ATCA: AN ARC TRAJECTORY BASED MODEL WITH CURVATURE ATTENTION FOR VIDEO FRAME INTERPOLATION

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ABSTRACT
Video frame interpolation is a classic and challenging low-level computer vision task. Recently, deep learning based methods have achieved impressive results, and it has been proven that optical flow based methods can synthesize frames with higher quality. However, most flow-based methods assume a line trajectory with a constant velocity between two input frames. Only a little work enforces predictions with curvilinear trajectory, but this requires more than two frames as input to estimate the acceleration, which takes more time and memory to execute. To address this problem, we propose an arc trajectory based model (ATCA), which learns motion prior from only two consecutive frames and also is lightweight. Experiments show that our approach performs better than many SOTA methods with fewer parameters and faster inference speed.

Index Terms— Video frame interpolation, Optical flow, Arc trajectory, Curvature attention

1. INTRODUCTION
Video frame interpolation (VFI) is a classic low-level task of video enhancement in computer vision, which aims to synthesize one or more intermediate frames between the consecutive input frames. It has many practical applications, such as frame rate conversion, video editing, motion deblurring, inter-frame compression and medical imaging.

Recently, deep learning based VFI methods can be categorized as kernel-based methods and flow-based methods. Long et al. [1] firstly introduce a CNN model which directly estimates the intermediate frame using two input frames. However, it usually causes blurry results. To address this problem, Niklaus et al. [2] apply kernel-based methods AdaConv and SepConv, which generate the intermediate frame by locally convolving the input frames. These methods focus on where to find the output pixel from the input frames. Besides, AdaCoF [3] proposes a novel operation, called adaptive collaboration of flows, that can refer to any number of pixels and any location. The second flow-based methods are to estimate the motion flows between the input frames using optical flow algorithms, warp the input frames and synthesize the target frame guided by the warped results. Liu et al. [4] propose Deep Voxel Flow (DVF), to estimate a flow map directly pointing to reference locations. Jiang et al. [5] propose Super-Slomo, which combines an U-Net flow estimator and kernel-based image synthesis with the warped results. After that, more advanced flow estimation models like PWC-Net [6], which uses coarse-to-fine architecture to iteratively refine the flow map, are applied in most frame interpolation pipelines [7, 8, 9, 10].

However, most of these approaches mentioned above are based on such an assumption that a pixel between consecutive frames moves along a straight line at a constant speed. Although Xu et al. [9] propose QVI, an acceleration-aware algorithm, that allows predictions with curvilinear trajectory and variable velocity, it takes four consecutive frames as input to estimate acceleration information, which is time consuming, and can not learn motion trajectory adaptively from the frame context. To alleviate this problem, we propose an Arc Trajectory based frame interpolation model with Curvature Attention (ATCA) in this paper. Overall, our major contributions are summarized as follows: 1) we propose ATCA to interpolate video frames, which takes two consecutive frames and assumes an arc trajectory between them, with the flow maps and curvature maps obtained by the joint estimator; 2) we introduce curvature attention into the synthesis network to improve the synthesis quality using the curvature maps; 3) our model is lightweight and fast, and outperforms many SOTA VFI methods.

Fig. 1. The geometric schematic of the arc trajectory model.
2. PROPOSED METHOD

With two consecutive frames $I_0$ and $I_1$, frame interpolation gives a prediction of the intermediate frame, denoted as $I_t$, to reconstruct the ground truth $I_t$ as accurate as possible, where $t \in (0, 1)$ denotes the arbitrary temporal position. To get high quality intermediate frame, we establish our model based on SoftSplat [7]. SoftSplat first estimates the bidirectional flows $F_{0 \rightarrow 1}$ and $F_{1 \rightarrow 0}$ between the input frames using an off-the-shelf optical flow method like PWC-Net [6]. And then it employs softmax splatting, a form of forward warping, to the-shelf optical flow method like PWC-Net [6]. Also unlike QVI [9], we only utilize two consecutive frames to synthesize the intermediate frame and propose a novel joint estimator with optical flow, to learn the prior information about the curvature of the arc trajectory at each pixel. The overview of our model is shown in Fig. 2.

