PriorityCut: Occlusion-guided Regularization for Warp-based Image Animation

Wai Ting Cheung and Gyeongsu Chae
MoneyBrain Inc.
{ken, gc}@moneybrain.ai

Abstract
Image animation generates a video of a source image following the motion of a driving video. State-of-the-art self-supervised image animation approaches warp the source image according to the motion of the driving video and recover the warping artifacts by inpainting. These approaches mostly use vanilla convolution for inpainting, and vanilla convolution does not distinguish between valid and invalid pixels. As a result, visual artifacts are still noticeable after inpainting. CutMix is a state-of-the-art regularization strategy that cuts and mixes patches of images and is widely studied in different computer vision tasks. Among the remaining computer vision tasks, warp-based image animation is one of the fields that the effects of CutMix have yet to be studied. This paper first presents a preliminary study on the effects of CutMix on warp-based image animation. We observed in our study that CutMix helps improve only pixel values, but disturbs the spatial relationships between pixels. Based on such observation, we propose PriorityCut, a novel augmentation approach that uses the top-k percent occluded pixels of the foreground to regularize warp-based image animation. By leveraging the domain knowledge in warp-based image animation, PriorityCut significantly reduces the warping artifacts in state-of-the-art warp-based image animation models on diverse datasets.

1 Introduction
Image animation takes a source image and a driving video as inputs and generates a video of the source image that follows the motion of the driving video. Traditional image animation requires a reference pose of the animated object such as facial keypoints or edge maps [Fu et al., 2019; Ha et al., 2019; Qian et al., 2019; Zhang et al., 2019; Oterdout et al., 2020]. Self-supervised image animation does not require explicit keypoint labels on the objects [Wiles et al., 2018; Kim et al., 2019; Siarohin et al., 2019a,b; Yao et al., 2020]. Warp-based self-supervised image animation warps the source image based on the estimated motion of the driving video and recovers the warping artifacts by inpainting. The warped image contains regions with a mixture of valid and invalid pixels. Applying vanilla convolutional filters to recover the warping artifacts in such regions causes ambiguity during training and results in visual artifacts such as color inconsistencies, blurry texture, and noticeable edge responses during testing as shown in the literature [Wiles et al., 2018; Kim et al., 2019; Siarohin et al., 2019a,b; Jeon et al., 2020; Yao et al., 2020].

CutMix is a state-of-the-art regularization strategy that cuts and mixes patches of different images to train image classifiers [Yun et al., 2019]. In addition to image classification, CutMix and its variants are widely studied in different computer vision tasks such as object recognition, object detection, and semantic segmentation [Chen, 2020; Duta et al., 2020]. Most of these tasks deal with only valid pixels in the images, little is known about the effects of CutMix on a mixture of valid and invalid pixels. There are recent attempts to apply CutMix on non-warp-based image generation [Schonfeld et al., 2020] and super resolution [Yoo et al., 2020], which involve a mixture of valid and invalid pixels. Among the remaining computer vision tasks, warp-based image animation is one of the fields that the effects of CutMix have yet to be studied. Our preliminary study on the effects of vanilla CutMix on warp-based image animation indicates that CutMix helps improve only pixel values, but disturbs the spatial relationships between pixels.

To reduce the ambiguity in recovering the artifacts in image warping, we propose PriorityCut, a novel augmentation inspired by CutMix that uses the top-k percent occluded pixels of the foreground for consistency regularization. We observed
We implemented PriorityCut on top of the state-of-the-art without loss or mixture of context. extended Monkey-Net by predicting Jacobians in keypoint on a source image, relative keypoint movements, and dense et al. Monkey-Net [Siarohin et al., 2019] to predict videos of an action class based on a single image. X2Face [Wiles et al., 2019] by inpainting. X2Face [Wiles et al., 2019] motion of the driving video and recovers the warping artifacts animation warps the source image based on the estimated animation for regularization. Leverage the domain knowledge of warp-based image animation. Then, we discuss the effects of CutMix on non-warp-based image generation [Schonfeld et al., 2020] and super resolution [Yoo et al., 2020], which involve a mixture of valid and invalid pixels. Among the remaining computer vision tasks, warp-based image animation is one of the fields that the effects of CutMix have yet to be studied.

2 Methodology

To understand the motivation of PriorityCut, we first present our preliminary study on the effects of vanilla CutMix on warp-based image animation. Then, we discuss the effects of vanilla convolution on regions with a mixture of valid and invalid pixels. Lastly, we present PriorityCut based on the observations of our preliminary study and vanilla convolution.

3.1 Preliminary Study

Given the lack of studies on the effects of CutMix on image animation, we first directly apply vanilla CutMix to an existing image animation model. We implemented vanilla CutMix on top of First Order Motion Model (FOMM) [Siarohin et al., 2019b], a state-of-the-art warp-based image animation model.

First Order Motion Model consists of a motion estimation module and an image generation module. The motion estimation module takes as inputs a source image S and a driving image D, and predicts a dense motion field $\hat{T}_{S \to D}$ and an occlusion mask $\hat{O}_{S \to D}$. The image generation module warps the source image based on the dense motion field $\hat{T}_{S \to D}$ and recovers warping artifacts by inpainting the occluded parts of the source image.

To implement CutMix on top of First Order Motion Model, we followed Schonfeld et al. [2020] to extend the discriminator to an U-Net architecture. The U-Net discriminator $D^U$ consists of an encoder $D^{enc}_U$ and a decoder $D^{dec}_U$ connected by skip connections. The encoder reuses the same architecture detection and an occlusion mask. Yao et al. [2020] generated images based on optical flow predicted on 3D meshes.

