Video Frame Interpolation via Deformable Separable Convolution

Xianhang Cheng,† Zhenzhong Chen†∗
†School of Remote Sensing and Information Engineering, Wuhan University, China
{xianhang, zzchen}@whu.edu.cn

Abstract

Learning to synthesize non-existing frames from the original consecutive video frames is a challenging task. Recent kernel-based interpolation methods predict pixels with a single convolution process to replace the dependency of optical flow. However, when scene motion is larger than the predefined kernel size, these methods yield poor results even though they take thousands of neighboring pixels into account. To solve this problem in this paper, we propose to use deformable separable convolution (DSepConv) to adaptively estimate kernels, offsets and masks to allow the network to obtain information with much fewer but more relevant pixels. In addition, we show that the kernel-based methods and conventional flow-based methods are specific instances of the proposed DSepConv. Experimental results demonstrate that our method significantly outperforms the other kernel-based interpolation methods and shows strong performance on par or even better than the state-of-the-art algorithms both qualitatively and quantitatively.

Introduction

Video frame interpolation is the task of synthesizing middle non-existent frames from two consecutive frames, which is considered as one of the important problems in the field of video processing. The ability to generate in-between frames could find applications in various domains, ranging from novel view interpolation (Flynn et al. 2016), slow motion generation (Jiang et al. 2018; Bao et al. 2019) to frame rate conversion (Bao et al. 2018b).

Traditional methods interpolate one frame with a two-step method which first estimate motion information, typically optical flow, and then perform the pixel synthesis operation guided by motion (Baker et al. 2011). However, a well-known problem behind this method is that visual artifacts can be introduced in challenging conditions (e.g. occlusion, illumination or nonlinear structural changes), suggesting that the two-step interpolation process struggles to reconstruct plausible results.

To better handle occlusion, recent approaches address the problem aforementioned with more elaborated pipelines by estimating flow information together with occlusion masks or visibility maps with deep convolutional neural networks (CNNs) (Jiang et al. 2018; Bao et al. 2019; 2018a; Liu et al. 2017; van Amersfoort et al. 2017; Liu et al. 2019; Xue et al. 2019; Peleg et al. 2019; Yuan et al. 2019; Hannemose et al. 2019).

Instead of using optical flow, another major trend in this research is to replace the two-step interpolation operation as a convolution process (Niklaus, Mai, and Liu 2017a; 2017b). For each output pixel, a pair of 2D kernels or four 1D kernels (two for horizontal and another two for vertical direction) are learned with a neural network. Notably, large
kernel size is required for these kernel-based interpolation methods to handle large motion. Though these methods are able to generate reasonable results, there are two main drawbacks: 1) These methods are limited to handle motion larger than kernel size. 2) It is expensive to consider thousands of pixels to synthesize only one output pixel.

In this paper, we address these drawbacks by presenting a more powerful and effective approach, known as Deformable Separable Convolution (DSepConv). We argue that the limitation of the previous kernel-based interpolation methods is because they process the pixels only in the local neighborhood, which takes no effect on pixels outside the regular grid. As shown in Figure 1, with large motion, the estimated kernels are incorrect despite they have considered 51 x 51 pixels in the local neighborhood. Drawing inspiration from the success of deformable convolution networks (Dai et al. 2017; Zhu et al. 2019), we propose to learn adaptive kernels, offsets and masks for interpolation, allowing us to use far fewer but more effective pixels to deal with large motion. Moreover, we show that conventional flow-based interpolation methods with CNNs are specific instances of our method. Our experiments show that the proposed method can greatly increase the performance of existing kernel-based methods and perform favorably against representative state-of-the-art interpolation methods.

The contributions of this paper are summarized as follows:

- A novel solution for frame interpolation DSepConv is proposed which learns not only spatially-adaptive separable convolution kernels, but also deformable offsets and masks. This approach is able to use small kernel size to handle strong motion.
- Both recent kernel-based and flow-based interpolation methods are demonstrated as special cases of our proposed DSepConv.
- Despite any complex information (like context, depth, flow and edge information) or post-processing process are not involved in our network, the design of jointly estimating kernels, offsets and masks makes our performance on par or even better than the state-of-the-art methods.

Related Work

Various methods to synthesize intermediate video frames have been introduced. In this section, we provide an overview of recent interpolation methods in the following three parts.