2.1. Arc Trajectory Model

The arc trajectory model is depicted in Fig. 1, where point $P_0$ and point $P_1$ denote the position of a pixel in the two input frames $I_0$ and $I_1$ respectively, with $P_0P_1^x = F_{0 \rightarrow 1}^x$ and $P_0P_1^y = F_{0 \rightarrow 1}^y$. And $P_0P_1$ is the arc trajectory with the center point $C$, the radius $R$ and the arc angle $\angle P_0CP_1 = \beta$, while $\alpha$ is the dip angle of $P_0P_1$. So we have the following geometric relations

$$d = P_0P_1 = \sqrt{F_{0 \rightarrow 1}^x{}^2 + F_{0 \rightarrow 1}^y{}^2},$$

$$\alpha = \arctan2(F_{0 \rightarrow 1}^y, F_{0 \rightarrow 1}^x), \quad \beta = \arcsin \frac{d}{2R},$$

\[
\theta_0 = \alpha + \frac{\pi}{2} + \beta, \quad \theta_1 = \alpha + \frac{\pi}{2} - \beta, \\
\theta_t = (\theta_1 - \theta_0)t + \theta_0 = -2\beta t + \alpha + \frac{\pi}{2} + \beta,
\]

where $\theta_0$ and $\theta_1$ denote the polar angle of $P_0$ and $P_1$ in polar coordinate system respectively, while $\theta_t$ denotes the polar angle of $P_t$ in the intermediate frame $I_t$ and is calculated under the constant velocity assumption.

2.2. Flow and Curvature Joint Estimator

Although there exist some advanced optical flow models such as PWC-Net [6], LiteFlowNet [11] and so on, we choose a more efficient model, FastFlowNet [12], for fast and accurate optical flow prediction, which consists of three parts: the pyramid feature extractor, the center dense dilated correlation layer and the efficient shuffle block decoder. It takes in two consecutive frames and generates six pyramid levels to get multi-scale coarse-to-fine flows, while we remove the coarsest level (the resolution in this paper since the top five levels are enough. Besides, the channel number of the flow decoder at every scale is increased to 3. The first two channels are corresponding to the horizontal and vertical flows as usual, while the additional channel is used to estimate the curvature information. Let $\sigma = \sin \beta = \frac{d}{2R}$, we use $\sigma$ to measure the curvature, which is scale-invariant. So the additional channel is fed into a $\tanh$ layer, the output value of which is restricted in $[-1, 1]$, to estimate the value of $\sigma$ for every pixel, forming a $\sigma$-map. The modified Fast-FlowNet is named mFastFlowNet in this paper and we use $h(\cdot)$ to represent it. With the two input frames $I_0$ and $I_1$, we have

$$F_{0 \rightarrow 1}^x, F_{0 \rightarrow 1}^y, \quad \sigma_{0 \rightarrow 1} = h(I_0, I_1),$$

$$R = \frac{d}{2\sigma_{0 \rightarrow 1}}, \quad \beta = \arcsin \sigma_{0 \rightarrow 1}.$$

Note that too small $\sigma(0)$ means too large $R(\infty)$, which
Fig. 3. Visualization of the forward computation process of ATCA. The arc trajectory obtained by ATCA is drawn in \( \hat{I}_t \).

