HyperCon: Image-To-Video Model Transfer for Video-To-Video Translation Tasks

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Abstract

Video-to-video translation for super-resolution, inpainting, style transfer, etc. is more difficult than corresponding image-to-image translation tasks due to the temporal consistency problem that, if left unaddressed, results in distracting flickering effects. Although video models designed from scratch produce temporally consistent results, training them to match the vast visual knowledge captured by image models requires an intractable number of videos. To combine the benefits of image and video models, we propose an image-to-video model transfer method called Hyperconsistency (HyperCon) that transforms any well-trained image model into a temporally consistent video model without fine-tuning. HyperCon works by translating a synthetic temporally interpolated video frame-wise and then aggregating over temporally localized windows on the interpolated video. It handles both masked and unmasked inputs, enabling support for even more video-to-video tasks than prior image-to-video model transfer techniques. We demonstrate HyperCon on video style transfer and inpainting, where it performs favorably compared to prior state-of-the-art video consistency and video inpainting methods, all without training on a single stylized or incomplete video.

1. Introduction

Recent developments in both large-scale datasets and deep neural networks (DNNs) have led to incredible advancements in image-to-image [8] and video-to-video [28] translation tasks such as color restoration [34, 36], super-resolution [3, 4], inpainting [16, 33], and style transfer [5, 10]. But compared to images, videos pose an additional challenge: not only does each frame need to satisfy the intended translation, but they must also be temporally consistent, otherwise they will exhibit flickering artifacts.

Existing techniques that address temporal consistency generally fall into one of two categories: the first enforces losses defined between frame pairs during training or inference [11, 12, 15, 23, 24]. This requires models and losses that are designed from scratch, defined exclusively on videos, and tuned for a specific application. The other category, known as blind video consistency, does frame-wise translation followed by a secondary pass that reduces flicker [1, 4, 13, 31]. This relaxes the need for task-specific video models and losses, and also enables image-to-image models to be applied immediately to videos without sacrificing consistency. However, prior methods require dense correspondences (i.e., dense optical flow) between input frames, which excludes video-to-video tasks with masked pixels such as video inpainting.

Similar to blind video consistency methods, we opt to impart image-to-image models with temporal consistency, motivated primarily by generalization issues inherent to video-tailored approaches. To elaborate, consider in Figure 1a failure case from the otherwise impressive state-of-the-art video inpainting network VINet [11]; here, it fails to hallucinate a sensible texture for the missing region. Now consider a state-of-the-art image inpainting model, Contextual Attention [33], which produces realistic textures on the same example but exhibits temporal inconsistency. Whereas the video model was trained on about five thousand examples from one of the largest video segmentation datasets to date [29], the image model was trained on over a million images from Places [37]. Regardless of application, the vast scale of image datasets enables image models to encapsulate broader visual knowledge than video models trained from scratch and, as a result, better generalize to new data (but at the cost of consistency). Hardware and cost limitations generally make it intractable to collect high-quality video datasets as diverse as modern image datasets, meaning that video-tailored models are doomed to generalize poorly compared to image models.

To overcome this challenging generalization issue, we propose image-to-video model transfer for video-to-video translation tasks, where we aim to transform a black-box image-to-image model into a strong video-to-video model without fine-tuning. Specifically, the framework should automatically induce temporal consistency while also achiev-
Figure 1: Video-to-video translation models designed and trained from scratch (e.g., VINet [11]) are temporally consistent, but exhibit poor generalization performance due to the limited size of video datasets. Image-to-image models (e.g., Contextual Attention [33]) generalize well thanks to large image datasets, but lack temporal consistency (notice the shifting texture). HyperCon leverages the generalization performance conferred by image datasets while enforcing the temporal consistency properties of video models. For each method, we show crops from three consecutive frames centered at the presented frame.

We call our method hyperconsistency, or HyperCon for short, since it enforces consistency by oversampling and aggregating frames using an artificially interpolated version of the input video. Specifically, it inserts frames into the video with a frame interpolation network, translates the interpolated video’s frames independently, and aggregates within overlapping windows of appropriate stride to obtain a final video whose length matches the original (Figure 2). The first among image-to-video model transfer techniques to reason in interpolated video space, HyperCon improves on prior work by handling video-to-video tasks with partially-masked inputs (e.g., inpainting) in addition to more common tasks without masked inputs (e.g., style transfer).

