

Supplementary Material: Onion-Peel Networks for Deep Video Completion

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1. Temporal Consistency Networks

For the video completion, we post-process frame-by-frame results with the temporal consistency network (TCN) [5]. We modified the original work [5] to match our purpose: stabilizing the inpainted videos. Here, we provide more detailed descriptions of the post-processing networks.

Network Design The network structure of TCN is shown in Fig. 1. The networks consists of the encoder, the convolutional GRU [2], and the decoder. The encoder inputs are the previous stabilized frame (P_{t-1}), the current frame to be stabilized (I_t), and their object masks. The output is the stabilized current frame (P_t). The convolutional GRU [2] is employed to capture a long-term temporal consistency. Skip-connections links the encoder and the decoder features. All the convolutional layer is the gated convolutional layer [10].

Loss Function. The networks is trained to balance between the temporal stability with the previous frame and the perceptual similarity with the current frame.

The temporal stability loss is defined as a pixel distance toward warped previous output:

$$\mathcal{L}_{ts} = \|M \odot (P_t - \hat{P}_{t-1})\|_1, \quad (1)$$

where \hat{P}_{t-1} is the previous output P_{t-1} warped by the optical flow $F_{t-1 \rightarrow t}$ and M is a visibility map. The optical flow is computed from the ground truth frames Y_t, Y_{t-1} (training frames without holes). We used PWC-Net for computing the optical flow [8]. The visibility map M is defined as $M = \exp(-100\|Y_t - \hat{Y}_{t-1}\|_2^2)$.

The perceptual similarity loss is defined as follows:

$$\mathcal{L}_{ps} = \|\phi_5(I_t) - \phi_5(P_t)\|_1, \quad (2)$$

where $\phi_s(\cdot)$ is the mapping to s -th pooled feature map of VGG-16 network [7] pre-trained on ImageNet.

The total loss is the weighted summation of two:

$$\mathcal{L}_{total} = 15 \cdot \mathcal{L}_{ts} + \mathcal{L}_{ps}. \quad (3)$$

Training Data. As the network targets for stabilizing inpainted video frames produced by our onion-peel network,

we directly uses output of the onion-peel network as input to the temporal consistency network. We use the same training images for the onion-peel network training.

2. Image Completion Result

In addition to Fig. 6 of the main paper, we provide more results for the image completion guided by reference images. In Fig. 2 - 5, we compare our method against Yu *et al.* [11] and Photoshop’s content aware fill [1].

3. Video Completion Results

We provide our object removal results on the DAVIS videos [6] with shadow annotations provided by [3]. We compare our method against two state-of-the-art methods: VINet [4] and Huang *et al.* [3]. In the video file, `video_completion.mp4`, we provide side-by-side comparisons on challenging test videos.

References

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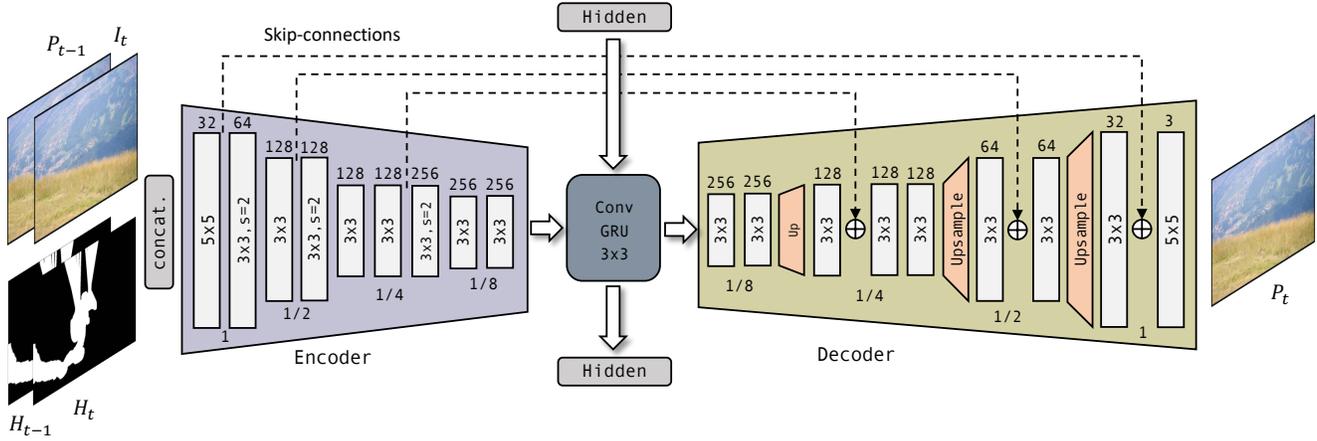


Figure 1: Temporal consistency networks. \oplus indicates the element-wise addition.