Warping images produce regions with a mixture of valid and invalid pixels. Vanilla convolutional layers treat all pixels as valid ones. When applying vanilla convolutional filters to recover the artifacts of a warped image, warped, unwarped, and synthesized pixels or features in different layers are all treated equally. This not only causes ambiguity during training, but also results in color inconsistencies, blurry texture, and noticeable edge responses during testing.

Applications of patch-based data augmentation in computer vision Patch-based data augmentation has been widely studied in the literature. Cutout and its variants drop random patches of an image [DeVries and Taylor, 2017; Singh et al., 2018; Chen, 2020]. Mixup blends two images to generate a new sample [Zhang et al., 2017]. CutMix cuts and mixes patches of random regions between images [Yun et al., 2019]. Given the success of CutMix, CutMix and its variants have been explored in a wide variety of computer vision tasks such as object recognition, object detection, and semantic segmentation [Chen, 2020; Duta et al., 2020]. Vanilla convolutional layers treat all pixels as valid ones. Using vanilla convolution makes sense for the tasks above as only real images or videos are involved. There are also recent attempts to apply CutMix on non-warp-based image generation [Schonfeld et al., 2020] and super resolution [Yoo et al., 2020], which involve a mixture of valid and invalid pixels. Among the remaining computer vision tasks, warp-based image animation is one of the fields that the effects of CutMix have yet to be studied.

2 Related Work

Warp-based image animation Warp-based image animation warps the source image based on the estimated motion of the driving video and recovers the warping artifacts by inpainting. X2Face [Wiles et al., 2018] uses an embedding network and a driving network to generate images. Kim et al. [2019] used a keypoint detector and a motion generator to predict videos of an action class based on a single image. Monkey-Net [Siarohin et al., 2019a] generates images based on a source image, relative keypoint movements, and dense motion. First Order Motion Model [Siarohin et al., 2019b] extended Monkey-Net by predicting Jacobians in keypoint that the amounts and locations of occlusion are closely related to how much and where the valid and invalid pixels are. Leveraging such domain knowledge, PriorityCut derives a new mask from the occlusion mask and the background mask. Using the PriorityCut mask, we apply CutMix operation that cuts and mixes patches of different images to regularize discriminator predictions. Compared to the vanilla rectangular CutMix mask, PriorityCut mask is flexible in both shapes and locations. Also, PriorityCut prevents unrealistic patterns and information loss unlike previous approaches [DeVries and Taylor, 2017; Yun et al., 2019; Zhang et al., 2017] shown in Figure 2. The subtle differences in our augmented image allow the generator to take small steps in learning, thus refining the details necessary for realistic inpainting. We implemented PriorityCut on top of the state-of-the-art image animation model [Siarohin et al., 2019b] and evaluated PriorityCut on VoxCeleb [Nagrani et al., 2017], BAIR [Ebert et al., 2017], and Tai-Chi-HD [Siarohin et al., 2019b] datasets. Our experimental results show that PriorityCut significantly reduces the visual artifacts in state-of-the-art warp-based image animation models.

Our contributions are summarized as follows:

1. To the best of our knowledge, we are the first to study the effects of CutMix and its variants on warp-based image animation.

2. We proposed PriorityCut, a novel augmentation that leverages the domain knowledge of warp-based image animation for regularization.

3. Our extensive evaluations on diverse datasets with solid baselines show that PriorityCut significantly reduces the warping artifacts in state-of-the-art warp-based image animation models.
We reconstruct a video by using the first frame as the source when applying CutMix in Schonfeld et al. with 22,496 videos from YouTube. We followed the same without CutMix for video reconstruction on The consistency regularization loss regularizes the U-Net decoder mirrors the architecture of the encoder. The decoder outputs on the CutMix image and the MixCut between the U-Net decoder outputs on real and fake images.

Table 1 compares First Order Motion Model with and without CutMix for video reconstruction on VoxCeleb. Green and red colors indicate better and worse results, respectively.

| Architecture   | $L_1$ ↓ | AKD ↓ | AED ↓ |
|----------------|---------|-------|-------|
| FOMM U-Net     | 0.0401±0.5 | 1.278±2e-3 | 0.1347±6e-4 |
| + CutMix       | 0.0394±0.5 | 1.295±2e-3 | 0.1365±6e-4 |

Table 1: Comparisons of First Order Motion Model with and without CutMix for video reconstruction on VoxCeleb. Green and red colors indicate better and worse results, respectively.

as the original discriminator implemented by its authors. The encoder mirrors the architecture of the encoder. The encoder predicts whether an image is real or fake as a whole while the decoder predicts if individual pixels are real or fake. We applied vanilla CutMix between driving and generated images, and trained the model with an additional consistency regularization loss as in Schonfeld et al. [2020]. The consistency regularization loss regularizes the U-Net decoder output on the CutMix image and the MixCut between the U-Net decoder outputs on real and fake images.

To capture the context of warp-based image animation, PriorityCut leverages the occlusion information to perform CutMix augmentation. Our approach is based on two key observations. One observation is that occlusion in warping-based image animation reflects the degrees of validity of the visual artifacts. Another observation is that it contains the spatial relations between regions of valid and invalid pixels. The occlusion information can serve as a guidance to the vanilla convolution layers of discriminator how much and where the valid and invalid pixels are.

