

Generative Image Inpainting with Segmentation Confusion Adversarial Training and Contrastive Learning

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Abstract

This paper presents a new adversarial training framework for image inpainting with segmentation confusion adversarial training (SCAT) and contrastive learning. SCAT plays an adversarial game between an inpainting generator and a segmentation network, which provides pixel-level local training signals and can adapt to images with free-form holes. By combining SCAT with standard global adversarial training, the new adversarial training framework exhibits the following three advantages simultaneously: (1) *the global consistency of the repaired image*, (2) *the local fine texture details of the repaired image*, and (3) *the flexibility of handling images with free-form holes*. Moreover, we propose the textural and semantic contrastive learning losses to stabilize and improve our inpainting model’s training by exploiting the feature representation space of the discriminator, in which the inpainting images are pulled closer to the ground truth images but pushed farther from the corrupted images. The proposed contrastive losses better guide the repaired images to move from the corrupted image data points to the real image data points in the feature representation space, resulting in more realistic completed images. We conduct extensive experiments on two benchmark datasets, demonstrating our model’s effectiveness and superiority both qualitatively and quantitatively.

Introduction

Image inpainting is the task that aims at estimating the missing pixels in corrupted images, which has a wide impact on many image editing applications such as object removal, image denoising, and image restoration, to name a few. As one of the most important research areas in computer vision, image inpainting has drawn a significant amount of attention in the community for a long time and yet remains an open challenge, for it is an inherently ill-posed problem. Prior to the recent dominance of deep generative inpainting methods, early traditional inpainting methods (Barnes et al. 2009; Bertalmio et al. 2000, 2003; Criminisi, Pérez, and Toyama 2004; Huang et al. 2014) typically utilize low-level features to fill holes by either propagating surroundings to the missing regions in a diffusive manner or iteratively searching for the best-matched patches in the internal image contexts or external image datasets. Though these meth-

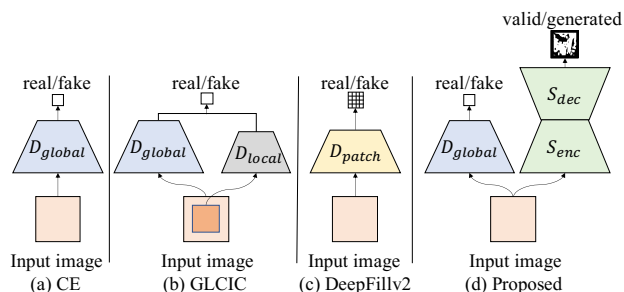


Figure 1: Different adversarial training frameworks of GAN-based inpainting models. In addition to a global discriminator, we introduce a segmentation network S in our model, which tries to label the valid and the generated regions in the input image.

ods perform considerably well in tasks like background inpainting, they lack the understanding of high-level semantics and can not capture the global structure of the image, thus failing to generalize when the missing regions are large or contain unique image statistics. In contrast, recent deep generative approaches (Pathak et al. 2016; Iizuka, Simo-Serra, and Ishikawa 2017; Yu et al. 2018, 2019), trained on large-scale datasets, benefit from the rich hierarchical features learned by the deep convolutional neural networks (DCNNs) (Krizhevsky, Sutskever, and Hinton 2012; Simonyan and Zisserman 2014; Szegedy et al. 2015; He et al. 2016) and the powerful generative capacity of generative adversarial networks (GANs) (Goodfellow et al. 2014), capable of synthesizing semantically correct and visually plausible inpainting results.

Among the deep generative inpainting methods, Context Encoder (CE) (Pathak et al. 2016) first proposed to train an encoder-decoder inpainting network with a combination of a reconstruction loss and an adversarial loss, showing the significance of adversarial training in bringing sharper predictions. Since then, exploring and designing more advanced and sophisticated adversarial training frameworks have become an important research direction for improving GAN-based inpainting models. For example, as CE only used a global context discriminator to distinguish real images from completed ones as a whole, GLCIC (Iizuka, Simo-Serra, and

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Ishikawa 2017) proposed to use global and local context discriminators simultaneously, which provides both global coherent consistency and local fine texture details for the inpainting results. However, the local discriminator of GL-CIC can only handle pre-defined fixed-sized holes, making it inflexible to process images with arbitrary free-form holes. In order to solve the problem, DeepFillv2 (Yu et al. 2019) proposed to adopt PatchGAN from the literature on image-to-image translation (Isola et al. 2017). The PatchGAN discriminator only consists of a few convolutional layers, which distinguishes patches of ground truth images from those of the repaired images. Moreover, Yu et al. (2019) applied spectral normalization (Miyato et al. 2018) to further stabilize PatchGAN training. Thenceforth, SN-PatchGAN has been vastly used in recent GAN-based inpainting models to handle images with free-form holes. However, DeepFillv2 does not involve a global discriminator for training, which may fail to guarantee the global consistency of the repaired images. We show the adversarial training frameworks of existing GAN-based inpainting models in Figure 1. Additionally, the comparison of these frameworks is summarized in Table 1, where the comparison is based on three dimensions: (1) the global consistency of the repaired image, (2) the local fine texture details of the repaired image, and (3) the flexibility of handling images with arbitrary free-form holes. Clearly, none of the existing adversarial training frameworks can satisfy the three requirements at the same time.