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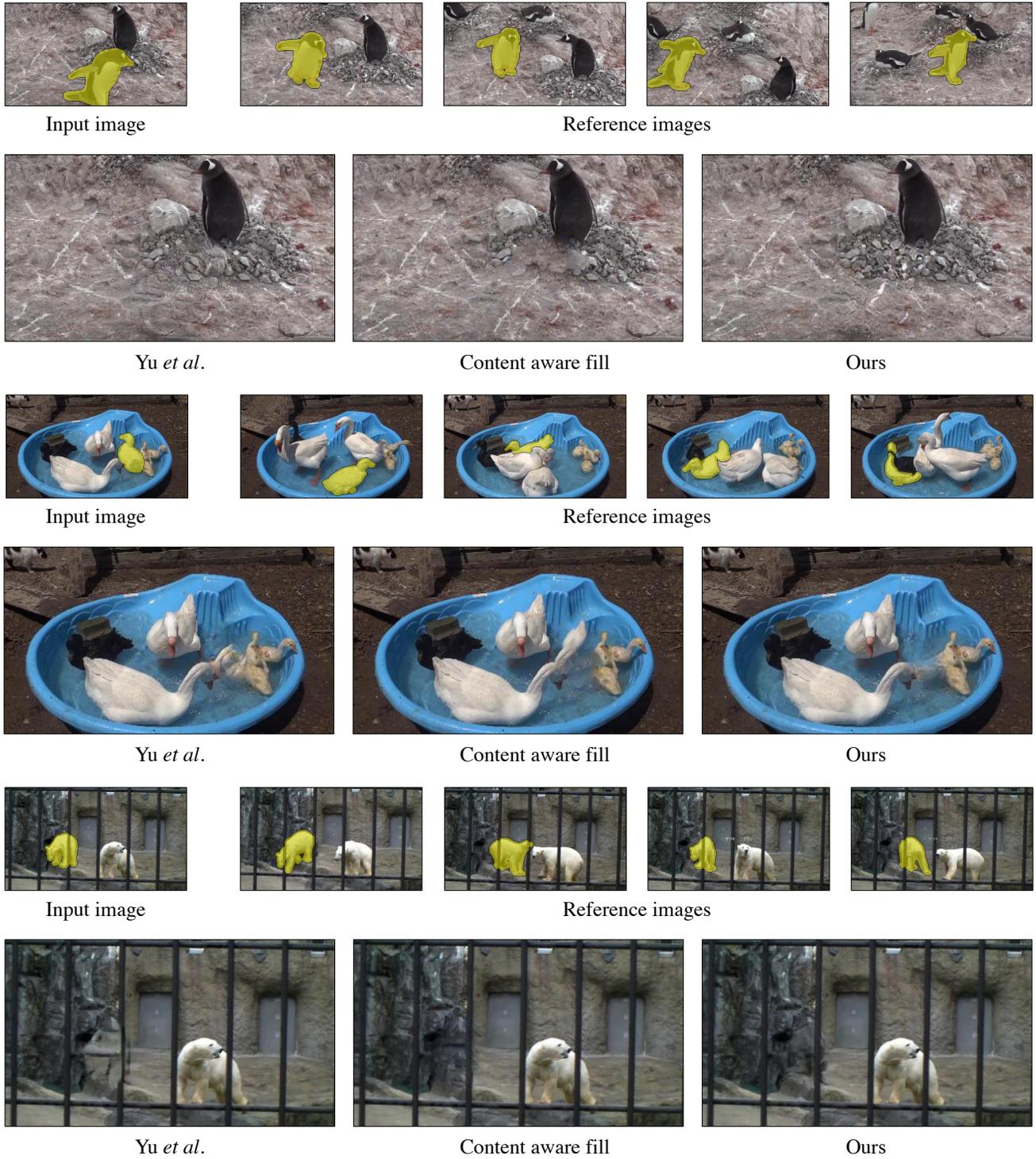


Figure 3: Examples of image completion using a group of photos (Best viewed on a high-resolution display with zoom-in). The images are from Youtube-VOS [9].