Flow Based Methods

Using optical flow is one of the most conventional strategies for video frame interpolation. Considering the reference frames are not equally informative due to occlusion, mask maps are often estimated together with optical flow for adaptively blending the warped frames. Specifically, Liu et al. (Liu et al. 2017) proposed a fully-convolutional encoder-decoder architecture named Deep Voxel Flow (DVF) to estimate 3D flow across space and time. The in-between frame was then warped by trilinear sampling. Similar method has been introduced by Jiang et al. (Jiang et al. 2018), who used two U-Net architectures to compute bi-directional optical flow and visibility maps. Moreover, CyclicGen (Liu et al. 2019) additionally used edge information (Xie and Tu 2015) and cycle consistency loss, which greatly improved the performance of DVF. In order to get more accurate optical flow, some methods leveraged advanced flow or depth estimation architectures as sub-modules in their networks. For instance, ToFlow (Xue et al. 2019) utilized SPyNet (Ranjan and Black 2017) to get flow information for interpolation. MEMCNet (Bao et al. 2018a) chose FlowNetS (Dosovitskiy et al. 2015) for motion estimation. DAIN (Bao et al. 2019) used PWC-Net (Sun et al. 2018) and a depth network (Chen et al. 2016) to explicitly detect the occlusion. Other interpolation methods such as CtxSyn (Niklaus and Liu 2018) and Zoom-In-to-Check (Yuan et al. 2019) warped not only input frames, but also their deep corresponding features. Despite the so far mentioned approaches have been shown effective, the performance can be limited provided that the optical flow or occlusion masks were less accurate.

Phase Based Methods

Several methods utilize phase information to learn the motion relationship for video frame interpolation. Meyer et al. (Meyer et al. 2015) proposed the phase-based method which utilized phase information across the levels of a multi-scale pyramid. Such an approach performs well when the motion is small while fails in difficult interpolation settings. To further increase the performance, combined with CNNs, PhaseNet (Meyer et al. 2018) was proposed to better handle challenging scenarios like brightness changes and motion blur. However, their performance can be less effective in coping with the level of detail.

Kernel Based Methods

Kernel based methods regard flow estimation as an intermediate step, which can be circumvented with a single convolution process. These methods have also been exploited in some other tasks like frame prediction (Reda et al. 2018) and motion blur synthesis (Brooks and Barron 2019). As a pioneer of kernel based methods, AdaConv (Niklaus, Mai, and Liu 2017a) was proposed to estimate a pair of spatially-adaptive convolutional kernels for each output pixel with a neural network. To reduce the large memory demand, Niklaus et al. (Niklaus, Mai, and Liu 2017b) proposed SepConv that separated each 2D convolution kernel into a vertical and a horizontal kernels. SepConv increased the performance to some extent, but it failed to handle motion larger than 51 (pixels) and yielded poor results.

Some recent efforts (Choi and Bajic 2019; Deng et al. 2019; Ahn, Jeong, and Kim 2019; Peleg et al. 2019) have been made to mitigate the limitations of SepConv (Niklaus, Mai, and Liu 2017b). However, they all process the information in a local neighborhood, making them have to use large kernels (51 x 51) or adaptively leverage down-sampled frames (half, one quarter or one eighth of the original frame size) to handle potential large motion. On the contrary, we propose to use far smaller separable kernels (5 x 1) with offsets and masks to adaptively convolve with input images in a non-local neighborhood. Concurrently, similar work like
ADC (Lee et al. 2019), has been proposed to find the spatial transform between the frames. However, different from their method, our proposed DSepConv estimates separable 1D kernels rather than learning 2D kernels. In addition, we learn scalar masks as a modulation mechanism for each shift of computational burden. Nonetheless, despite thousands of pixels have been considered, these methods are limited to motions up to n pixels between two input frames.