Based on the above observations, we propose PriorityCut, a novel augmentation that uses the top-k percent occluded pixels of the foreground as the CutMix mask. Figure 3 illustrates the derivation of PriorityCut masks from occlusion and background masks predicted by a warp-based image animation model. Suppose $M_{bg}$ is a predicted alpha background mask, ranging between 0 and 1. We first suppress the uncertain pixels of the alpha background mask $M_{bg}$ to obtain a binary background mask $M_{bg}$. $M_{bg}$ corresponds to the background mask predicted with high confidence. The occlusion map $\hat{O}_{fg} \in [0, 1]^{H \times W}$ is an alpha mask, with 0 being fully occluded and 1 being not occluded. Equation 2 utilizes $M_{bg}$ to compute the occlusion map of the foreground $\hat{O}_{fg}$:

$$\hat{O}_{fg} = \hat{M}_{bg} + (1 - \hat{M}_{bg}) \odot \hat{O}_{\text{pc}}$$

where $\odot$ denotes the Hadamard product. It retains only the foreground portions of the occlusion masks shown in Figure 3, which are also alpha masks. Given a percentile $k$, we denote the PriorityCut mask $M_{pc}$ as the top-k percent occluded pixels of the foreground $\hat{O}_{fg}$. Following Yun et al. [2019], we randomize the values of $k$ in our experiments. Equation 3 utilizes the PriorityCut mask to perform CutMix between the real images $x$ and the generated images $x'$. To avoid sharp transitions, PriorityCut performs CutMix on the driving image $D$ and its reconstruction $\tilde{D}$.

$$\text{mix}(x, x', M_{pc}) = M_{pc} \odot x + (1 - M_{pc}) \odot x'$$
In Figure 3, the augmented image looks almost identical to the driving or the generated images with only subtle differences in fine details. PriorityCut always assigns the fake pixels to locations where there are large changes in motion, creating incentives for the generator to improve. For example, borders, edges, in-between regions of distinct objects (e.g., face, mic, wall), or parts of objects (e.g., hair, eyes, nose, mouth). The design philosophy of PriorityCut follows that of CutBlur [Yoo et al., 2020]. The augmented images have no sharp transitions, mixed image contents, or loss of the relationships of pixels unlike previous approaches shown in Figure 2. PriorityCut also adds another degree of flexibility to the mask shapes. The discriminator can no longer rely on a rectangular area like the vanilla CutMix to predict where the real and fake pixels concentrate at. This encourages the discriminator to learn properly the locations of the real and fake pixels. Figure 4 compares the discriminator predictions on individual pixels between PriorityCut and vanilla CutMix. PriorityCut helps the discriminator learn clear distinctions between real and fake pixels around locations with large changes in motion. In contrast, vanilla CutMix helps the discriminator learn only vague estimations. This supports our observations in Sections 3.1 and 3.2 that vanilla CutMix is not good at learning spatial relationships.

4 Experiments

4.1 Experimental setup

Datasets We followed [Siarohin et al., 2019b] to preprocess high-quality videos on the following datasets and resized them to $256 \times 256$ resolution: the VoxCeleb dataset [Nagrani et al., 2017] (18,398 training and 512 testing videos after preprocessing); the Tai-Chi-HD dataset [Siarohin et al., 2019b] (2,994 training and 285 testing video chunks after preprocessing); the BAIR robot pushing dataset [Ebert et al., 2017] (42,880 training and 128 testing videos).

Evaluation protocol We followed [Siarohin et al., 2019b] to quantitatively and qualitatively evaluate video reconstruction. For video reconstruction, we used the first frame of the input video as the source image and each frame as the driving image. We evaluated the reconstructed videos against the ground truth videos on the following metrics: pixel-wise differences ($L_1$); PSNR, SSIM, and their masked versions (M-PSNR, M-SSIM); average keypoint distance (AKD), missing keypoint rate (MKR), and average Euclidean distance (AED) of feature embeddings detected by third-party tools. For details on dataset preprocessing and metric computation, refer to Section B in the appendix.

4.2 Comparison with state-of-the-art

We quantitatively and qualitatively compared PriorityCut with state-of-the-art warp-based image animation methods with publicly available implementations.

- **X2Face.** The reenactment system with an embedding and a driving network [Wiles et al., 2018].
- **Monkey-Net.** The motion transfer framework based on a keypoint detector, a dense motion network, and a motion transfer generator [Siarohin et al., 2019a].
- **First Order Motion Model.** The motion transfer network that extends Monkey-Net by estimating affine transformations for the keypoints and predicting occlusion for inpainting [Siarohin et al., 2019b]. We compared two versions of First Order Motion Model. The baseline model (FOMM) corresponds to the one in their published paper. The adversarial model (FOMM+) is a concurrent work with an adversarial discriminator. Since its authors have released both models, we evaluated the baseline model and additionally the adversarial model.
- **Ours.** Our implementation using First Order Motion Model as backbone with U-Net discriminator to provide discriminator predictions on individual pixels and PriorityCut to regularize inpainting.

Quantitative comparison Table 2, 3, and 4 show the quantitative comparison results of video reconstruction on the VoxCeleb, BAIR, and Tai-Chi-HD datasets, respectively. For all tables, the down arrows indicate that lower values mean better results, and vice versa. We show the 95% confidence intervals, highlight the best results in bold and underline the second-best. For variants of the baseline model that do not produce the best or the second best results, the red and green texts indicate worse and better results than the baseline, respectively. This serves a similar purpose as the ablation study, indicating the effectiveness of certain components in improving the baseline. Since the pre-trained model of FOMM+ for BAIR is not publicly available at the time of writing, we evaluated BAIR only on the baseline FOMM.