Our extensive experiments across widely differing video-to-video translation tasks show that HyperCon can transform image models into strong temporally consistent video models for many applications. Specifically, HyperCon generates consistent videos with substantially fewer flickering artifacts compared to naïve frame-wise translation, despite using an image model as a core component. It also outperforms a prior state-of-the-art video consistency model [13] in terms of reducing flicker and preserving the intended color profile of the task. Furthermore, it is competitive with prior state-of-the-art in video-to-video tasks as challenging and varied as inpainting and style transfer despite not being trained with any masked or stylized videos.

Our contributions are as follows. First, we motivate image-to-video model transfer as a way to leverage the superior generalization performance of image models without sacrificing consistency. Second, we propose HyperCon, which supports a wider span of video-to-video tasks than prior video consistency work thanks to its support for masked and unmasked inputs. Finally, we show that HyperCon yields favorable performance compared to prior state-of-the-art video consistency and inpainting methods without fine-tuning on these tasks.

2. Related Work

Image-to-image translation [2, 8, 17, 32, 38] has garnered significant attention thanks to advancements in conditional generative adversarial networks [18]. This has helped spur interest in video-to-video translation [28], where the pioneering approach uses a factorized foreground-background generative network with spatio-temporal discriminators. For specific tasks, performance can be further improved by incorporating a task-based objective, e.g., pixel-wise reconstruction loss for inpainting [16, 33] or style reconstruction and total variation losses for style transfer [10]. Unlike these works, our goal is not to train an image or video model optimally from scratch, but to transform a trained image model into a strong, temporally consistent video model to boost generalization performance.

Among existing work, our goals for image-to-video model transfer best align with those of blind video consistency [1, 4, 13, 31], which reduces flicker from frame-wise translated videos by leveraging correspondences in the input. For example, Bonneel et al. [11] minimize an energy functional with a flow-based temporal consistency term and an edge-based scene consistency term defined between corresponding frame-wise translated and output frames; Lai et al. [13] train a DNN with loss terms that emulate this functional. These methods require accurate dense correspondences between input frames, making them unsuitable for video-to-video tasks where certain regions have no meaningful structure, e.g., inpainting. Our method does not rely on dense correspondences in the input, allowing it to be applied to inpainting. Additionally, whereas prior methods operate on the original frame rate of the input video, ours...
operates in interpolated video space, forgoing the traditional two-pass pipeline.

3. HyperCon for Unmasked Videos

HyperCon can handle video-to-video translation tasks whether the input video contains masked pixels or not (e.g., inpainting and style transfer, respectively). For clarity, we describe the three components of our method for the case of unmasked inputs in this section; we describe additional considerations for the case of masked inputs in Section 4.

Let us define the notation for our problem. Given an input video \( V = \{v_1, \ldots, v_N\} \), our goal is to generate an output video \( O = \{o_1, \ldots, o_N\} \) representing the \( N \) frames of \( V \) translated by some image-to-image model \( g \). The frames of \( O \) should closely resemble the frames of \( V \) translated frame-wise by \( g \); at the same time, \( O \) should be temporally consistent, i.e., exhibit as few flickering effects as possible.

In HyperCon, we generate \( O \) as follows. First, we insert \( i \) frames between each pair of frames in \( V \) with a frame interpolation network (Section 3.1). Let us denote this interpolated version of \( V \) as \( V^s = \{v^s_1, \ldots, v^s_N\} \), where \( N' \) is the number of frames in the interpolated video. Then, we independently translate each frame in \( V^s \) with \( g \), yielding \( O^s = \{o^s_1, \ldots, o^s_{N'}\} \) (Section 3.2). Finally, we align and pool frames in \( O^s \) over a temporal sliding window with an appropriate stride to produce the frames of the final output video \( O \) (Section 3.3). We visualize HyperCon in Figure 2.

3.1. Generating the Interpolated Video

To generate the interpolated video \( V^s \), we insert \( i \) interpolated frames between each pair of frames in \( V \), which essentially allows us to obtain several perturbed versions of each input frame for translation. We opt for a vector-based sampling method for frame interpolation instead of a kernel-based one (which, as we justify in Section 4, allows us to handle the case of masked inputs appropriately). Specifically, for each pair of consecutive frames \( v_a \) and \( v_{a+1} \) (\( a \in \{1, \ldots, N-1\} \)), we predict two warping grids \( F^s_{a+b' \rightarrow a}F^s_{a+b' \rightarrow a+1} \) and a weight mask \( w_{a+b'} \) (where \( b' \equiv \frac{b+1}{2} \)) with some function \( \text{wrpgrd} \) (e.g., a pre-trained DNN), and use them to generate the corresponding interpolated frame \( v^s_j \) (\( j \in \{1, \ldots, N'\} \)):

\[
(F^s_{a+b' \rightarrow a}, F^s_{a+b' \rightarrow a+1}, w_{a+b'}) = \text{wrpgrd}(v_a, v_{a+1}, b'),
\]

\[
v^s_j = (1 - w_{a+b'}) \odot \text{warp}(v_a, F^s_{a+b' \rightarrow a}) + w_{a+b'} \odot \text{warp}(v_{a+1}, F^s_{a+b' \rightarrow a+1}),
\]

where \( \odot \) is an element-wise product and \( \text{warp}(v, F) \) bilinearly samples from \( v \) using the displacements specified by the vector field \( F \).

