m_s = S_{HW}(A^m_s \odot x)$$

where $G^m_s \in \mathbb{R}^T$, $m = 1, ..., M$ and $S_{HW}$ represents the squeeze operation [Hu et al., 2018] along $HW$. Now, we calculate a set of temporal attention maps as

$$A_t = \text{softmax}_T(f_t(x'))$$

where $A_t \in \mathbb{R}^{N \times T}$. $f_t$ is 1D convolutional operator, $x' \in \mathbb{R}^{1 \times T}$ is the spatially pooled version of the input feature $x$, $\text{softmax}_T$ is softmax operation along $T$. Given the set of temporal attention maps $A_t$ and the spatially aggregated features $G^m_s$, we apply the $N$ temporal attention maps on each of the $G^m_s$: $m = 1, ..., M$ and aggregate temporal information as

$$G_{st} = G_s A^T_t$$

where $G_{st} \in \mathbb{R}^{MN}$, $G_s \in \mathbb{R}^{M \times T}$, $T_t$ represents transpose operation. Intuitively, each of these $MN$ elements contains global spatio-temporal information, which has been aggregated using the factorized $M$ spatial attention maps and $N$ temporal attention maps resulting in a total of $MN$ possible combinations. After aggregating global information, we adaptively distribute it to each pixel. We generate a pixelwise attention map $A_p$ as

$$A_p = \text{softmax}_1(f_p(x^R))$$

where $A_p \in \mathbb{R}^{MN \times HW}$. $f_p$ is 2D convolutional operation, $x^R \in \mathbb{R}^{1 \times HW}$ is the feature map of the current frame. Each pixel will adaptively select a particular combination of total $MN$ spatio-temporal attention map using $A_p$. Now, we distribute the global information to each pixel as

$$y^R = G_{st} A_p$$

where $y^R \in \mathbb{R}^{1 \times HW}$ is the output feature map corresponding to the current frame.

4 Experiments

Implementation Details: We compare our model with existing works on GOPRO dataset [Nah et al., 2017] under the standard training and testing settings of previous state-of-the-art methods [Pan et al., 2020, Nah et al., 2019]. The size of training patch is $256 \times 256$ with minibatch size of 8. We use the ADAM optimizer learning rate of $1 \times 10^{-4}$, which decreases to half after every 200 epochs. We implement our algorithm based on the PyTorch on an Ubuntu 16 system, Intel Xeon E5 CPU, and an NVIDIA Titan Xp GPU.
Table 1: Quantitative evaluations on the GOPRO dataset [Nah et al. 2017] in terms of PSNR and SSIM.

| Methods                  | PSNRs | SSIMs   |
|--------------------------|-------|---------|
| Tao et al. [2018]        | 30.29 | 0.9014  |
| Su et al. [2017]         | 27.31 | 0.8255  |
| Wieschollek et al. [2017]| 25.19 | 0.7794  |
| Hyun Kim et al. [2017]   | 26.82 | 0.8245  |
| Nah et al. [2019]        | 29.97 | 0.8947  |
| Wang et al. [2019]       | 26.83 | 0.8426  |
| Zhou et al. [2019]       | 28.59 | 0.8608  |
| Ours                     | 31.61 | 0.91    |

Figure 2: Deblurred results on GOPRO dataset.

Quantitative Comparisons: To evaluate the performance of the proposed algorithm, we compare it against the following state-of-the-art algorithms: Tao et al. [2018], Su et al. [2017], Wieschollek et al. [2017], Hyun Kim et al. [2017], Nah et al. [2019], Wang et al. [2019], Zhou et al. [2019]. Table 1 shows the quantitative results, where the proposed algorithm performs favorably against the state-of-the-art methods in terms of PSNR and SSIM.

Quantitative Comparisons: Fig. 2 show some deblurred results from the testset of Nah et al. [2017]. We observe that the results of prior works suffer from incomplete deblurring or artifacts. In contrast, our network is able to restore scene details more faithfully, which are noticeable in the regions containing text, edges, etc.

5 Conclusion

We have proposed an adaptive approach for video deblurring. The proposed model performs favorably against state-of-the-art methods while being efficient. Such a system can be extended to existing video deblurring methods or other video-processing tasks and will be explored in our future works. Refined and complete version of this work appeared in CVPR 2021.

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