Motivated by the analysis above, we propose a new adversarial training framework for image inpainting by first introducing a novel segmentation confusion adversarial training (SCAT) paradigm. The proposed SCAT is inspired by *how humans recognize a low-quality repaired image*. We human beings can easily judge whether a repaired image is of poor quality by looking for the regions that are distorted or inconsistent with the surrounding textures in the image. To mimic such human behavior, we introduce a segmentation network to label the generated and the valid regions in the input images, which is essentially a two-class dense semantic segmentation task. On the contrary, the inpainting generator tries to deceive the segmentation network by filling the missing regions with more visually plausible and consistent contents, making it more difficult for the segmentation network to label the two regions. We further combine the introduced SCAT with the global per-image adversarial training (see Figure 1(d)), where the final framework can meet the three aforementioned requirements simultaneously. Complementary to the global per-image adversarial training, the SCAT additionally provides fine-grained pixel-level training signals and the flexibility of handling images with arbitrary free-form holes for our framework, significantly improving the image quality and visual consistency of the inpainting results.

On the other hand, training GAN is known to be notoriously difficult, for it requires searching a Nash equilibrium of a non-convex game in an extremely high-dimensional parameter space (Goodfellow 2016; Salimans et al. 2016). Besides, the discriminator has to adapt to the continuously changed generated distribution during the training procedure to perform the classification task, which means GAN’s

Models	CE	GLCIC	DeepFillv2	Proposed
global consistency	✓	✓	✗	✓
local texture details	✗	✓	✓	✓
free-form holes	✗	✗	✓	✓

Table 1: Comparison of different adversarial training frameworks for image inpainting.

training is in a non-stationary environment (Salimans et al. 2016; Thanh-Tung and Tran 2020). Consequently, GAN-based inpainting models can exhibit unstable and cyclic issues, which may cause degraded inpainting results. To stabilize and improve our model’s training, we further propose contrastive learning losses by exploiting the feature representation space of the discriminator, in which the inpainting images are constantly pulled closer to the ground truth images but pushed farther from the corrupted images. As the training process of image inpainting can be regarded as learning a mapping from the corrupted images to the ground truth images, our proposed contrastive losses can better guide the process with their pull and push forces, which brings more realistic inpainting results. To the best of our knowledge, this is the first effective usage of contrastive learning in image inpainting.

We conduct extensive experiments on two benchmark datasets: Places2 (Zhou et al. 2017) and CelebA (Liu et al. 2018b), demonstrating our model’s effectiveness and superiority both qualitatively and quantitatively.

The main contributions in the paper are four-fold: **(i)** we present a new adversarial training framework for image inpainting with segmentation confusion adversarial training (SCAT) and contrastive learning; **(ii)** the proposed SCAT helps provide local pixel-level training signals and adapt to images with arbitrary free-form holes for our framework; **(iii)** the proposed contrastive learning losses stabilize and improve our model’s training, resulting in more realistic inpainting images; and **(iv)** extensive experiments on two benchmark datasets have been conducted to verify our model’s effectiveness and superiority.

Related Works

Generative Adversarial Networks

GANs are composed of two networks: a discriminator that distinguishes real data samples from generated samples and a generator that tries to generate samples to fool the discriminator. Many important works have been proposed to improve the original GAN for more stabilized training or producing high-quality samples, such as by proposing better loss functions or regularizations (Arjovsky, Chintala, and Bottou 2017; Gulrajani et al. 2017; Miyato et al. 2018), changing network structures (Radford, Metz, and Chintala 2015; Karras, Laine, and Aila 2019; Brock, Donahue, and Simonyan 2018; Schonfeld, Schiele, and Khoreva 2020), or combining GANs with inference networks or autoencoders (Donahue, Krähenbühl, and Darrell 2016; Dumoulin et al. 2016; Larsen et al. 2016; Srivastava et al. 2017; Ulyanov, Vedaldi, and Lempitsky 2018). Our pro-