PriorityCut outperforms state-of-the-art models in every single metric for VoxCeleb and BAIR, and in most of the metrics for Tai-Chi-HD. Note that adversarial training alone (FOMM+) does not always guarantee improvements, as highlighted in red for VoxCeleb.

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1https://github.com/AliaksandrSiarohin/first-order-model
Table 2: Comparison with state-of-the-art approaches for video reconstruction on VoxCeleb. Bold and underline indicate the best and the second best results, respectively. For variants of FOMM that do not produce the best or the second best results, red indicates worse results compared to the baseline FOMM.

| Model     | $\mathcal{L}_1 \downarrow$ | PSNR ↑ | SSIM ↑ | AKD ↓ | AED ↓ |
|-----------|----------------------------|--------|--------|-------|-------|
| X2Face    | $0.0739\pm.006$           | 20.04  | 30.65  | 0.625 | 6.847 |
|           | $\pm.006$                 | ±0.02  | ±0.04  | ±0.04 | ±2e-4 |
| Monkey-Net| $0.0477\pm.006$           | 23.92  | 34.43  | 0.769 | 1.892 |
|           | $\pm.006$                 | ±0.02  | ±0.04  | ±0.04 | ±3e-4 |
| FOMM      | $0.0413\pm.006$           | 26.17  | 36.19  | 0.825 | 1.290 |
|           | $\pm.006$                 | ±0.02  | ±0.04  | ±0.04 | ±4e-4 |
| FOMM+     | $0.0409\pm.006$           | 26.26  | 36.26  | 0.822 | 1.305 |
|           | $\pm.006$                 | ±0.02  | ±0.04  | ±0.04 | ±4e-4 |
| Ours      | $0.0401\pm.006$           | 25.35  | 36.45  | 0.826 | 1.286 |
|           | $\pm.006$                 | ±0.02  | ±0.04  | ±0.04 | ±3e-4 |

Table 3: Comparison with state-of-the-art approaches for video reconstruction on Tai-Chi-HD. Bold and underline indicate the best and the second best results, respectively.

| Model     | $\mathcal{L}_1 \downarrow$ | PSNR ↑ | SSIM ↑ | AKD ↓ | MKR ↓ | AED ↓ |
|-----------|----------------------------|--------|--------|-------|-------|-------|
| X2Face    | $0.0729\pm.006$           | 21.08  | 22.24  | 0.580 | 0.215 | 0.244 |
|           | $\pm.006$                 | ±0.02  | ±0.02  | ±1e-3 | ±1e-3 | ±4e-4 |
| Monkey-Net| $0.0691\pm.006$           | 22.02  | 22.70  | 0.599 | 0.214 | 0.231 |
|           | $\pm.006$                 | ±0.02  | ±0.04  | ±1e-3 | ±1e-3 | ±4e-4 |
| FOMM      | $0.0569\pm.006$           | 24.65  | 25.18  | 0.651 | 0.215 | 0.167 |
|           | $\pm.006$                 | ±0.03  | ±0.04  | ±1e-3 | ±1e-3 | ±4e-4 |
| FOMM+     | $0.0555\pm.006$           | 24.74  | 25.21  | 0.654 | 0.215 | 0.167 |
|           | $\pm.006$                 | ±0.03  | ±0.04  | ±1e-3 | ±1e-3 | ±4e-4 |
| Ours      | $0.0549\pm.006$           | 24.98  | 25.33  | 0.653 | 0.215 | 0.167 |
|           | $\pm.006$                 | ±0.03  | ±0.04  | ±1e-3 | ±1e-3 | ±4e-4 |

Table 4: Comparison with state-of-the-art approaches for video reconstruction on BAIR. Bold and underline indicate the best and the second best results, respectively.

| Model     | $\mathcal{L}_1 \downarrow$ | PSNR ↑ | SSIM ↑ |
|-----------|----------------------------|--------|--------|
| X2Face    | $0.0419\pm.006$           | 21.31  | 6.73   |
|           | $\pm.006$                 | ±0.01  | ±1e-3  |
| Monkey-Net| $0.0340\pm.006$           | 23.10  | 6.74   |
|           | $\pm.006$                 | ±0.01  | ±1e-3  |
| FOMM      | $0.0292\pm.006$           | 24.81  | 6.75   |
|           | $\pm.006$                 | ±0.01  | ±1e-3  |
| Ours      | $0.0276\pm.006$           | 25.31  | 6.78   |
|           | $\pm.006$                 | ±0.01  | ±1e-3  |

**Qualitative comparison**: Figure 5 shows the qualitative comparison for the VoxCeleb dataset. X2Face causes identity leak: the model tries to fit the source image into the shapes of the driving images, causing face distortions. Monkey-Net shows trivial warping artifacts near the right shoulder and on top of the head, and does not closely follow the pose angles. Since FOMM, FOMM+, and PriorityCut all use the same backbone, they share similar coarse shapes and geometries and differ in fine details. First, both FOMM and FOMM+ are weak at spatial relationships: they are aware that some hairs should be inpainted, but the hairs are inpainted at wrong locations. Also, the baseline FOMM is inconsistent with the amounts of hairs to be inpainted for similar pose angles. With adversarial training, FOMM+ amplifies the inpainted hairs at wrong locations. In contrast, PriorityCut inpaints the hairs with proper amounts and locations. Our qualitative comparison suggests that PriorityCut helps reduce the ambiguity in spatial relationships observed in the vanilla convolutional layers of FOMM and FOMM+. For additional qualitative comparisons, refer to Section C of the appendix and the corresponding video for each figure.