Inspired from recent deformable convolution networks (Dai et al. 2017; Zhu et al. 2019), we propose to use much smaller convolution kernels with additional offsets and masks, which allow us to focus on fewer but more relevant pixels rather than all the pixels in a large neighborhood (shown in Figure 2(b)). Given a convolution kernel and its corresponding local patch with specific kernel size n (n = 5 in our method), let p_{i,j} denote the pre-specified offset for the j-th (j ∈ [0, n^2)) location in a specific patch and i represents either of the two input frames. Thus each pixel in patch P_i(x, y) centered at (x, y) in frame I_i can be represented as P_i(x, y; p_{i,j}). In our method, learnable offset Δp_{i,j} and modulation scalar Δm_{i,j} are estimated for each pixel located at p_{i,j} in each patch. As a result, the pixels in the modulated patches can be expressed as

\[
\begin{align*}
\hat{I}(x, y) &= K_1(x, y) \ast P_1(x, y) + K_2(x, y) \ast P_2(x, y), \quad (1) \\
\hat{I}(x, y) &= K_1(x, y) \ast P_1(x, y; p_{1,j}) + K_2(x, y) \ast P_2(x, y; p_{2,j}) + \Delta m_{1,j} \ast \Delta p_{1,j}, \quad (3)
\end{align*}
\]

As the offsets are typically fractional, pixels located at non-integer coordinates are bilinearly sampled. In addition to the modulated patches, we estimate 1D separable kernels to approximate 2D kernels in Eq. (2). Therefore, our final interpolation process is expressed as

\[
\begin{align*}
\hat{I}(x, y) &= k_{1,v}(x, y) \cdot k_{1,h}^T(x, y) \ast \hat{P}_1(x, y) + k_{2,v}(x, y) \cdot k_{2,h}^T(x, y) \ast \hat{P}_2(x, y), \quad (4)
\end{align*}
\]

In our method, both previous kernel-based methods (Niklaus, Mai, and Liu 2017b) and conventional flow-based methods are specific instances. In Eq. (3), it is easy to make out that when Δp = 0 and Δm = 1, the interpolation process is the same as the one in SepConv (Niklaus, Mai, and Liu 2017a; 2017b) and our method. Our method can obtain pixels (pink points) outside the local neighborhood with additional learnable offsets (purple arrows), allowing us to better handle large motion. Modulation scalars are omitted for clarity.
Liu 2017b). On the other hand, specifically, when \( n = 1 \), the patches become single pixels via bilinear interpolation. Therefore, the vectors in Eq. (4) become scalars. In this case, the interpolation process can be reformulated as

\[
\hat{I}(x, y) = k_{1,v}(x, y) \cdot k_{1,h}(x, y) \cdot I_1(x + \Delta x_1, y + \Delta y_1) \cdot \Delta m_1 + k_{2,v}(x, y) \cdot k_{2,h}(x, y) \cdot I_2(x + \Delta x_2, y + \Delta y_2) \cdot \Delta m_2,
\]

where \( \Delta x_1, \Delta y_1, \Delta x_2, \Delta y_2 \) represent learnable offsets and \( \Delta m_1, \Delta m_2 \) denote masks. Notably, Eq. (5) can be seen as a bi-directional warping function, where each offset can be regarded as a component of optical flow and \( k_{1,v}(x, y) \cdot k_{1,h}(x, y) \cdot \Delta m_1 \) as well as \( k_{2,v}(x, y) \cdot k_{2,h}(x, y) \cdot \Delta m_2 \) can be considered as occlusion masks.

**Network Architecture**

We use a fully convolutional neural network which is similar to SepConv (Niklaus, Mai, and Liu 2017b). The whole network can be divided into the following sub-modules: the encoder-decoder architecture, kernel estimator, offset estimator and mask estimator as illustrated in Figure 3. The detailed configurations are provided in Section 2 of the Supplementary Material.

**Encoder-decoder Architecture**

Given two input frames, the encoder-decoder architecture aims to extract deep features for estimating kernels, masks and offsets for each output pixel. We use a U-Net architecture which is the same as the one in (Niklaus, Mai, and Liu 2017b), where skip-connections are employed to facilitate the feature mixture across encoder and decoder.

**Kernel Estimator**

The kernel estimator consists of four parallel sub-networks with analogous structure to estimate vertical and horizontal 1D kernels for each pixel of the two frames. For each sub-network, three \( 3 \times 3 \) convolution layers with Rectified Linear Units (ReLU) (Nair and Hinton 2010), a bilinear upsampling layer and another \( 3 \times 3 \) convolution layer are stacked, yielding a tensor with \( n \) channels. Subsequently, the estimated four 1D kernels are used to approximate two 2D kernels described in Eq. (2).

