SDM: Spatial Diffusion Model for Large Hole Image Inpainting

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Figure 1. Our spatial diffusion model supports photo-realistic large-hole inpainting for various scenarios. The first example is a high-resolution image captured in the wild, while the others (512 × 512) come from Places2 [82] and CelebA-HQ [23] datasets.

Abstract

Generative adversarial networks (GANs) have made great success in image inpainting yet still have difficulties tackling large missing regions. In contrast, iterative algorithms, such as autoregressive and denoising diffusion models, have to be deployed with massive computing resources for decent effect. To overcome the respective limitations, we present a novel spatial diffusion model (SDM) that uses a few iterations to gradually deliver informative pixels to the entire image, largely enhancing the inference efficiency. Also, thanks to the proposed decoupled probabilistic modeling and spatial diffusion scheme, our method achieves high-quality large-hole completion. On multiple benchmarks, we achieve new state-of-the-art performance. Code is released at https://github.com/fenglinglwb/SDM.

1. Introduction

Image inpainting, a fundamental computer vision task, aims to fill the missing regions in an image with visually pleasing and semantically appropriate content. It has been extensively employed in graphics and imaging applications, such as photo restoration [60, 61], image editing [3, 21], compositing [32], re-targeting [8], and object removal [10]. This task, especially filling large holes, is more ill-posed than other restoration problems, necessitating models of stronger generation abilities.

In past years, generative adversarial networks (GANs) have made great processes in image inpainting [34, 37, 43, 62, 69, 71]. By implicitly modeling a target distribution through a min-max game, GANs-based methods significantly outperform traditional exemplar-based techniques [9, 10, 16, 55] in terms of visual quality. However, the
one-shot generation of these approaches sometimes results in unstable training [14, 28, 51] and makes it challenging to learn a complex distribution, particularly when inpainting large holes in high-resolution images.

Conversely, autoregressive models [42, 57, 58] and denoising diffusion models [11, 19, 53] recently demonstrated remarkable power in content generation [44, 49, 52, 73]. With tractable probabilistic modeling, they iteratively improve the image based on the prior estimation. In this regard, the training is more stable, and better coverage is attained. It is also common knowledge that autoregressive models process images pixel by pixel, making it difficult to handle high-resolution data. On the other hand, denoising diffusion models usually require thousands of iterations to reach good estimations. Thus, using these methods directly in image inpainting incurs respective drawbacks – strategies for high-quality large-hole high-resolution image inpainting still fall short.

To complete the map of inpainting, in this paper, we develop a new spatial diffusion model (SDM) tailored for the large-hole scenario. SDM works in an iterative way, where all pixels are predicted in parallel at each iteration, and only qualified ones are kept for the next iteration. It acts as a process to gradually diffuse trustful pixels to unknown locations. Our core design lies in a simple yet highly effective decoupled probabilistic modeling (see Sec. 3.1.1), which enjoys the merits of GANs’ efficient optimization and the tractability of probabilistic models. In detail, our model simultaneously predicts an inpainted result (i.e., the mean term) and an uncertainty map (i.e., the variance term). The mean term is optimized by implicit adversarial training, yielding more accurate predictions with fewer iterations. The variance term, contrarily, is modeled explicitly using Gaussian regularization.

This decoupled strategy yields several advantages. First, the number of iterative steps is significantly decreased thanks to adversarial optimization. As shown in Fig. 2, a few iterations can produce promising results. Second, the variance term yielded from Gaussian regularization naturally acts as an uncertainty measure, allowing us to choose reliable estimates for iterative refinement (see Sec. 3.1.2). Also, explicit distribution modeling makes continuous sampling possible, leading to predictions with improved quality and diversity, as demonstrated in Sec. 4. Finally, the uncertainty measure aids in building an uncertainty-guided attention mechanism (see Sec. 3.2), which encourages the network to exploit more informative pixels for efficient reasoning. As a result, our SDM completes large missing regions with photo-realistic content, as illustrated in Fig. 1.

Our contributions can be summarized as follows:

- We develop a novel spatial diffusion model (SDM) customized for large-hole image inpainting. Thanks to the proposed decoupled probabilistic modeling and spatial diffusion scheme, our model achieves efficient optimization and high-quality completion.
- Our method reaches cutting-edge performance on both Places [82] and CelebA-HQ [23] benchmark datasets. Notably, our SDM outperforms popular denoising diffusion models, e.g., LDM [46], by a large margin, yielding 1.1 FID improvement on Places2 [82] while being significantly more light-weighted (20% parameters, 10× faster).