### 4.3 Ablation study

To validate the effects of each proposed component, we evaluated the following variants of our model. **Baseline**: the published First Order Motion Model used in their paper; **Adv**: the concurrent work of First Order Motion Model with a global discriminator; **U-Net**: the architecture of the global discriminator extended to the U-Net architecture; **PriorityCut**: our proposed approach that uses the top-k percent occluded pixels of the foreground as the CutMix mask.

**Quantitative ablation study**: Table 5 quantitatively compares the results of video reconstruction on the VoxCeleb dataset [Nagrani et al., 2017]. First, adversarial training improves only the $\mathcal{L}_1$ distance and the non-salient parts, but worsens other metrics. U-Net discriminator improves $\mathcal{L}_1$ by a margin with better AKD as a positive side bonus, at the cost of further degraded AED. We experimented with adding either PriorityCut or vanilla CutMix on top of the U-Net architecture. After adding PriorityCut, the full model outperforms the baseline model in every single metric. In particular, the improvement of AED shows the effectiveness of PriorityCut in guiding the model to inpaint realistic features.

**Qualitative ablation study**: Figure 6 qualitatively compares different variants of implementations on VoxCeleb dataset [Nagrani et al., 2017]. Similar to Figure 5, the baseline FOMM shows hair artifacts near the shoulder and adversarial training amplifies the artifacts. Extending the discriminator to U-Net architecture slightly reduces the artifacts. Finally, adding PriorityCut minimizes the artifacts produced.
Without proper guidance, the generator struggles at recovering warp-based image animation techniques. This section summarizes the key observations and findings.

### Table 5: Quantitative ablation study for video reconstruction on VoxCeleb

| Architecture | $L_1 \downarrow$ | PSNR $\uparrow$ | SSIM $\uparrow$ | AKD $\downarrow$ | AED $\downarrow$ |
|--------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|              | All | Salient $\searrow$ Salient | All | Salient $\searrow$ Salient |
| Baseline     | 0.0413 ± 9e-5 | 24.28 ± 0.02 | 25.19 ± 0.02 | 0.791 ± 4e-4 | 0.825 ± 4e-4 | 0.969 ± 2e-4 | 1.290 ± 2e-3 | 0.1324 ± 6e-4 |
| + Adv        | 0.0409 ± 9e-5 | 24.26 ± 0.02 | 25.17 ± 0.02 | 0.790 ± 4e-4 | 0.822 ± 2e-4 | 0.970 ± 1e-4 | 1.305 ± 2e-3 | 0.1339 ± 6e-4 |
| + U-Net      | 0.0401 ± 9e-5 | 24.34 ± 0.02 | 25.29 ± 0.02 | 0.791 ± 4e-4 | 0.824 ± 4e-4 | 0.969 ± 2e-4 | 1.278 ± 2e-3 | 0.1347 ± 6e-4 |
| + PriorityCut | 0.0401 ± 9e-5 | 24.45 ± 0.02 | 25.35 ± 0.02 | 0.793 ± 4e-4 | 0.826 ± 4e-4 | 0.970 ± 1e-4 | 1.286 ± 2e-3 | 0.1303 ± 6e-4 |

Bold and underline indicate the best and the second best results, respectively. For results that are not the best or the second best, red and green indicate worse and better results compared to the baseline FOMM, respectively.

Figure 5: Qualitative comparison of state-of-the-art approaches for image animation on VoxCeleb.

Figure 6: Qualitative ablation study on VoxCeleb.

### 5 Discussion

This section summarizes the key observations and findings.

#### Limitations of warp-based image animation

Existing warp-based image animation techniques recover the warping artifacts by inpainting. We observed that vanilla convolution does not distinguish valid and invalid pixels during inpainting. Without proper guidance, the generator struggles at recovering the visual artifacts with proper texture. While the literature demonstrated the effectiveness of vanilla CutMix in different computer vision tasks, we observed in our preliminary study that directly applying it to warp-based image animation improves only the pixel values, ignoring the spatial relationships.

#### The role of PriorityCut in recovering artifacts

Based on the above observations, we proposed PriorityCut to regularize image animation based on domain knowledge from occlusion, guiding the generator to learn the spatial relationships between pixels. Our quantitative and qualitative results with solid baselines and diverse datasets show that PriorityCut outperforms state-of-the-art models in recovering the warping artifacts. Since we implemented PriorityCut on top of FOMM, the artifacts seen in FOMM also exist in our results. However, PriorityCut alleviates them by reducing the ambiguity of the baseline FOMM. In addition, PriorityCut depends only on an occlusion mask and a background mask and does not depend on specific model architectures. We anticipate any warp-based image animation approaches can adopt PriorityCut with proper modifications.

#### Potential applications of PriorityCut

Given that the only dependencies of PriorityCut are an occlusion mask and a background mask, we expect PriorityCut to be widely applicable to any research areas involving image warping, occlusion, motion or optical flow estimation such as facial expression and body pose manipulation, image inpainting, and video frame interpolation.

### 6 Conclusion

We proposed PriorityCut, a novel augmentation approach that leverages the domain knowledge to guide the model learning the spatial relationships between pixels. PriorityCut outperforms state-of-the-art image animation models in terms of the pixel-wise difference, low-level similarity, keypoint distance, and feature embedding distance. Our experimental results demonstrated the effectiveness of PriorityCut in minimizing the visual artifacts in state-of-the-art image animation models.