3.2. Translating the Interpolated Video

At this point, we have computed the interpolated video \( V^s \). We generate the translated interpolated video \( O^s \) by simply translating each frame in \( V^s \) independently:

\[
o^s_j = g(v^s_j), \quad j \in \{1, \ldots, N'\}.
\]

Clearly, \( O^s \) is not temporally coherent. However, we expect that most spatial regions in this video will exhibit consensus within small temporal windows. For example, a patch might
be a distinct color in one frame, but a common color in most other frames. Since we have more frames in $O^s$ than frames needed in the output, we can remove the spurious artifacts of frame-wise translation by mapping several neighboring frames in $O^s$ to one frame in our desired output video $O$. We call this mapping temporal aggregation (Section 3.3).

3.3. Temporal Aggregation Over A Sliding Window

We perform temporal aggregation over a sliding window on the translated interpolated video $O^s$ (Figure 3). The stride of the window is such that the frame in each window’s center, a.k.a. the reference frame, corresponds to a frame from the (non-interpolated) input video. Within each window, we align the off-center frames, a.k.a. the context frames, to the reference frame via optical flow warping, and then pool the reference and aligned context frames pixel-wise (e.g., with a mean or median filter) to produce a final frame in the output video $O$.

Figure 3: Temporal aggregation. Context frames from the translated interpolated video $O^s$ are aligned via optical flow to the reference frames (in orange) and then pooled at each pixel location to generate the final video $O$.

More precisely, for an interpolated frame index $j \in \{1, 1+(i+1), \ldots, N'-(i+1), N'\}$, we first estimate the optical flow between reference frame $a_j$ and each context frame in $\{o_{j-dc}^s, o_{j-dc}^s, \ldots, o_{j-dc}^s, \ldots, o_{j+dc}^s, o_{j+dc}^s\}$ (denoted $F_{j\to(a)}$), where $c$ and $d$ respectively parameterize the number of frames in the sliding window and a temporal dilation factor. We then warp the context frames, and afterwards perform pixel-wise pooling over $o_{j}^s$ and the warped context frames:

$$o_{j,b} = \begin{cases} o_{b}^s & b = j \\ \text{warp}(a_{b}, F_{j\to(b)}) & b \neq j \\ 
\end{cases}, b \in \{j-dc, \ldots, j+dc\},$$

$$o_j = \text{pool}(\{o_{j-dc}^s, \ldots, o_{j+dc}^s\}).$$

In the cases where the sliding window samples outside the valid frame range, we only align and pool over valid frames.

4. HyperCon for Masked Videos

In this section, we extend HyperCon to handle video-to-video tasks in which the input frames have masked pixels (e.g., inpainting). This case differs from the unmasked input case (Section 3) in three ways. First, we now have as input a mask video $M = \{m_1, \ldots, m_N\}$ in addition to the normal RGB video $V$. Second, when generating the interpolated data, we must create an interpolated mask video $M^s = \{m^s_1, \ldots, m^s_N\}$ to accompany the interpolated RGB video $V^s$. Finally, the image-to-image model $g$ now takes a mask as input in addition to an RGB video frame.

We modify the interpolated video generation step (Section 3.1) to produce both $V^s$ and $M^s$; this is done by inserting $i$ interpolated frames between each pair of frames in $V$ and $M$. For this to be valid, the motion of the interpolated mask video must match that of the interpolated RGB video—for example, if we interpolate the motion of a removed person, the mask must cover that person throughout the interpolated sequence. If this is not handled properly, we risk polluting the final result with mask placeholder values. Thus, we opt for a vector-based sampling method for frame interpolation instead of a kernel-based one, since the same warping grid can be applied to both RGB and mask frames to achieve the desired result.