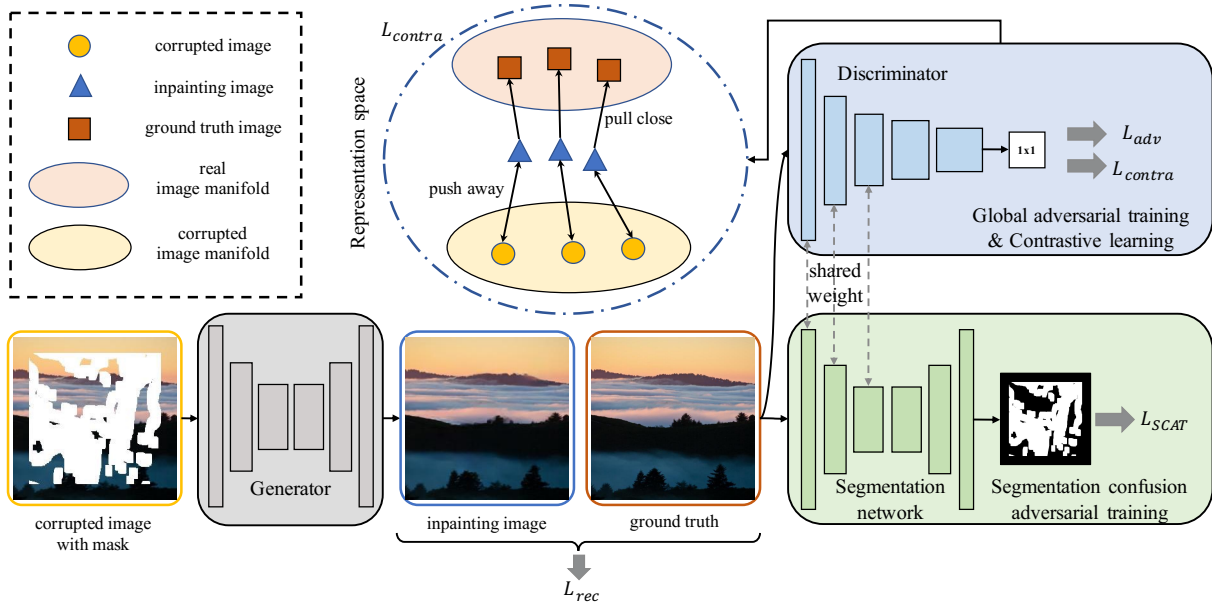


Figure 2: The overall framework of the proposed model, which consists of an inpainting generator G , a discriminator D , and a segmentation network S .

posed SCAT is related to U-net GAN (Schonfeld, Schiele, and Khoreva 2020), while it differs from U-net GAN in two aspects: (1) SCAT is inspired by *how humans recognize low-quality repaired images*; (2) In contrast to simply classifying all pixels as real or fake in U-net GAN, SCAT identifies the generated and the valid regions in the input images, which is specially tailored for image inpainting tasks.

Deep Generative Inpainting Methods

The seminal CE (Pathak et al. 2016) work first proposed a global adversarial training framework for image inpainting. GLCIC (Iizuka, Simo-Serra, and Ishikawa 2017) improved it by using global and local context discriminators simultaneously, exhibiting globally and locally consistent inpainting results. GLCIC also proposed to use dilated convolutional layers instead of standard ones in the feature encoder to enlarge the receptive field of the encoded feature for better context reasoning. Further, DeepFillv1 (Yu et al. 2018) proposed the attention module in its two-stage coarse-to-fine framework, leveraging the neural patch similarities between the known and the missing regions of the inpainting image for better results. While previous works mainly focused on repairing images with centered rectangular holes, PConv (Liu et al. 2018a) proposed partial convolutions to handle images with irregular free-form holes, where the convolution is masked and renormalized to be conditioned only on valid pixels. DeepFillv2 (Yu et al. 2019) proposed a learnable mask-update mechanism in its framework plus SN-PatchGAN (Miyato et al. 2018; Isola et al. 2017) to improve free-form image inpainting. There are also many methods proposing to solve the difficult hole-filling problem in a progressive (Guo et al. 2019; Zeng et al. 2019) or recurrent way (Li et al. 2020; Zeng et al. 2020), achieving promising

results. Some studies focus on incorporating structure priors (e.g., edges (Nazeri et al. 2019; Guo, Yang, and Huang 2021) or frequency knowledge (Yu et al. 2021; Suvorov et al. 2022) in their frameworks. Notably, many methods (Zheng, Cham, and Cai 2019; Zhao et al. 2020, 2021; Wan et al. 2021) aimed at achieving diversified results for image inpainting. Very recently, transformer-based image inpainting frameworks (Wan et al. 2021; Li et al. 2022; Dong, Cao, and Fu 2022; Liu et al. 2022) shined with stunning results as transformers are more expressive than DCNNs. The most related work to ours in the literature is PAL4Inpaint (Zhang et al. 2022), which trained a segmentation model to detect inpainting perceptual artifacts and apply the model for inpainting model evaluation and iterative refinement. The main distinction between ours and theirs is that we train the segmentation network and the inpainting generator adversarially.