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A Architectures and Training Details

Architectures We followed Schonfeld et al. [2020] to adapt a U-Net architecture in the discriminator. A U-Net discriminator \( D^U \) consists of both an encoder \( D^U_{enc} \) and a decoder \( D^U_{dec} \). The U-Net encoder \( D^U_{enc} \) progressively downsamples the input image to predict global realism like the discriminator of a vanilla GAN. The U-Net decoder \( D^U_{dec} \) progressively upsamples the feature map to predict the realism of individual pixels. It uses skip connections to feed information between matching resolutions of \( D^U_{enc} \) and \( D^U_{dec} \), enhancing its capability in segmenting fine details. The U-Net discriminator learns both the global and the local differences between real and fake images.

Table A1 summarizes the differences between all our discriminator architecture and that of First Order Motion Model+ \(^2\), the concurrent work of First Order Motion Model [Siarohin et al., 2019b] with a global discriminator. Our U-Net encoder uses the same architecture like that of the global discriminator of First Order Motion Model+. Our U-Net decoder is a symmetry of the U-Net encoder architecture, with skip connections feeding information between the matching resolutions of the two modules. Both discriminators use \( ch = 64 \) for channels. For the keypoint detector and the generator, we use the same architectures as those of the baseline First Order Motion Model.

Hyperparameters We followed Siarohin et al. [2019b] to use the Adam [Kingma and Ba, 2014] optimizer for training with learning rate 2e-4 and batch size 20. For regularization with PriorityCut, we followed Schonfeld et al. [2020] to linearly increase the probability of augmentation from 0 to 0.5 for the first \( n \) epochs. This gives the generator sufficient time to warm up and does not make the discriminator too strong in the beginning.

Training losses Following Siarohin et al. [2019b] and Schonfeld et al. [2020], we used a combination of losses for both the discriminator and the generator. The loss of the U-Net discriminator \( D^U \) consists of the adversarial loss of the U-Net encoder \( L_{D^U} \), the adversarial loss of the U-Net decoder \( L_{D^U_{dec}} \), and the consistency regularization loss \( L_{D^U_{dec}}^{cons} \) for the CutMix operation between the real and the fake images.

\[
L_{D^U} = L_{D^U_{enc}} + L_{D^U_{dec}} + \lambda L_{D^U_{dec}}^{cons}
\]

In particular, the consistency regularization loss consists of two terms. Suppose \( M_{pc} \) is the PriorityCut mask. The first term is the output of the U-Net decoder \( D^U_{dec} \) on the CutMix image. The second term is the CutMix between the outputs of \( D^U_{dec} \) on real and fake images. The consistency regularization loss computes the \( L^2 \) norm between the first and the second terms.

\[
L_{D^U_{dec}}^{cons} = \| D^U_{dec} (\text{mix}(x, x', M_{pc})) - \text{mix}(D^U_{dec}(x), D^U_{dec}(x'), M_{pc}) \|^2
\]

The loss of the generator consists of the reconstruction loss \( L_{rec} \), the equivariance loss \( L_{equiv} \), the adversarial loss \( L_{adv} \), and the feature matching loss \( L_{feat} \).

The published First Order Motion Model paper uses only the reconstruction loss \( L_{rec} \) and the equivariance loss \( L_{equiv} \) [Siarohin et al., 2019b]. We followed its concurrent work to include the adversarial loss \( L_{adv} \) and the feature matching loss \( L_{feat} \) for adversarial training.

\[
L_G = L_{rec} + L_{equiv} + L_{adv} + L_{feat}
\]

The reconstruction loss \( L_{rec} \) is the multi-scale perceptual loss based on the activations of the pre-trained VGG-19 network [Simonyan and Zisserman, 2014] between real and fake images. The equivariance loss \( L_{equiv} \) encourages consistent keypoint predictions given known geometric transformations. It is based on the following equivariance constraint on local motion approximations:

\[
T_{x\rightarrow r} \equiv T_{x\rightarrow y} \circ T_{y\rightarrow r}
\]

The adversarial loss \( L_{adv} \) is the sum of the feedback from the encoder \( D^U_{enc} \) and the decoder \( D^U_{dec} \) of the U-Net discriminator \( D^U \). The feature matching loss \( L_{feat} \) matches the feature maps of each layer of the U-Net encoder \( D^U_{enc} \) between the driving and the generated images, similar to that of pix2pixHD [Wang et al., 2018].

B Experimental Setup Details

Datasets We followed the preprocessing protocols of Siarohin et al. [2019b] to obtain high-quality videos on the following three datasets. At the time of data collection, some videos are no longer available on YouTube. We report the number of videos used in our experiments.

- The VoxCeleb dataset [Nagrani et al., 2017] is a face dataset with 22,496 videos from YouTube. We tracked the face until it is too far from its initial position and cropped the frames using the smallest crop containing all the bounding boxes. Then, we removed videos of resolution lower than \( 256 \times 256 \) and resized the remaining videos to \( 256 \times 256 \). After preprocessing, we obtained 18,398 videos for training and 512 videos for testing.

- The BAIR robot pushing dataset [Ebert et al., 2017] contains videos of a Sawyer robotic arm pushing objects over a table. It contains 42,880 videos for training and 128 videos for testing.

- The Tai-Chi-HD dataset [Siarohin et al., 2019b] contains 280 tai-chi videos from YouTube. We used similar preprocessing steps as VoxCeleb to split the videos into short clips and resized all high-quality videos to \( 256 \times 256 \). After preprocessing, we obtained 2,994 video chunks for training and 285 video chunks for testing.