**Offset Estimator**

The offset estimator, sharing the same structure as the kernel one described above, contains four parallel sub-networks to learn two directional (vertical and horizontal) offsets for each location of the two frame patches. With a specific kernel size \( n \), there are \( n^2 \) pixels in each regular grid patch. Therefore, the number of the output channel in each sub-network is set to be \( n^2 \).

**Mask Estimator**

Inspired by (Zhu et al. 2019), learnable masks \( \Delta m \) are introduced as a modulation mechanism that expands the scope of modeling and gives a significant improvement in performance. The design of mask estimator is similar, whose only difference is that the output channels are fed to a sigmoid layer. There are two parallel sub-networks, each of which produces tensors with \( n^2 \) channels.

**Deformable Convolution**

The deformable convolution utilizes the estimated kernels, offsets and mask to adaptively convolve one input frame, yielding an intermediate interpolation result. Note that this operation is adaptive and represents Eq. (3) and (4) in this paper, which does not totally resemble the process described in (Zhu et al. 2019). Finally, the target frame is generated by adding the two intermediate results. In the right part of Figure 3, the intermediate results generated from deformable convolution look dimmer than the final result in brightness except area with occlusion (e.g. area around the red ball), suggesting the effectiveness of deformable convolution to handle motion and occlusion.

**Training**

**Loss Functions**

We combine two kinds of loss functions to penalize the interpolated frame \( \hat{I} \) that is not similar to the ground truth \( I^{GT} \). In addition, to encourage the network to be invariant to the temporal order of the input frames, a temporal symmetry term is added in each loss function (Peleg et al. 2019). Here we assume \( \hat{I} \) to represent the result generated by the temporal flipping of the input frames.
The first loss measures the difference between the interpolated pixel color and the ground-truth color with the function:
\[
L_c = \rho(\hat{I} - \hat{I}_{GT}) + \rho(\hat{I}^T - \hat{I}_{GT}^T),
\]
(6)
\[
\rho(x) = \sqrt{x^2 + \epsilon^2},
\]
(7)
where \(\rho(\cdot)\) represents the Charbonnier penalty function (Charbonnier et al. 1994) and the constant \(\epsilon\) is set to be 1e-6.

The second loss function aims to sharpen the generated frame by penalizing the differences of frame gradient predictions (Mathieu, Couprie, and LeCun 2015), which is defined as:
\[
L_{gdl} = \sum_{i,j} \|\hat{I}_{i,j} - \hat{I}_{i-1,j}\|_1 + \|\hat{I}^T_{i,j} - \hat{I}^T_{i-1,j}\|_1 + \|\hat{I}_{i,j} - \hat{I}_{i,j-1}\|_1 + \|\hat{I}^T_{i,j} - \hat{I}^T_{i,j-1}\|_1.
\]
(8)
Finally, the total loss function is given as:
\[
L = L_c + L_{gdl}.
\]
(9)

Training Strategy Our training dataset is Vimeo90K (Xue et al. 2019). The triplets in this dataset were randomly flipped horizontally or vertically for data augmentation.

The network was trained using Adam optimizer (Kingma and Ba 2014). We first trained our network for 120 epochs using a learning rate schedule of 1e-4, dropping by half every 40 epochs. The training patch size was randomly cropped into 128 x 128 pixels and the batch size was 16. Inspired by some previous work training their networks with larger patches (Niklaus and Liu 2018; Bao et al. 2018a; 2019), we fine-tuned our network using patches of size 256 x 256 and the entire frames with learning rates of 6.25e-6 and 3.125e-6, respectively.

Experiments

Evaluation Datasets and Metrics
We test our network on several datasets with different resolutions, including UCF101 (Soomro, Zamir, and Shah 2012), Vimeo90K (Xue et al. 2019) and Middlebury dataset (Baker et al. 2011). For UCF101 dataset, we use 379 triplets chosen by Liu et al. (Liu et al. 2017) with a resolution of 256 x 256 pixels. The Vimeo90K dataset contains 3,782 triplets in the test set with a resolution of 256 x 448 pixels. The Middlebury benchmark has been widely used for assessing frame interpolation methods, which consists an Evaluation set (hidden ground truth) and an Other set (with ground truth).

For quantitative evaluation, we use Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) on UCF101 and Vimeo90K datasets. In addition, we report the average Inerpolation Error (IE) on the Middlebury dataset.