Contrastive Learning

In recent years, contrastive learning has achieved great success in self-supervised representation learning (Chen et al. 2020; He et al. 2020). Many low-level vision tasks have benefited from utilizing contrastive learning as well. For example, contrastive learning has been utilized in one-sided unpaired image-to-image translation (Park et al. 2020), class-conditioned image generation (Kang and Park 2020), artistic style transfer (Chen et al. 2021), and single image de-hazing (Wu et al. 2021). In image inpainting, Ma et al. (2020) proposed to improve context encoding by using a self-supervised inference network (He et al. 2020), which pulls two identical images with different masks to be close in the context feature space. We argue its strategy may be unreasonable, because the two identical images with different masks may differ significantly. Unlike previous approaches,

we propose to use contrastive learning to stabilize and improve our proposed inpainting model’s training by exploiting the feature representation space of the discriminator, in which the inpainting images are better guided to move from the corrupted images to the real images.

Proposed Method

Notations

The overall framework of the proposed model is illustrated in Figure 2, where we assume that the real images and the corrupted images lie in two manifolds which are denoted as the real image manifold and the corrupted image manifold, respectively. During training, given an ground truth image $x \in \mathbb{R}^{H \times W \times 3}$, a mask $m \in \mathbb{R}^{H \times W \times 3}$ is applied to it to get the corrupted input image $\tilde{x} = x \odot m$, where each pixel of the mask m contains values of either 0s or 1s, denoting the missing and the valid regions of the corrupted image, respectively. In both training and inference phases, the inpainting generator G takes the corrupted input image \tilde{x} and the mask m as the inputs and then outputs an estimate of the repaired image $\hat{x} \in \mathbb{R}^{H \times W \times 3}$ such that $\hat{x} = G(\tilde{x}, m)$. The final inpainting result \bar{x} is obtained by combining the masked regions of \hat{x} and the valid regions of \tilde{x} where $\bar{x} = (1 - m) \odot \hat{x} + m \odot \tilde{x}$.

Segmentation Confusion Adversarial Training

The proposed segmentation confusion adversarial training (SCAT) plays an adversarial game between the inpainting generator G and the segmentation network S . Different from the global per-image adversarial training in standard GANs, the segmentation network S tries to label the valid and the generated regions in the input image at a pixel level according to the input mask image. On the contrary, the inpainting generator G tries to improve its inpainting results by filling the missing regions with more realistic and coherent contents so that the segmentation network S is not able to label the two regions anymore. The segmentation confusion adversarial training loss $\mathcal{L}_{\text{SCAT}}$ for the segmentation network S and the inpainting generator G are defined as follows, respectively:

$$\begin{aligned} \mathcal{L}_{\text{SCAT}}(S) = & -\mathbb{E} \left[\frac{1}{HW} \sum_{i=1}^{HW} [m_i \log S(\bar{x})_i + (1 - m_i) \log(1 - S(\bar{x})_i)] \right. \\ & \left. + \frac{1}{HW} \sum_{i=1}^{HW} [\bar{m}_i \log S(x)_i + (1 - \bar{m}_i) \log(1 - S(x)_i)] \right] \end{aligned} \quad (1)$$

$$\begin{aligned} \mathcal{L}_{\text{SCAT}}(G) = & -\mathbb{E} \left[\frac{1}{HW} \sum_{i=1}^{HW} [\bar{m}_i \log S(\bar{x})_i + (1 - \bar{m}_i) \log(1 - S(\bar{x})_i)] \right], \end{aligned} \quad (2)$$

where \bar{m} is a mask filled with all 1s and the output activation function of the segmentation network is the sigmoid function. When training the segmentation network S , we use the

masks m and \bar{m} as the supervisions for the repaired image \bar{x} and the ground truth image x , respectively. On the other hand, when training the inpainting generator G , we use the mask \bar{m} as the supervision for the repaired image \bar{x} , encouraging G to produce better repaired images such that S mistakes the generated regions in the repaired image as valid regions.

Textural and Semantic Contrastive Learning

Two contrastive learning losses, namely textural and semantic contrastive learning losses, are proposed to stabilize and improve our inpainting model’s adversarial training. Since the discriminator D learns discriminative features to distinguish between the ground truth images and the completed images, its feature representation space is a natural choice for our proposed contrastive losses. As illustrated in Figure 2, the pull force of our contrastive losses encourage realistic completed contents by matching the feature statistics of the repaired images to those of the ground truth images, while the push force of our contrastive losses prevent degraded or cyclic inpainting results by keeping the repaired images to be farther and farther away from the corrupted images in the representation space of the discriminator, stabilizing and improving the adversarial training in our model.