Unlike First Order Motion Model paper [Siarohin et al., 2019b], we did not experiment on the UvA-NEMO dataset [Dibeklioğlu et al., 2012], since the VoxCeleb dataset is a more difficult one to learn. The VoxCeleb dataset contains videos of different pose angles while the UvA-NEMO dataset contains only frontal faces. Also, the UvA-NEMO dataset has a simple uniform dark background and the facial features are the only moving parts with subtle movements.

\(^2\)https://github.com/AliaksandrSiarohin/first-order-model
Metrics We provide additional details on the metrics and the third-party tools used for computation.

- **L1.** This measures the pixel-wise differences between the generated and the ground truth videos.
- **Peak Signal-to-Noise Ratio (PSNR).** This measures the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. It evaluates how good the model is at reconstructing the low-level details of the ground truth videos.
- **Structural Similarity (SSIM).** This compares the low-level structures between the generated and the ground truth videos. It evaluates also how good the model is at reconstructing the low-level details.
- **Masked PSNR and SSIM (M-PSNR, M-SSIM).** We used a variety of masks to evaluate the masked PSNR and SSIM on both the foreground and the background. The salient masks in Tables 2 and 3 cover the most noticeable parts of the images. The top-k masks in Tables A2, A3 and A4 correspond to the parts of the images that are the most difficult to inpaint. To compute a salient mask, we first used DeepLabv3+ [Chen et al., 2018], a semantic image segmentation library, to generate a binary mask. Then, we used an automatic trimap generator [Nugraha, 2018] to generate a trimap from the binary mask. We used the image matting library F, B, α Matting [Forte and Pitié, 2020] to generate a final alpha mask for the foreground. The background mask is the inversion of the foreground mask.

We used the same methodology as Section 3.3 to obtain the masks based on the top-k percent occluded pixels. The top-k masks are derived from the occlusion masks predicted by the baseline model (FOMM). Similar to salient masks, we used the top-k masks to evaluate the foreground and their inversions to evaluate the background.

- **Average Keypoint Distance (AKD).** This measures the average keypoint distance between the generated and the ground truth videos. Following Siarohin et al. [2019b], we used a face alignment library [Bulat and Tzimiropoulos, 2017] to detect face keypoints for the VoxCeleb dataset and a human pose estimation library [Cao et al., 2017] to detect pose keypoints for the Tai-Chi-HD dataset.
- **Missing Keypoint Rate (MKR).** This measures the percentage of keypoints detected in the ground truth videos but not in the generated ones. This evaluates the appearance quality of the generated videos. Following Siarohin et al. [2019b], we used the binary label returned by the human pose estimation library [Cao et al., 2017] to count if a keypoint is detected or not for the Tai-Chi-HD dataset.
- **Average Euclidean Distance (AED).** This measures the distance of the feature embedding between the generated and the ground truth videos. Following Siarohin et al. [2019b], we used OpenFace [Baltrusaitis et al., 2018] to extract the face identity embedding for the VoxCeleb dataset and a person re-id library [Hermans et al., 2017] to extract the person re-identification embedding for the Tai-Chi-HD dataset.

### Additional Evaluations

Quantitative comparison We additionally evaluated masked PSNR and SSIM on state-of-the-art approaches based on the top-k percent occluded pixels. In Tables A2, A3 and A4, the columns top-k represent the masks of the k percent heaviest occluded pixels. The columns ¬ top-k are the inversions of the top-k masks. We evaluated both masks to check if the models compromise the quality of certain parts of the image to achieve the desired performance. For both metrics, the larger the values, the better the results. The bold texts represent the best results. The red and green texts
| k   | 10% | 20% | 30% | 40% | 50% |
|-----|-----|-----|-----|-----|-----|
|     | top-k | ~top-k | top-k | ~top-k | top-k | ~top-k | top-k | ~top-k | top-k | ~top-k |
| X2Face | 28.42±0.02 | 19.94±0.02 | 25.41±0.02 | 20.74±0.02 | 23.72±0.02 | 21.59±0.02 | 22.57±0.02 | 22.51±0.02 | 21.70±0.02 | 23.55±0.02 |
| Monkey-Net | 30.81±0.02 | 23.50±0.02 | 28.00±0.02 | 24.44±0.02 | 26.45±0.02 | 25.41±0.02 | 25.41±0.02 | 26.44±0.02 | 24.65±0.02 | 27.57±0.02 |
| FOMM | 32.99±0.02 | 25.24±0.02 | 30.07±0.02 | 26.14±0.02 | 28.46±0.02 | 27.09±0.02 | 27.37±0.02 | 28.11±0.02 | 26.55±0.02 | 29.24±0.02 |
| FOMM+ | 32.91±0.02 | 25.24±0.02 | 30.00±0.02 | 26.16±0.02 | 28.39±0.02 | 27.12±0.02 | 27.30±0.02 | 28.15±0.02 | 26.49±0.02 | 29.30±0.02 |
| Ours | 33.14±0.02 | 25.42±0.02 | 30.21±0.02 | 26.34±0.02 | 28.60±0.02 | 27.29±0.02 | 27.51±0.02 | 28.32±0.02 | 26.70±0.02 | 29.46±0.02 |

(a) Masked PSNR on top-k percent occluded pixels.