To generate $M^s$, recall that we predict warping grids and a weight map $(F_{a+b\to a}, F_{a+b-1\to a+1}, w_{a+b})$ from frames in $V$ using Equation 1. To obtain the interpolated masks, we apply these parameters to the input masks, and then follow up with a thresholding operation:

$$m^s_j = (1 - w_{a+b}) \odot \text{warp}(m_{a}, F_{a+b-1\to a})$$

$$+ w_{a+b} \odot \text{warp}(m_{a+1}, F_{a+b\to a+1}) \odot \text{thresh}(m^s_j, 1).$$

Warping the masks in this way allows us to detect the “partially-masked” pixels in $v^s_j$, i.e., the ones that received a contribution from an masked pixel in either $v_a$ or $v_{a+1}$.

Specifically, if a pixel in $m^s_j$ is not 1, then the warping operation used a source value of 0 from $m_a$ or $m_{a+1}$, which corresponds to borrowing from a masked pixel. Thus, thresholding turns partially-masked pixels into fully-masked pixels in the interpolated masks so that the subsequent translation step is not incorrectly influenced by these pixels.

At this point, we have generated the interpolated video and masks $V^s$ and $M^s$, so we apply the image-to-image model $g$ to them:

$$o_j^s = g(v_j^s, m_j^s), \quad j = 1, \ldots, N',$$

and then apply temporal aggregation (Section 3.3) as usual.

5. Implementation Details

General HyperCon framework. For the frame interpolation step, we use Super SloMo [9] as our wrpgrd function to predict warping grids and weight masks. This method is well-suited for our approach since it predicts warping parameters for multiple intermediate time steps, contrasting with kernel-based sampling methods that interpolate one
frame (e.g., [20]). Since the original authors do not provide a trained model, we use the snapshot from Sun et al. [26]. To estimate optical flow in the temporal aggregation step, we use a third-party implementation of PWC-Net [25].

HyperCon for style transfer. To demonstrate HyperCon on unmasked inputs, we apply it to video style transfer. For the frame-wise style transfer subroutine, we use the Fast Style Transfer (FST) models from Johnson et al. [10]. Our experiments use the four pre-trained models from the official examples in the PyTorch repository.

HyperCon for video inpainting. To evaluate HyperCon on masked inputs, we apply it to video inpainting. For the frame inpainting subroutine, we re-train the Contextual Attention inpainting model from Yu et al. [33] using a modified training scheme that yields higher-quality predictions. Specifically, whereas Yu et al. use the WGAN-GP formulation [21] to update the discriminators of their adversarial loss, we use the original cross-entropy GAN formulation [6] with spectral normalization layers [19] in the discriminator, which stabilize GAN training. Under the same evaluation setting on the Places dataset [37], our image inpainting model achieves a PSNR of 20.41 dB, outperforming the original reported performance of 18.91 dB.

6. Experiments: Video Style Transfer

6.1. Experimental Setup

In this section, our goal is to transfer the desired style to all video frames while minimizing flickering effects in the output video as much as possible. To evaluate this quantitatively, we use the two standard metrics from prior video consistency work [13]. The first metric, warping error, quantifies smoothness between output frames by measuring flow-based photometric consistency between consecutive frames in the final prediction $o_a$ and $o_{a+1}$:

$$ e_{\text{warp}}(o_a, o_{a+1}) = \frac{1}{\sum_p M^f_a(p)} \sum_p M^f_a(p) \| D_a(p) \|_2^2. \tag{9} $$

Here, $D_a = o_a - \text{warp}(o_{a+1}, F_{a\rightarrow a+1})$ (where $F_{a\rightarrow a+1}$ is the estimated flow between input frames $v_a$ and $v_{a+1}$; $p$ indexes the pixels in the frame; and $M^f_a$ indicates pixels with reliable flow (1 for reliable, 0 for unreliable). The flow reliability mask is computed based on flow consistency and motion boundaries as defined by Ruder et al. [23]. The second metric quantifies the similarity between a frame-wise translated video and the output by computing LPIPS distance [35] between corresponding frames:

$$ d_{\text{LPIPS}}(p_a, o_a) = \phi_{\text{LPIPS}}(p_a, o_a; \theta_{\text{LPIPS}}), \tag{10} $$

where $p_a$ and $o_a$ respectively are frames obtained via frame-wise translation and the model to evaluate, and $\phi_{\text{LPIPS}}$ is a distance between several layers of feature activations extracted from a perceptual distance network $\theta_{\text{LPIPS}}$. We denote $D_{\text{LPIPS}}$ and $E_{\text{warp}}$ as the mean of $d_{\text{LPIPS}}$ and $e_{\text{warp}}$ over all test frames, and use the evaluation code from Lai et al. [13] to compute them.