As DCNNs learn hierarchical feature representations (Zeiler and Fergus 2014), where the shallow and deep layers’ feature maps typically contain low-level (*e.g.*, local texture details) and high-level features (*e.g.*, global semantic information) respectively, we design the textural and semantic contrastive learning losses by utilizing the low-level and high-level features extracted from the discriminator accordingly.

The textural contrastive loss is defined as follows:

$$\mathcal{L}_{\text{contra}}^{\text{text}} = \mathbb{E} \sum_{i=1}^N \frac{d(D_i(\bar{x}), D_i(x))}{d(D_i(\bar{x}), D_i(\tilde{x}))}, \quad (3)$$

where $d(\cdot, \cdot)$, $D_i(\cdot)$, and N denote a distance metric, the discriminator D ’s i -th layer’s output feature map, and the number of total used shallow layers, respectively. Equation 3 is slightly different from the standard InfoNCE’s formulation due to the relatively large dimensionality of the shallow layer’s feature maps. In implementation, we adopt the $L1$ -norm as the distance metric.

On the other hand, the semantic contrastive learning loss is built upon the discriminator D ’s last output feature map as shown below:

$$\mathcal{L}_{\text{contra}}^{\text{sem}} = -\mathbb{E} \left[\log \left(\frac{\exp(D(\bar{x})^T D(x)/t)}{\exp(D(\bar{x})^T D(x)/t) + \sum_{j=1}^M \exp(D(\bar{x})^T D(\tilde{x}_j)/t)} \right) \right], \quad (4)$$

where we build M different corrupted versions of x , *i.e.* $\{\tilde{x}_1, \tilde{x}_2, \dots, \tilde{x}_M\}$, as the negative samples, and t is the temperature that controls the push and pull forces.

Our total contrastive loss $\mathcal{L}_{\text{contra}}$ is defined by combining Equation 3 and Equation 4:

$$\mathcal{L}_{\text{contra}} = \lambda_{\text{text}} \mathcal{L}_{\text{contra}}^{\text{text}} + \lambda_{\text{sem}} \mathcal{L}_{\text{contra}}^{\text{sem}}, \quad (5)$$

where λ_{text} and λ_{sem} are the weights that balance the two corresponding losses, respectively.