| k   | 10% | 20% | 30% | 40% | 50% |
|-----|-----|-----|-----|-----|-----|
|     | top-k | ~top-k | top-k | ~top-k | top-k | ~top-k | top-k | ~top-k | top-k | ~top-k |
| X2Face | 0.9519±9e-5 | 0.6792±5e-4 | 0.9108±1e-4 | 0.7262±5e-4 | 0.8721±2e-4 | 0.7702±4e-4 | 0.8344±2e-4 | 0.8114±4e-4 | 0.7977±3e-4 | 0.8499±3e-4 |
| Monkey-Net | 0.9640±7e-5 | 0.7755±4e-4 | 0.9333±1e-4 | 0.8134±4e-4 | 0.9041±2e-4 | 0.8473±3e-4 | 0.8757±2e-4 | 0.8779±3e-4 | 0.8483±3e-4 | 0.9053±2e-4 |
| FOMM | 0.9736±6e-5 | 0.8270±4e-4 | 0.9497±1e-4 | 0.8573±3e-4 | 0.9264±2e-4 | 0.8842±3e-4 | 0.9034±2e-4 | 0.9085±2e-4 | 0.8813±3e-4 | 0.9301±2e-4 |
| FOMM+ | 0.9734±6e-5 | 0.8259±4e-4 | 0.9493±1e-4 | 0.8563±3e-4 | 0.9260±2e-4 | 0.8834±3e-4 | 0.9028±2e-4 | 0.9079±2e-4 | 0.8805±3e-4 | 0.9297±2e-4 |
| Ours | 0.9741±6e-5 | 0.8287±4e-4 | 0.9505±1e-4 | 0.8587±3e-4 | 0.9275±2e-4 | 0.8854±3e-4 | 0.9048±2e-4 | 0.9094±2e-4 | 0.8829±2e-4 | 0.9308±2e-4 |

(b) Masked SSIM on top-k percent occluded pixels.

Table A2: Comparison with state-of-the-art approaches for video reconstruction on VoxCeleb. Bold indicates the best results. For variants of FOMM that do not produce the best results, red and green indicate worse and better results compared to the baseline FOMM, respectively.

Table A3: Comparison with state-of-the-art approaches for video reconstruction on BAIR. Bold indicates the best results.

represent performance loss and gain compared to the baseline model (FOMM), respectively.

We evaluated the masked versions on the VoxCeleb, BAIR, and Tai-Chi-HD datasets. Table A2 shows the results for VoxCeleb. For both PSNR and SSIM, PriorityCut outperforms state-of-the-art approaches in different thresholds k. Note that adversarial training alone does not guarantee performance gains. For PSNR, the adversarial model (FOMM+) compromises the quality of the hardest parts to inpaint (top-k masks) and pursues the easy targets (~top-k masks). For SSIM, adversarial training performs worse in every setting. Table A3 shows the results for BAIR. Since the pre-trained model of FOMM+ for BAIR is not publicly available at the time of writing, we evaluated BAIR only on the baseline FOMM. For both PSNR and SSIM, PriorityCut consistently outperforms state-of-the-art approaches. Table A4 shows the results for Tai-Chi-HD. For PSNR, PriorityCut outperforms state-of-the-art approaches in all settings. For SSIM, PriorityCut is on par with the adversarial model.
Qualitative comparison: We performed additional qualitative comparisons between state-of-the-art approaches on each dataset. Figures A1, A2, and A3 show the qualitative comparisons for VoxCeleb, BAIR, and Tai-Chi-HD datasets respectively. For each figure, we include corresponding videos for reference. Since we implemented PriorityCut on top of First Order Motion Model (FOMM), the artifacts seen in FOMM also exist in our results. However, PriorityCut alleviates them by reducing the ambiguity of the baseline FOMM.

For VoxCeleb in Figure A1, X2Face shows severe warping artifacts and face distortions. Monkey-Net shows noticeable warping artifacts around locations of large changes in motion. FOMM shows overlapping hairs and blurry background in the first example and blurry texture behind the right ear in the second example. FOMM+ further amplifies these visual artifacts in both examples. In contrast, PriorityCut minimizes these ambiguous visual artifacts.

For BAIR in Figure A2, X2Face shows trivial warping artifacts and broken texture on the robot arms. Monkey-Net shows warping artifacts around the robot arms. FOMM erases the objects and fills with background texture in the first example and shows broken texture on the robot arms in the second example. In contrast, PriorityCut minimizes the ambiguity without replacing the objects with background texture and preserves the robot arm texture.

For Tai-Chi-HD in Figure A3, both MonkeyNet and X2Face show trivial warping artifacts. Both FOMM and FOMM+ fill the head area with background texture while the heads are visible for PriorityCut. Our qualitative comparisons on diverse datasets show the effectiveness of PriorityCut in alleviating the visual artifacts in state-of-the-art image animation models.

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Figure A1: Qualitative comparison of state-of-the-art approaches for image animation on VoxCeleb. FOMM and FOMM+ produce noticeable visual artifacts such as overlapping hairs and blurry background in the first example and confusing background texture in the second example. PriorityCut helps reduce these ambiguous visual artifacts in FOMM.
Figure A2: Qualitative comparison of state-of-the-art approaches for image animation on BAIR. FOMM replaces the background objects by the background texture in the first example and produces broken texture in the second example. PriorityCut minimizes these ambiguous visual artifacts in FOMM.
Figure A3: Qualitative comparison of state-of-the-art approaches for image animation on Tai-Chi-HD. FOMM and FOMM+ inpaint the head areas with background texture while the heads are visible in the results of PriorityCut.