2. Related Work

2.1. Traditional Methods

Image inpainting is a classical computer vision problem. Early methods make use of image priors, such as self-similarity and sparsity. Diffusion-based methods [2, 5], for instance, convey information to the holes from nearby undamaged neighbors. Another line of exemplar-based approaches [9, 12, 16, 29, 31, 55] looks for highly similar patches to complete missing regions using human-defined distance metrics. The most representative work is Patch-Match [3], which employs heuristic searching in a multi-scale image space to speed up inpainting greatly. However, due to a lack of context understanding, they do not guarantee visually appealing and semantically consistent results.

2.2. Deep Learning Based Methods

Using a great amount of training data to considerably increase the ability of high-level understanding, deep-neural-network-based methods [36, 43, 64, 69, 75] achieve success. Pathak et al. [43] introduce the adversarial loss [13] to
inpainting, yielding visually realistic results. Several approaches along this line continually push the performance to new heights. For example, in order to obtain locally fine-grained details and globally consistent structures, Iizuka et al. [20] adopt two discriminators for adversarial training. Additionally, partial [35] and gated [72] convolution layers are proposed to reduce artifacts, e.g., color discrepancy and blurriness, for irregular masks. Moreover, intermediate cues, including foreground contours [68], object structures [40, 45], and segmentation maps [54] are used in multi-stage generation. Despite nice inpainting content for small masks, these methods still do not guarantee large-hole inpainting quality.

2.3. Large Hole Image Inpainting

To deal with large missing regions, a surge of effort was made to improve the model capability. Attention techniques [37, 67, 70, 71] and transformer architectures [34, 62, 81] take advantage of context information. They work well when an image contains repeating patterns. Besides, Zhao et al. [80] propose a novel architecture, bridging the gap between image-conditional and unconditional generation, improving free-form large-scale image completion. There are also attempts to study the progressive generation. This line is to select only high-quality pixels each time and gradually fill holes. We note that these methods heavily rely on specially designed update algorithms [15, 33, 41, 78], or consume additional model capacity for assessing the accuracy of prediction [77], or need more training stages [7] when processing images.

Recently, benefiting from exact likelihood computation and iterative samplings, autoregressive models [62, 66, 74] and denoising diffusion models [1, 38, 46, 48] have shown great potential in producing diversified and realistic content. They inevitably incur high inference costs with thousands of steps and require massive computation resources. In this work, we present a novel framework that gradually diffuses the most reliable predictions based on an inherent uncertainty measure, supporting high-quality image completion with substantially fewer iterations.

3. Our Method

Our objective is to use photo-realistic material to complete a masked image with substantial missing areas. In this section, we first formulate our spatial diffusion model (SDM) along with a comprehensive analysis. It is followed by the details of model design and loss functions.

3.1. Spatial Diffusion Model

Although GANs-based methods achieve significantly better results than traditional ones, they still face great difficulties handling large missing regions. We attribute one of the reasons to the one-shot nature of GANs and instead propose iterative inpainting. In each pass, since there are inevitably some good predictions, we use these pixels as clues to assist the next-time generation. In this way, our spatial diffusion model gradually propagates valuable information to the entire image. In the following, we first discuss the single-pass modeling before moving on to the diffusion process.

3.1.1 Decoupled Probabilistic Modeling

For iterative inpainting, it is essential to find a mechanism to evaluate the accuracy of predictions. One intuitive solution is introducing a tractable probabilistic model so that uncertainty information can be analytically calculated. However, this requirement often leads to the assumption that...
the approximated target distribution is Gaussian, which is considerably too simple to explain the truly complicated distributions. Although several iterative models, such as denoising diffusion models [19], enrich the expression of marginal distribution by including a number of hidden variables and optimizing the variational lower evidence bound, these methods typically yield a high inference cost.

To address these key issues, we propose a decoupled probabilistic modeling tailored for efficient iterative inpainting. The essential insight is that we leverage the advantages of implicit GANs-based optimization and explicit Gaussian regularization in a decoupled way. Thus we can simultaneously obtain accurate predictions and explicit uncertainty measures.