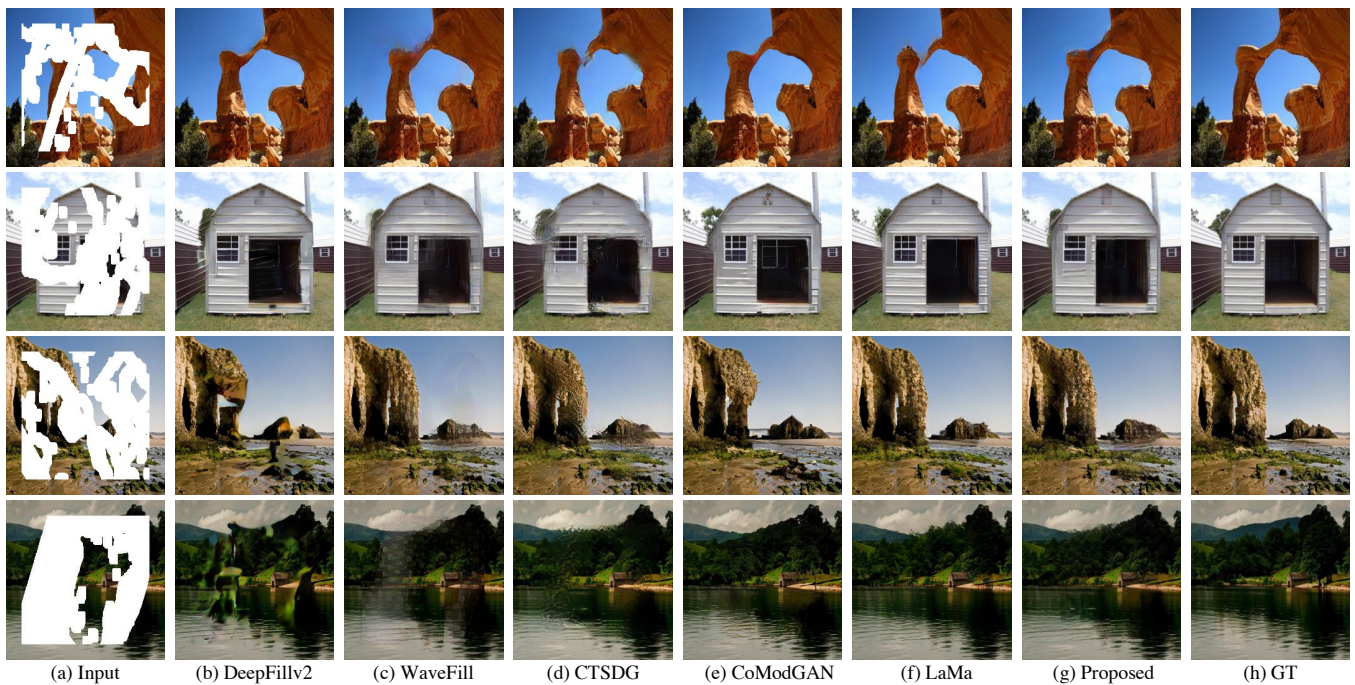


Figure 3: Qualitative results on Places2. Please zoom in to see more details.

Other Training Objectives

Aside from our introduced segmentation confusion adversarial training and contrastive learning objectives, we additionally use two training objectives for optimization. A standard global adversarial training loss is used in our framework to encourage the global consistency of the repaired images as follows:

$$\mathcal{L}_{adv} = \min_G \max_D \mathbb{E}_x [\log D(x)] + \mathbb{E}_{\bar{x}} [\log(1 - D(\bar{x}))]. \quad (6)$$

We also use an $L1$ reconstruction loss to encourage the inpainting image to be the same as the ground truth image:

$$\mathcal{L}_{rec} = \mathbb{E} \|\hat{x} - x\|_1. \quad (7)$$

Overall Objective

The overall training objective for our model is defined as follows:

$$\mathcal{L}_{total} = \lambda_{adv}(\mathcal{L}_{adv} + \mathcal{L}_{SCAT}) + \mathcal{L}_{contra} + \lambda_{rec}\mathcal{L}_{rec} \quad (8)$$

where λ_{adv} and λ_{rec} are the weights that control the importance of the corresponding losses, respectively.

Experiments

Experimental Settings

Implementation Details We train our model with a batch size of 8 on a single 24G NVIDIA RTX3090 GPU. All the masks and images for training and evaluation are of size 256×256 . Our inpainting generator consists of a few downsampling and upsampling layers with several AOT-blocks (Zeng et al. 2022) in-between. The segmentation network S in our framework is implemented as a U-net. We

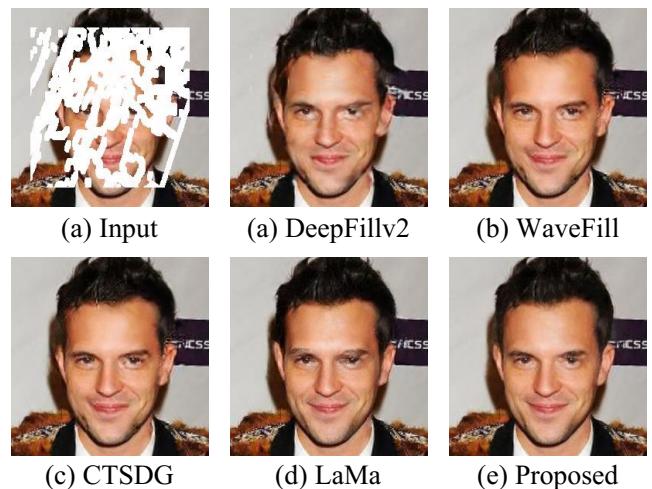


Figure 4: Qualitative results on CelebA. Please zoom in to see more details.

adopt hinge loss (Lim and Ye 2017) for both global adversarial training and SCAT and apply spectral normalization (Miyato et al. 2018) on all S and D 's layers. The negative sample size for the semantic contrastive learning loss is 8. We conduct experiments on the CelebA dataset to select the hyper-parameters from a set of empirical values, i.e. $[0.1, 1, 5, 10]$, and find that setting $\lambda_{adv} = 1$, $\lambda_{text} = 10$, $\lambda_{sem} = 1$, and $\lambda_{rec} = 10$ works fine for our model.