may cause numerical instability and gradient explosion in the training stage. Actually, the arc degenerates into a line when \( \sigma = 0 \), hence we set a threshold to enforce the linear trajectory when \( \sigma \) is too small. Then, the intermediate flow \( F_{0 \rightarrow t} \) can be calculated according to Eq. 1,2,3 and Fig. 1 as

\[
F^x_{0 \rightarrow t} = \begin{cases} 
R(\cos \theta_t - \cos \theta_0) & |\sigma_{0 \rightarrow 1}| > \sigma_s, \\
\frac{t}{F^x_{0 \rightarrow 1}} & |\sigma_{0 \rightarrow 1}| \leq \sigma_s,
\end{cases}
\]

\[
F^y_{0 \rightarrow t} = \begin{cases} 
R(\sin \theta_t - \sin \theta_0) & |\sigma_{0 \rightarrow 1}| > \sigma_s, \\
\frac{t}{F^y_{0 \rightarrow 1}} & |\sigma_{0 \rightarrow 1}| \leq \sigma_s,
\end{cases}
\]

where \( \sigma_s \) means the threshold value and is set to 0.01 in this paper. And \( F_{1 \rightarrow t} \) can also be obtained similarly. Another thing to emphasize is that \( R \) can be either positive or negative since \( \sigma \in [-1, 1] \). To make the sign meaningful, we let positive \( R \) (or \( \sigma \)) indicate clockwise trajectory and negative indicate counter-clockwise, as shown in Fig. 1 (c).

2.3. Forward Warping and Synthesis Network

After getting the intermediate flows \( F_{0 \rightarrow t} \) and \( F_{1 \rightarrow t} \), forward warping is used to warp \( I_0 \) and \( I_1 \) to the temporal position \( t \). We simply implement forward warping via average splatting \( \hat{\Phi} \) introduced in SoftSplat [7]. Besides, we use a 3-level pyramid feature extractor \( \psi(\cdot) \), which is the same as that in SoftSplat, to obtain the multi-scale features of both \( I_0 \) and \( I_1 \). Then these features are also warped, which is proven to bring significant improvements in the interpolation quality in [7]. Moreover, we additionally warp the curvature map \( \sigma_{0 \rightarrow 1} \) and \( \sigma_{1 \rightarrow 0} \) to implement curvature-based spatial attention in the synthesis network, which will be introduced next. The warping and synthesis process can be formulated as

\[
f^0_1, f^2_0, f^3_0 = \psi(I_0), \quad f^1_1, f^2_1, f^3_1 = \psi(I_1),
\]

\[
\tilde{\sigma}_{0 \rightarrow 1}, \tilde{I}_0, \tilde{f}^1_0, \tilde{f}^2_0, \tilde{f}^3_0 = \hat{\Phi}(\{\sigma_{0 \rightarrow 1}, I_0, \psi(I_0)\}, F_{0 \rightarrow t}),
\]

\[
\tilde{\sigma}_{1 \rightarrow 0}, \tilde{I}_1, \tilde{f}^1_1, \tilde{f}^2_1, \tilde{f}^3_1 = \hat{\Phi}(\{\sigma_{1 \rightarrow 0}, I_1, \psi(I_1)\}, F_{1 \rightarrow t}),
\]

\[
\hat{I}_t = g(\tilde{\sigma}_{0 \rightarrow 1}, \tilde{\sigma}_{1 \rightarrow 0}, \tilde{I}_0, \tilde{I}_1, \tilde{f}^1_0, \tilde{f}^1_1, \tilde{f}^2_0, \tilde{f}^2_1, \tilde{f}^3_0, \tilde{f}^3_1),
\]

where \( \tilde{\cdot} \) denotes the warped results and \( g(\cdot) \) denotes the final synthesis network.

The synthesis network utilizes the warped results to generate the intermediate frame \( \hat{I}_t \). Its detailed structure is depicted in the right part of Fig. 2. Following [7, 8], we employ a modified version of GridNet [13] to avoid checkerboard artifacts. Differently, our model applies a GridNet with three rows and four columns. Besides, we add the curvature attention mechanism in the synthesis network, which is a type of spatial attention and takes in the concatenation of \( \tilde{\sigma}_{0 \rightarrow 1} \) and \( \tilde{\sigma}_{1 \rightarrow 0} \). The motivation is that pixels with high \( \sigma \) values imply motion boundaries, hence the curvature attention can help to improve the quality of the synthesis frames.