Ablation Study
In this section, we perform comprehensive ablations to analysis our network structure, including different size of the estimated kernels and the usage of the mask estimator.

| Methods       | UCF101 | Vimeo90K | M.B. |
|---------------|--------|----------|------|
|               | SSIM   | PSNR     | SSIM | PSNR | IE |
| 1 x 1 + M     | 0.9666 | 34.45    | 0.9659| 33.63| 2.57 |
| 3 x 3 + M     | 0.9680 | 34.79    | 0.9731| 34.52| 2.21 |
| 5 x 5         | 0.9680 | 34.98    | 0.9728| 34.55| 2.11 |
| 5 x 5 + M     | **0.9686**| **35.08**| **0.9738**| **34.73**| **2.06**|

Table 1: Quantitative evaluation on different network architecture: kernel size of \(N \times N\) with \((N \times N + M)\) or without masks \((N \times N)\). M.B. is short for the Other set of Middlebury dataset. The bold numbers and underlined numbers depict the best and the second best performances.

Kernel Size For each pixel to be synthesized, the kernel size \(n\) indicates how many pixels in the non-regular grid augmented with offsets could be referenced. Larger kernel size enables the network take more pixels into consideration. However, it inevitably introduces an increase computation.

To understand the effect of different numbers of reference pixels in each pixel synthesis, we trained several models that generate kernels with different size \((n = 1, 3, 5, \text{ respectively})\) and show the quantitative results in Table 1. Larger kernel sizes like \(n = 7, 9, 11\) are not considered as they increase the FLOPs of the network when \(n = 5\) by 12.8%, 69.0% and 173.8%, respectively. We can observe that referencing more pixels can lead to a better performance. When increasing the kernel size from 1 x 1 to 5 x 5, the network has a PSNR gain of 0.65 dB and 1.04 dB on UCF101 and Vimeo90K, respectively. A visualization of the referenced pixels with different kernel size is shown in the first row of Figure 4. And we show their representative kernels in the second row. By referencing more relevant pixels in color, the model that uses larger kernel size can generate shaper and clearer interpolation result.

Mask Estimator To examine the effectiveness of the mask estimator in our network, we trained a network without estimating masks. As shown in Table 1 and Figure 4, network with mask estimator gives a significant improvement in performance. This can be attributed to the capability of the modulation mechanism which adjusts offsets in perceiving input patches (Zhu et al. 2019).
Table 2: Quantitative comparisons and analysis on different frame interpolation algorithms using CNNs. The bold numbers and underlined numbers depict the best and the second best performances. Our method is comparable even without using any complex information.

Comparisons with State-of-the-arts

We compare our method with state-of-the-art interpolation methods, including DVF (Liu et al. 2017), ToFlow (Xue et al. 2019), AdaConv (Niklaus, Mai, and Liu 2017a), SepConv (Niklaus, Mai, and Liu 2017b), CtxSyn (Niklaus and Liu 2018), CyclicGen (Liu et al. 2019), MEMC-Net* (Bao et al. 2018a), IM-Net (Peleg et al. 2019), DAIN (Bao et al. 2019) and ADC (Lee et al. 2019). Notably, considering that some methods provide more than one version of the same model, we evaluate all their performances and treat them differently (e.g. SepConv-$L_f$ and SepConv-$L_f$ are trained with different loss functions, CyclicGen and CyclicGen_large are de-
In this paper we propose deformable separable convolution for video frame interpolation. The key to make the method practical is that our method can adaptively process the information in a non-local neighborhood by learning offsets and masks besides separable kernels. Effectively this allows us to handle large motion even with a small size of convolution kernels. The MEMC-Net* and DAIN methods generate obvious artifacts despite they use a couple of sub-modules in their networks. Toflow can not well reconstruct the legs of the man due to a wrong estimation of local convolution kernels. The MEMC-Net* and ADC suffer from some blur.

Discussions and Limitations

Compared with previous methods, the proposed DSepConv is not constrained by neither the kernel size nor the accuracy of optical flow. However, like other kernel-based methods, our approach can only generate a single in-between frame.
our method and we perform favorably against the state-of-the-arts on diverse datasets qualitatively and quantitatively.

Acknowledgments
This work was supported in part by National Natural Science Foundation of China under contract No. 61771348 and National Key R&D Program of China under contract No. 2017YFB1002202.

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