As shown in Fig. 3, given an input image \( x_t \) at time \( t \) with large holes, our model (see architecture details in Sec. 3.2) predicts the inpainting result \( \mu_t \) as well as an uncertainty map \( \sigma^2_t \). We use the adversarial loss (along with other losses of Sec. 3.3) to supervise image prediction \( \mu_t \), while jointly treating \((\mu_t, \sigma^2_t)\) as the mean and diagonal covariance of Gaussian distribution. GANs’ implicit optimization makes it possible to approximate the true distribution as closely as possible, greatly reducing the number of iterations. It also supplies us with an explicit uncertainty measure for the mean term, allowing us to select reliable pixels. The Gaussian regularization is mainly applied to the variance term using negative log likelihood (NLL) \( L_{\text{all}} \) as

\[
L_{\text{all}} = -\sum_{i=1}^{D} \log \int_{\delta_+(y)}^{\delta_-(y)} N \left( y; \sg(x), \sigma^2 \right) dy,
\]

where \( D \) is the data dimension and \( i \) is the pixel index, \( \theta \) denotes model parameters, and input \( x \) and output \( y \) are scaled to \([-1, 1]\). \( \delta_+(y) \) and \( \delta_-(y) \) are defined as

\[
\delta_+(y) = \begin{cases} 
\infty & \text{if } y = 1, \\
y + \frac{1}{255} & \text{if } y < 1,
\end{cases}
\]

\[
\delta_-(y) = \begin{cases} 
-\infty & \text{if } y = -1, \\
y - \frac{1}{255} & \text{if } y > -1.
\end{cases}
\]

Specifically, we include a stop-gradient operation \((i.e., \sg(\cdot))\), which encourages the Gaussian constraint only to optimize the variance term and allows the mean term to be estimated from more accurate implicit modeling.

**Discussion.** We use the estimated mean and variance for sampling during the diffusion process, while taking the deterministic mean term as the output for the final iteration. The feasibility of this design is proved by the experiments in Sec. 4. Additionally, the probabilistic modeling enables us to apply continuous sampling during diffusion, yielding higher quality and more diverse estimations. Finally, we find the uncertainty measure also enables us to design a more effective attention mechanism in Sec. 3.2.

### 3.1.2 Spatial Diffusion Scheme

We use a feed-forward network, denoted as \( f_\theta(\cdot) \), to gradually diffuse informative pixels to the entire image, starting from known regions as

\[
x_t, m_t, u_t = f_\theta(x_{t-1}, m_{t-1}, u_{t-1}),
\]

where \( t \) is the time step, \( x_t \) refers to the masked image, \( m_t \) stands for a binary mask, and \( u_t \) is the uncertainty map. The output includes the updated image, mask, and uncertainty map. Network parameters are shared across all iterations.

We use several iterations for both training and testing to improve performance. Specifically, as shown in Fig. 3 and Eq. (4), our method runs as follows at the \( t \)-th iteration.

1. **Predict.** Given the masked image \( x_{t-1} \), mask \( m_{t-1} \), and uncertainty map \( u_{t-1} \), our method estimates mean \( \mu_t \) and variance \( \sigma^2_t \) for all pixels. Then a preliminary uncertainty map \( \hat{u}_t \) scaled to \([0, 1]\) is generated by converting the variance map.

2. **Pick.** We first sort the uncertainty scores for unknown pixels. According to the pre-defined mask schedule, we calculate the number of pixels that are to be added in this iteration, and insert those with the lowest uncertainty to the known category, updating the mask to \( m_t \). Based on the preliminary uncertainty map \( \hat{u}_t \), by marking locations that are still missing as \( 1 \) and the initially known pixels as \( 0 \), we obtain the final uncertainty map \( u_t \).

3. **Sample.** We consider two situations. First, for the initially known locations \( m_0 \), we always use the original input pixels \( x_0 \). Second, we apply continuous sampling in accordance with \( \mu_t \) and \( \sigma_t \) for the inpainting areas. The result is formulated as

\[
x_t = x_0 + (m_t - m_0) \circ (\mu_t + \alpha \cdot \sigma_t \odot z),
\]

where \( \alpha \) is an adjustable ratio and \( z \sim N(0, I) \), and \( \circ \) denotes the Hadamard product. Note that we do not use the \( \sigma_t \odot z \) term in the final iteration.

### 3.2 Model Architecture

We use a deep U-Net [47] architecture with a Style-GAN [25, 26] decoder, reaching large receptive fields with stacked convolutions to take advantage of context information in images [4, 6, 39, 63]. In addition, we introduce multi-ple attention blocks at various resolutions, in light of the discovery that global interaction significantly improves reconstruction quality on much larger and more diverse datasets at higher resolutions [11, 70, 71].

Based only on feature similarity, the conventional attention mechanism [59] offers equal opportunity for pixels to exchange information. For the inpainting task, however,
missing pixels are initialized with the same specified values, making them close to one another. As a result, it is usually unable to effectively leverage useful information from visible regions. Even worse, the valid pixels are compromised, resulting in blurry content and unpleasing artifacts.