$D_{\text{LPIPS}}$ is used in blind video consistency to measure adherence to the intended task and video content [13]; however, it has a crucial limitation that highlights the need for a more meaningful metric. Specifically, lower is supposed to be better, but an excessively low value indicates that the evaluated method is reproducing the frame-wise translated video instead of resolving the flickering issue that our work tries to address. On the other hand, $D_{\text{LPIPS}}$ has merit in that a very high value indicates blurriness and/or incongruity with the intended stylization. Proposing a new metric is outside the scope of this work; instead, we report $D_{\text{LPIPS}}$ for the sake of completeness and conformity with prior work, and preface our analysis with the aforementioned issues.

Datasets. For evaluation, we use the YouTube-VOS [29] and DAVIS [22] video datasets, which primarily consist of dynamic outdoor scenes of animals, dancers, bikers, etc. We pre-process all videos by resizing and center-cropping them to 832 × 480 resolution, and scaling RGB values to (-1, 1). From YouTube-VOS, we randomly sample a total of 1,000 videos from the official training split, and further divide them into 500 validation and 500 test videos; we refer to these splits as YouTube-VOS-val and YouTube-VOS-test respectively. As for DAVIS, we use all 90 videos as a test set. We use YouTube-VOS-val to tune HyperCon’s interpolation and aggregation hyperparameters, but otherwise use the datasets solely for evaluation (i.e., we do not fine-tune network weights on any YouTube-VOS or DAVIS videos).

6.2. Comparison To Prior State-of-the-Art

Now we compare HyperCon to the state-of-the-art video consistency method from Lai et al. [13], denoted as FST-vcons. For this baseline, we first apply the same image style transfer model as HyperCon, and then apply the consistency model of Lai et al. as a post-translation step.

In Figure 4, we visually compare frame-wise style transfer (FST), FST-vcons, and HyperCon on two DAVIS videos. Naturally, FST generates temporally inconsistent predictions as evidenced by the moving red spot in Figure 4a and the flash of brightness in Figure 4d. Meanwhile, FST-vcons has two systematic failures. First, it greatly darkens predictions as shown in Figure 4e. Second, it leaves inconsistencies intact as a result of darkening regions instead of shifting their hue; e.g., it fails to properly modulate the moving
Figure 4: Visual comparison of HyperCon (our method) to frame-wise style transfer (FST) and baseline blind video consistency (FST-vcons). For each model, we show one full frame and crops from three consecutive frames centered at the presented frame. Our method removes the moving red spot on the fence (left), and homogenizes the color of the rock without darkening the region like FST-vcons (right). HyperCon, on the other hand, properly addresses both of these challenges. For example, in Figure 4c HyperCon retains the global color profile of the frame-wise prediction while producing consistent colors for the fence across multiple frames; in Figure 4f HyperCon maintains a consistent color for the rock without darkening it like FST-vcons.

This qualitative comparison is consistent throughout the evaluated test sets and styles; to justify this concretely, we provide a holistic quantitative comparison between FST-vcons and HyperCon in Table 1. In most cases, HyperCon obtains a better $E_{\text{warp}}$ (only performing significantly worse on YouTube-VOS-test Udnie), indicating that it usually generates more temporally consistent results than FST-vcons. However, it consistently obtains a higher $D_{\text{LPIPS}}$ as well; as shown in Figure 4, this is because HyperCon resolves flickering artifacts, thereby deviating from frame-wise prediction in a desirable manner, whereas FST-vcons replicates them. This result illustrates the need for better metrics to measure style and content agreement for video consistency as discussed in Section 6.1.

### 7. Experiments: Video Inpainting

#### 7.1. Experimental Setup

To enable quantitative evaluation for inpainting, we propose two reconstruction tasks based on those used in prior work [14, 27, 30]. In the first task, Simulated Watermark Removal (SWR, Figure 5a), there is a masked rectangle at a fixed location throughout time that we want to inpaint with the original content. We generate these masks randomly, restricting their height and width to be between 15-50% of the full frame. In the second task, Simulated Object Removal (SOR, Figure 5b), we mask the given video with the foreground mask of another and try to recover the given video’s missing content.