Dataset		Places2			CelebA		
Mask Ratio		0%-20%	20%-40%	40%-60%	0%-20%	20%-40%	40%-60%
Mean l_1^\dagger	DeepFillv2	0.017	0.053	0.112	0.0102	0.0316	0.0729
	WaveFill	0.015	0.042	0.117	0.0086	0.0230	0.0580
	CTSDG	0.012	0.041	0.089	0.0062	0.0235	0.0567
	CoModGAN	0.015	0.049	0.109	N/A	N/A	N/A
	LaMa	0.012	0.042	0.089	0.0070	0.0255	0.0609
	Proposed	0.010	0.038	0.087	0.0057	0.0217	0.0548
PSNR*	DeepFillv2	30.37	22.92	18.76	35.47	27.36	22.18
	WaveFill	30.73	25.26	19.73	37.24	29.54	24.23
	CTSDG	32.76	24.98	20.66	38.08	29.33	24.10
	CoModGAN	31.35	23.50	18.97	N/A	N/A	N/A
	LaMa	32.13	24.71	20.52	37.12	28.87	23.64
	Proposed	33.52	25.50	20.85	38.87	30.14	24.49
SSIM*	DeepFillv2	0.946	0.829	0.680	0.968	0.896	0.783
	WaveFill	0.950	0.860	0.674	0.976	0.922	0.832
	CTSDG	0.959	0.857	0.716	0.979	0.920	0.824
	CoModGAN	0.953	0.842	0.690	N/A	N/A	N/A
	LaMa	0.956	0.856	0.721	0.974	0.910	0.810
	Proposed	0.964	0.870	0.732	0.981	0.928	0.836
FID †	DeepFillv2	3.07	10.48	24.35	1.82	5.19	10.25
	WaveFill	3.23	7.03	39.35	1.27	2.45	7.57
	CTSDG	2.74	11.27	31.45	1.09	4.72	12.26
	CoModGAN	2.00	6.29	15.51	N/A	N/A	N/A
	LaMa	1.85	5.82	14.68	1.07	3.51	7.66
	Proposed	1.68	5.71	13.83	0.71	2.40	6.15

Table 2: Quantitative comparison on Places2 and CelebA datasets. *Higher is better. † Lower is better. N/A indicates the result is not available.

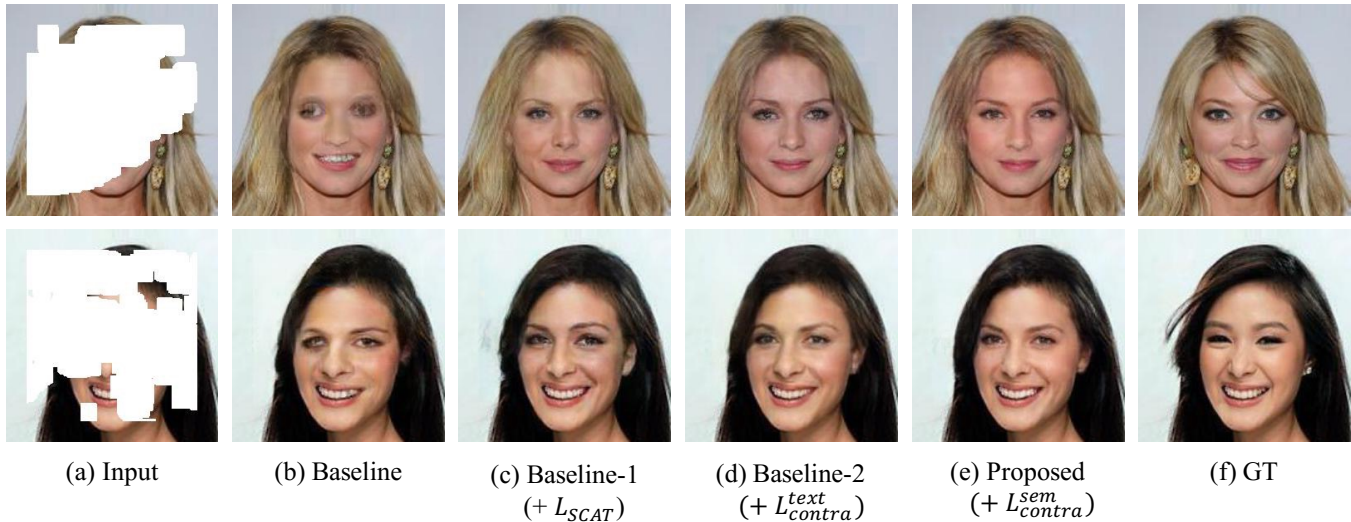


Figure 5: Qualitative results of ablation studies on CelebA. Please zoom in to see more details.

Datasets. We adopt an irregular mask dataset (Liu et al. 2018a) for training and evaluation, which contains 12,000 masks with mask ratio from 0% to 60%. We train and evaluate our method on two benchmark datasets Places2 (Zhou et al. 2017) and CelebA (Liu et al. 2018b) following their official training/validation splits.

Baselines. We compare our method with five state-of-the-art methods: DeepFillv2 (Yu et al. 2019), CTSDG (Guo,

Yang, and Huang 2021), WaveFill (Yu et al. 2021), Co-ModGAN (Zhao et al. 2021), and LaMa (Suvorov et al. 2022) by using their officially-released pre-trained models or models trained with their officially-released codes.