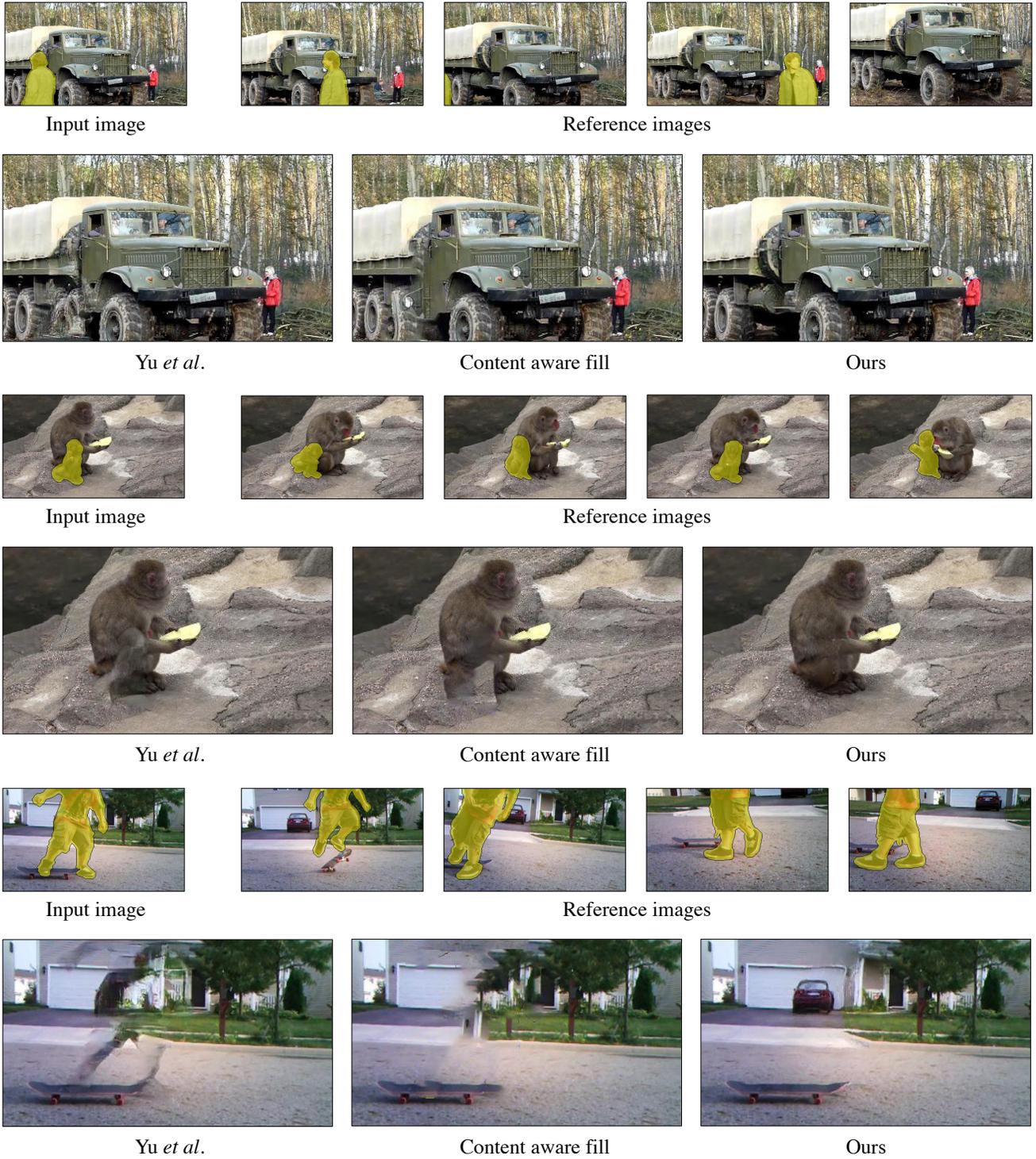


Figure 4: Examples of image completion using a group of photos (Best viewed on a high-resolution display with zoom-in). The images are from Youtube-VOS [9].

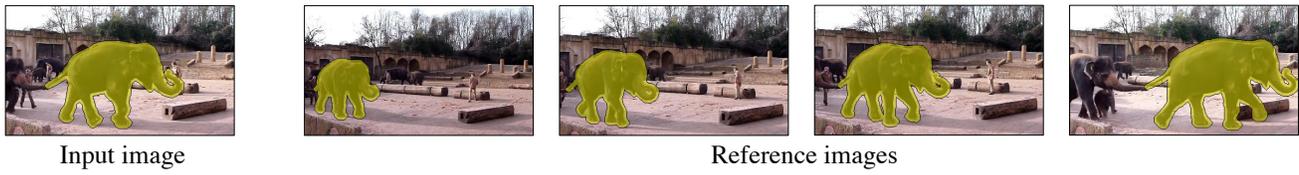
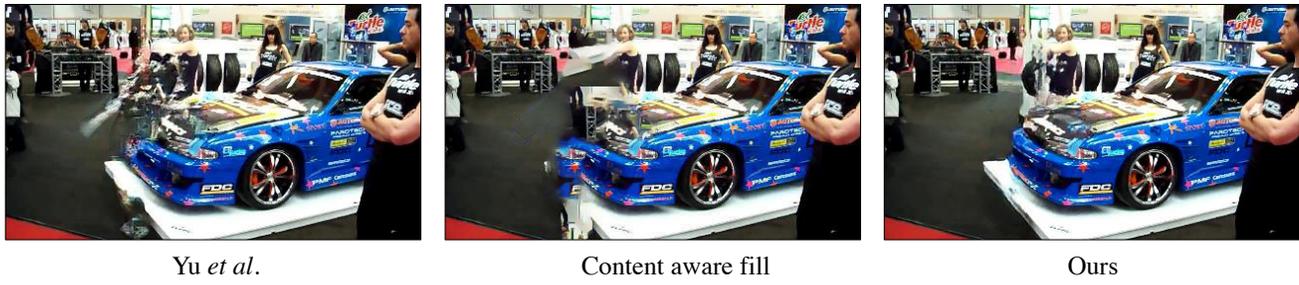


Figure 5: Examples of image completion using a group of photos (Best viewed on a high-resolution display with zoom-in). The images are from Youtube-VOS [9].