For both tasks, we report three standard image reconstruction metrics used in video completion literature [14, 26, 30]: Peak Signal-Noise Ratio (PSNR), Structural Similarity (SSIM), and LPIPS distance [35]. We compute them between the ground-truth frame and the composited frame (i.e., the predicted frame with known pixels replaced by the ground truth), and report averages across all reconstructed
Table 2: Comparison between our HyperCon method and the baselines on the simulated reconstruction tasks for video inpainting. Higher PSNR and SSIM is better; lower \( D_{\text{LPIPS}} \) and \( E_{\text{warp}} \) is better. Italics indicates where our method outperforms the image-to-video model transfer baselines Cxtattn and Cxtattn-vcons, and bold indicates where it outperforms VINet.

| Method          | Simulated Watermark Removal (SWR) | Simulated Object Removal (SOR) |
|-----------------|-----------------------------------|--------------------------------|
|                 | PSNR  | SSIM  | \( D_{\text{LPIPS}} \) | \( E_{\text{warp}} \) | PSNR  | SSIM  | \( D_{\text{LPIPS}} \) | \( E_{\text{warp}} \) |
| Cxtattn         | 27.51 | 0.9550| 0.002063         | 0.0036         | 30.78 | 0.9500| 0.003456         | 0.0043         |
| Cxtattn-vcons   | 27.47 | 0.9595| 0.001625         | 0.0031         | 27.96 | 0.9560| 0.003837         | 0.0042         |
| VINet           | 27.47 | 0.9571| 0.001721         | 0.0034         | 27.96 | 0.9560| 0.003837         | 0.0042         |
| HyperCon (ours) | 28.01 | 0.9580| 0.001520         | 0.0036         | 30.78 | 0.9405| 0.003456         | 0.0043         |

Datasets. We use the same YouTube-VOS and DAVIS splits described in Section 6.1. These splits all contain foreground object segmentations, which we use as our masks for Simulated Object Removal and Real-World Object Removal (RWOR). Since YouTube-VOS only provides foreground masks for every fifth frame, we temporally downsample the videos to match the frame rate of the mask annotations. DAVIS provides masks for every frame, so no temporal downsampling is needed.

7.2. Comparison to Prior State-of-the-Art

We compare HyperCon to three baseline methods. The first method, Contextual Attention (Cxtattn), inpaints frames independently with the contextual attention inpainting network \([33]\). The second method, Cxtattn-vcons, inpaints frame-wise using Cxtattn, then reduces flickering with the blind video consistency method of Lai et al. \([13]\). The second phase of Cxtattn-vcons takes the original video and the frame-wise translated video as inputs, which in this case correspond to the masked video (with a placeholder value in the masked region) and the frame-wise inpainted video respectively. Both Cxtattn-based baselines use the same image inpainting model weights as HyperCon. The final method, VINet \([11]\), is a state-of-the-art DNN specifically designed and trained for video inpainting; we use their publicly-available inference code in our experiments. Among the evaluated methods, VINet is the only one tasked with inpainting videos at training time, and thus has the advantage of observing natural motion in masked videos.

In Table 2, we report quantitative results on our DAVIS and YouTube-VOS test sets under the SWR and SOR tasks.
We conclude our analysis by contrasting HyperCon with VINet [11], the only evaluated method to have seen masked videos during training. We highlight two systematic failures of VINet that HyperCon overcomes: (i) boundary distortion and (ii) textureless prediction. Regarding the first failure, VINet often corrupts its inpainting result over time by incorrectly warping the inpainted structure. For example, in Figure 7a, VINet warps the outline of the wall due to the continuous occlusion in that region; meanwhile, HyperCon successfully hallucinates the rigid wall boundary. As for the second issue, VINet sometimes initializes the inpainted region with a textureless prediction and fails to populate it with realistic texture throughout the video. In Figure 7b, we compare this behavior with HyperCon, which generates sensible background textures. We posit that HyperCon is better able to hallucinate missing details because it has seen substantially more scenes than VINet during training (i.e., millions of images versus thousands of videos).

The main advantage that VINet has over HyperCon is memory. Thanks to its ConvLSTM unit, VINet is capable of remembering what was behind a masked region for longer periods of time than HyperCon. For instance, in Figure 8, VINet recreates the sign and fence behind the car, while HyperCon propagates the edges of the nearby statue downward. This highlights that memory is a crucial part of properly handling masked regions over long time durations.

8. Discussion and Conclusion

This paper presents HyperCon to achieve image-to-video model transfer for video-to-video translation tasks. Our extensive experiments have shown numerous advantages of HyperCon over state-of-the-art video consistency and video inpainting methods in two widely different tasks. Our inpainting results are especially compelling because they demonstrate that image-to-video model transfer can improve the generalization performance of video models by leveraging the massive scale of image datasets.

In terms of weaknesses, HyperCon does not enforce long-range temporal dependencies beyond the aggregation dilation rate, so it cannot commit to stylization choices or inpainting decisions for the entirety of extremely long videos. In addition, as with other image-to-video model transfer methods, HyperCon is subject to egregious errors of the frame-wise model, which can propagate downstream in certain cases.