2.4. Loss Function

Our training loss function is consisted of two terms. The first reconstruction term aims to reduce the absolute difference between the model output \( \hat{I}_t \) and ground truth \( I_t \)

\[
\mathcal{L}_r = \| \hat{I}_t - I_t \|_1
\]

Following Liu et al. [4], we use the robust generalized Charbonnier penalty function \( \rho(x) = \sqrt{x^2 + \epsilon^2} \) to optimize \( \ell_1 \) norm in the expression of \( \mathcal{L}_r \), where \( \epsilon = 0.001 \).

The second term is the perceptual loss, which has been found to produce more visually realistic outputs [14]. It is calculated with the feature extractor \( F \) from conv4_3 layer of the pretrained VGG16 network as follow

\[
\mathcal{L}_p = \| F(\hat{I}_t) - F(I_t) \|_2
\]

Finally, the total loss function is \( \mathcal{L} = \mathcal{L}_r + \lambda \mathcal{L}_p \), where \( \lambda \) is the weight coefficient and we set \( \lambda = 0.01 \) in the experiments.

3. EXPERIMENTS

3.1. Dataset, Metric and Training Strategy

We train our model on Vimeo-90k dataset [15]. It has 51,312 triplets for training and 3,782 triplets for testing, where each triplet contains three consecutive frames with a resolution of \( 448 \times 256 \). We randomly augment the training data, including horizontal and vertical flipping, temporal order reversing,
and rotating by 90 degrees. Note that the three frames in each triplet are equally spaced, which means we fix \( t = 0.5 \). And we test our model on Vimeo-90k [15], UCF101 [16] and Middlebury [17] benchmarks. For quantitative evaluation, we measure the peak signal-to-noise ratio (PSNR), structural similarity (SSIM), and interpolation error (IE). Higher PSNR and SSIM scores and lower IE usually indicate better image quality. Our model is optimized by Adam [18] for 150 epoches on \( 256 \times 256 \) patches from original frames and batch size is set to 8. The learning rate is initially set to 0.0002 and decays half every 30 epochs. All the experiments are conducted on two NVIDIA Tesla V100 GPUs.

### 3.2. Ablation Studies

To verify the effectiveness of our proposed ATCA model, we make several ablation studies. Specifically, We study on the effects of the two components: the arc trajectory and the curvature attention, hence we train another two networks without the two components respectively. Besides, we also train the complete ATCA without the perceptual loss, to verify the significance of this loss term. The study results are listed in Table 1, which shows that the two components and the perceptual loss can lead to better performance. We also visualize the forward computation process of ATCA in Fig. 3, including the bidirectional flow maps and \( \sigma \)-maps, intermediate flows and final output \( \hat{I}_t \) with arc trajectories tagged on it. Note that brighter pixels in \( \sigma \)-maps have higher values, that correspond to the regions with large curvilinear motion in flow maps. This can explain why the curvature attention is helpful.

### 3.3. Comparisons with SOTA Methods

We compare ATCA with some previous SOTA approaches [3, 7, 19, 20, 21]. Quantitative and Qualitative comparison results are shown in Table 2 and Fig. 4 respectively. Note that in SoftSplat method, we choose PWC-Net without fine-tuning as its flow estimator for fair comparison. We can find that our model performs better than these SOTA methods on Vimeo-90k and UCF101, and rank second on Middlebury. Moreover, ATCA has fewer parameters and relative fast speed. Obviously, our model have achieved high quality frames with clearer details and fewer artifacts as shown in Fig. 4.

### 4. CONCLUSION

In this paper, we propose a novel ATCA: an arc trajectory based model with curvature attention synthesis network, to synthesize video frames. Our model is trained on Vimeo-90k and tested on Vimeo-90k, UCF101 and Middlebury benchmarks. Ablation studies show that the proposed two components and the perceptual loss are effective in frame interpolation. Besides, our approach outperforms most of the SOTA methods and is also lightweight and fast.
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