Metrics. Four widely-adopted quantitative metrics are used for evaluation: mean l_1 error, PSNR, SSIM, and FID (Heusel et al. 2017).

Models	Baseline (w/o $\mathcal{L}_{\text{SCAT}}$ & $\mathcal{L}_{\text{contra}}$)	Baseline-1 (+ $\mathcal{L}_{\text{SCAT}}$)	Baseline-2 (+ $\mathcal{L}_{\text{contra}}^{\text{text}}$)	Proposed (+ $\mathcal{L}_{\text{contra}}^{\text{sem}}$)
Mean l_1^\dagger	0.0593	0.0576	0.0561	0.0548
PSNR*	23.86	24.11	24.27	24.49
SSIM*	0.822	0.825	0.832	0.836
FID †	7.84	7.20	6.52	6.15

Table 3: Quantitative results of ablation studies on CelebA. The results are obtained using masks with mask ratio from 40% to 60%. *Higher is better. † Lower is better.

Qualitative Evaluations

Figure 3 and 4 compare our method’s inpainting results with the state-of-the-art methods’ on Places2 and CelebA, respectively. As shown in Figure 3, thanks to our dual adversarial training in both global and pixel level plus contrastive losses, our method performs more favorably compared to the other state-of-the-art methods in maintaining the structural integrity of the objects and repairing large-scale missing areas in the natural landscape. LaMa and CoModGAN sometimes produce inpainting results with distorted structures. CTSDG tends to create small edge-like artifacts, which may be caused by the incorrect edge predictions in its framework. WaveFill is prone to synthesize blurry contents in the context of large-scale missing textures and DeepFillv2’s results often contain distorted structures or unrealistic artifacts. For results on CelebA, our method’s results are comparable to the state-of-the-art methods, exhibiting global consistency and fewer local artifacts (*e.g.*, the areas of eyes and ears in Figure 4). The qualitative comparison on the two datasets subjectively verify the superiority of our method.

Quantitative Evaluations

We perform quantitative evaluations on Places2 and CelebA datasets by randomly selecting 5K images from each dataset’s validation set and then applying the same irregular masks on them to obtain the quantitative results. Table 2 presents the numerical results with different mask ratios on the two datasets. As we see, the proposed method outperforms the other state-of-the-art methods in all cases by considerable margins, especially on FID, objectively demonstrating the superiority of our method.

Ablation Studies

We perform ablation studies of our proposed methods on CelebA dataset to evaluate their effectiveness. We denote the model that ablates all our proposed methods, including the SCAT and the two contrastive learning objectives, as the Baseline model. The Baseline model actually follows the global adversarial training framework of CE (Pathak et al. 2016). We then augment the Baseline model with the SCAT $\mathcal{L}_{\text{SCAT}}$, the textural contrastive learning $\mathcal{L}_{\text{contra}}^{\text{text}}$, and the semantic contrastive learning $\mathcal{L}_{\text{contra}}^{\text{sem}}$ sequentially for training, where the resulting models are denoted as Baseline-1, Baseline-2, and the Proposed full model, accordingly. We show the qualitative and quantitative results of the ablation

studies in Figure 5 and Table 3, respectively. As can be observed from Figure 5, the Baseline model creates globally consistent completed images, but the results contain obvious local artifacts (*e.g.*, the eyes). By adding the SCAT, Baseline-1 produces inpainting images with finer local details. Further, by adding the textural contrastive learning, Baseline-2 makes the textural details of the repaired images more realistic (*e.g.*, smoother skins and less artifacts around the eyes, the ears, and hairs). Finally, the Proposed full model’s inpainting results are more visually appealing and globally coherent by adding the semantic contrastive learning. Also, as shown in Table 3, each of our proposed losses helps improve the quantitative metrics, and the Proposed full model achieves the best results. Both the qualitative and quantitative results of our ablation studies verify the proposed methods’ effectiveness.

Concluding Remarks

A new adversarial training framework for image inpainting with segmentation confusion adversarial training (SCAT) and contrastive learning is presented in the paper. SCAT formulates a novel adversarial game between an inpainting generator and a segmentation network, providing pixel-level local training signals and the flexibility of processing images with free-form holes for our framework. On the other hand, the proposed contrastive learning losses stabilize and improve our framework’s training and bring more realistic inpainting images by pulling the inpainting images closer to the ground truth images and pushing them farther away from the corrupted images in the representation space of the discriminator. Extensive experiments on two benchmark datasets demonstrate the effectiveness of the proposed method. Future work may include verifying the effectiveness of the proposed objectives on other GAN-based inpainting frameworks and extending our framework to diversified inpainting.

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