As for future directions, there are limitations in the way that current video consistency methods evaluate proximity to the intended translation task; therefore, we encourage the community to propose a more meaningful metric. In addition, we see opportunities in applying HyperCon to other video-to-video tasks, as well as investigating which interpolation and aggregation parameters are optimal under which kinds of videos. We see great potential in image-to-video model transfer for video-to-video tasks, and hope that this work helps pave the way for progress in this direction.

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A. Additional Qualitative Results for Style Transfer

This section provides additional qualitative results comparing HyperCon’s improved ability to reduce flickering for style transfer compared to the baselines. We visualize these results in Figures 9 and 10.

Figure 9: Comparison of flickering artifacts on the candy style. The baselines (FST and FST-vcons) exhibit a circle in the cropped area that appears for one frame, whereas HyperCon almost completely removes it.

Figure 10: Comparison of flickering artifacts on the mosaic style. The baselines (FST and FST-vcons) modify the lines inside the cat’s arm at each frame, whereas HyperCon fades out these unstable artifacts.

B. Additional Qualitative Results for Inpainting

This section provides additional qualitative results for the inpainting task on the DAVIS dataset for the Real-World Object Removal task. In Figure 11, we depict additional examples where HyperCon reduces flickering and boundary distortion effects compared to the baselines. Next, in Figure 12, we show examples in which the baseline methods produce checkerboard artifacts and HyperCon does not. Finally, in Figure 13, we compare our method to Cxtattn-vcons in cases where Cxtattn-vcons fails to make a prediction that blends well with the known pixels due to the hue shift problem.
(a) HyperCon reduces artifacts better than the image-to-video model transfer baselines. The gray circle is apparent in the Cxtattn and Cxtattn-vcons prediction, but not in the HyperCon one.

Figure 11: Additional examples of flickering (left) and boundary distortion (right) effects from the baselines versus HyperCon for video inpainting.

(b) VIINet fails to connect the boundary of the mat in the background, whereas HyperCon successfully does connect the boundary.

Figure 11: Additional examples of flickering (left) and boundary distortion (right) effects from the baselines versus HyperCon for video inpainting.

Figure 12: HyperCon generates substantially fewer checkerboard artifacts than Cxtattn and Cxtattn-vcons due to their instability across frames.

Figure 13: Cxtattn-vcons distorts the hue of the inpainted region; HyperCon does not. As a result, our HyperCon predictions blend in more convincingly with the surrounding area.
C. Style Transfer Ablation Studies

In this section, we investigate how the parameters of our HyperCon method influence the final result (given a fixed frame-wise style transfer model). For each style, we search for the optimal parameters on our YouTube-VOS-val split in two phases. In Phase 1, we perform a grid search over the number of frames to insert between each pair $i$, the total number of interpolated frames to aggregate for each output frame $c' = 2c + 1$, and the spacing between aggregated interpolated frame $d$ (Figure 14). All of these models use optical flow alignment and pixel-wise mean pooling. In Phase 2, we compare the best Phase 1 model to variants that either omit alignment or replace mean pooling with median pooling.

![Figure 14: Visualization of the hyperparameters included in Phase 1 of the style transfer model grid search.](image)

As shown in Figure 15a, $D_{LPIPS}$ generally decreases with more interpolated frames, fewer aggregated frames, and a smaller dilation rate. This indicates that to obtain outputs that are most similar to frame-wise predictions (which is not ideal as discussed in the main paper), HyperCon needs to aggregate interpolated frames that are as similar to the reference frame as possible. As for $E_{warp}$ (Figure 15b), there is an optimal number of interpolated frames given a fixed dilation rate and vice-versa. The optimum value for one parameter increases as the other increases, suggesting that there is an ideal effective frame rate over which frames should be aggregated. In any case, $E_{warp}$ generally decreases with more aggregated frames, meaning that the smoothest videos are obtained from aggregating many frames. These trends exist across all evaluated styles; we provide full quantitative results in Table 3.

Turning to qualitative observations, we have found on average that a higher $D_{LPIPS}$ indicates blurrier results, and that a higher $E_{warp}$ indicates greater flickering. However, strictly minimizing one or the other does not yield the most visually-satisfying results. For example, the model with the minimum $D_{LPIPS}$ (Figure 16b) very slightly shifts colors to conform with neighboring frames. However, it copies too much information from frame-wise prediction, particularly the flickering.

![Figure 15: Ablation study results for the rain-princess style on YouTube-VOS-val. $i$, $c$, and $d$ indicate the number of interpolated frames per pair, the total number of aggregated frames, and the dilation rate (Figure 14). Lower values are better.](image)

![Figure 16: Qualitative comparison of models from the style ablation study, Phase 1. For each model, we show one full frame and crops from three consecutive frames centered at the presented frame. The yellow arrow indicates an area with flicker.](image)
### Table 3: Style transfer ablation study, Phase 1. We underline the values of the model selected for Phase 2 as described in Appendix C.

![Image](https://via.placeholder.com/150)

### Table 3: Style transfer ablation study, Phase 1. We underline the values of the model selected for Phase 2 as described in Appendix C.

![Image](https://via.placeholder.com/150)

artifacts that we seek to remove. The model that minimizes $E_{\text{warp}}$ (Figure 16c) blurs several predictions together. While this substantially reduces flicker by producing more gradual changes in color, it blurs individual frames beyond an acceptable level. These results suggest that it is important to strike a balance between $D_{\text{LPIPS}}$ and $E_{\text{warp}}$ that maximizes temporal consistency without overly blurring frames. Motivated by this principle, we select our representative align + mean model by only considering those whose $D_{\text{LPIPS}}$ lies under the 10th percentile (among all models from the Phase 1 grid search for the given style), and then choosing the one with the lowest $E_{\text{warp}}$.

Next, given the best model from the Phase 1 grid search (align + mean), we perform further ablations by either omitting alignment to reference frames (no align + mean) or applying the median at each pixel location instead of the mean (align + median). From Figure 17 we see that not aligning frames yields poor performance: both $D_{\text{LPIPS}}$ and $E_{\text{warp}}$ are higher.

![Image](https://via.placeholder.com/150)

### Figure 17: Quantitative comparison of ablation study models for style transfer, Phase 2. Lower values are better. no align + mean gives worse $D_{\text{LPIPS}}$ and $E_{\text{warp}}$. align + median gives the best $D_{\text{LPIPS}}$ but increases $E_{\text{warp}}$ compared to align + mean.
than when we align frames, suggesting lower-quality per-frame predictions and sustained flickering artifacts. Meanwhile, applying median pooling instead of mean pooling lowers $D_{\text{LPIPS}}$, but increases $E_{\text{warp}}$, suggesting higher-quality per-frame predictions but sustained flickering artifacts. The qualitative results shown in Figure 18 corroborates these results: compared to align + mean, no align + mean gives blurrier results (Figure 18b), and align + mean sharpens results slightly but induces slightly more flicker (Figure 18c). Given our emphasis on temporal consistency, we opt for the align + mean model for experiments in the main paper, but acknowledge that align + median may be suitable if sharpness is deemed more important.

![Figure 18: Qualitative comparison of models from the style ablation study, Phase 2.](image)

**D. Inpainting Ablation Studies**

In this section, we provide results for the HyperCon hyperparameter search and ablation studies that led to the model used in the main paper. We follow the same two-phase procedure as the one used for style transfer (Appendix C). In Table 4, we show quantitative results for Phase 1. We select the model that has achieved the best score on three out of the four metrics (PSNR, SSIM, and $E_{\text{warp}}$).

In Table 5 we show the quantitative results for Phase 2 of the ablation study. No align + mean performs worse across all metrics, suggesting that it yields predictions that are less realistic and less temporally-consistent. Meanwhile, mean and median pooling yield comparable quantitative results. Mean pooling yields slightly better SSIM and $E_{\text{warp}}$, and median pooling yields slightly better $D_{\text{LPIPS}}$ (both yield the same PSNR).

Finally, in Figure 19 we show qualitative results comparing the Phase 2 models. We observe that not aligning frames

![Table 4: Inpainting ablation study, Phase 1, on the YouTube-VOS-val Simulated Object Removal task. We underline the values of the model selected for Phase 2.](table)

![Table 5: Inpainting ablation study, Phase 2, on the YouTube-VOS-val Simulated Object Removal task.](table)
Figure 19: Qualitative comparison for inpainting ablation study, Phase 2, on the YouTube-VOS-val Simulated Object Removal task. The orange boundary outlines the mask, and the yellow boundary indicates the crop for visualization. No align + median gives the blurriest results; align + mean gives stronger results; and align + median gives the sharpest results that blend in best with the surrounding area.

results in overly blurry inpainting predictions. As for mean versus median pooling, we observe that median pooling yields slightly sharper predictions that blend in better with the surrounding area. We thus opt to use the align + median model in the experiments of our main paper.