In this situation, as shown in Fig. 4, we take into account the pixels’ uncertainty scores to adjust the aggregating weights in attention. It properly resolves the problem mentioned above. The attention output is computed by

\[
\text{Attention}(q, k, v, u) = \text{Softmax} \left( \frac{qk^T}{\sqrt{dk}} + \mathcal{F}(u) \right) v, \tag{6}
\]

where \(\{q, k, v\}\) are the query, key, value matrices, \(dk\) denotes the scaling factor, and \(\mathcal{F}\) represents learnable functions that predict biased pixel weights based on the uncertainty map \(u\) and also include a reshape operation.

### 3.3. Loss Functions

In each iteration, our model outputs the mean and variance estimates, as shown in Fig. 3. The mean term is optimized using adversarial loss [13] \(\mathcal{L}_{adv}\) and perceptual loss [22, 56] \(\mathcal{L}_{pep}\), which aims to produce natural-looking images. The losses are described as follows.

**Adversarial loss.** We formulate the adversarial loss as

\[
\mathcal{L}_{adv} = -\mathbb{E}_x [\log (D(\hat{x}))] \tag{7}
\]

\[
\mathcal{L}_{adv} = -\mathbb{E}_x [\log (D(x))] - \mathbb{E}_\varepsilon [\log (1 - D(\varepsilon))] \tag{8}
\]

where \(D\) is the discriminator implemented as [25], \(x\) and \(\hat{x}\) are real and predicted images.

**Perceptual loss.** We adopt a high receptive field perceptual loss [56], which is formulated as

\[
\mathcal{L}_{pep} = \sum_i \|\phi_i(x) - \phi_i(\hat{x})\|_2^2, \tag{9}
\]

where \(\phi_i\) is the layer output of a pre-trained ResNet50 [17].

As discussed in Sec. 3.1.1, we apply the negative log likelihood \(\mathcal{L}_{nll}\) to constrain the variance for uncertainty modeling. Thus the final loss function for the generator is

\[
\mathcal{L} = \sum_j \lambda_1 \mathcal{L}_{adv}^j + \lambda_2 \mathcal{L}_{pep}^j + \lambda_3 \mathcal{L}_{nll}^j, \quad \tag{10}
\]

where \(j\) is the number of diffusion iterations. We empirically set \(\lambda_1 = 1, \lambda_2 = 2\) and \(\lambda_3\) to \(1 \times 10^{-4}\).

### 4. Experiments

#### 4.1. Datasets and Metrics

We train our models at \(512 \times 512\) resolution on Places2 [82] and CelebA-HQ [23] in order to adequately assess the proposed method. Places2 is a large-scale dataset with nearly 8 million training images in various scene categories. Additionally, 36,500 images make up the validation split. During training, images undergo random flipping, cropping, and padding, while testing images are centrally cropped to the \(512 \times 512\) size. For CelebA-HQ, we employ 24,183 and 2,993 images, respectively, to train and test our models. We construct free-form masks using rectangles and brush strokes with different sizes, shapes, and positions, which follows the widely used setup [56, 72, 80]. Besides, we evaluate all models using identical masks provided by [34] for a fair comparison.

Despite being adopted in early inpainting work, L1 distance, PSNR, and SSIM [65] are found not strongly associated with human perception when assessing image quality [30, 50]. In this work, in light of [34, 80], we use FID [18], P-IDS [80], and U-IDS [79], which robustly measures the perceptual fidelity of inpainted images, as more suitable metrics.

#### 4.2. Implementation Details

We use an encoder-decoder architecture. The encoder is made up of convolution blocks, while the decoder is adopted from StyleGAN2 [26]. The encoder’s channel size starts at 64 and doubles after each downsampling until the maximum of 512. The decoder has a symmetrical configuration. We adopt attention blocks at \(32 \times 32\) and \(16 \times 16\) resolutions for both the encoder and decoder. The uncertainty map is initialized as “1 - mask” at the first iteration.

During training, images undergo random flipping, cropping, and padding, while testing images are centrally cropped to the \(512 \times 512\) size. For CelebA-HQ, we employ 24,183 and 2,993 images, respectively, to train and test our models. We construct free-form masks using rectangles and brush strokes with different sizes, shapes, and positions, which follows the widely used setup [56, 72, 80]. Besides, we evaluate all models using identical masks provided by [34] for a fair comparison.

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Table 1. Quantitative ablation study of the number of training iterations, modeling and sampling strategies, and architecture designs. Model “A” refers to the full model. Models “B” and “C” use fewer iterations. We tease apart the decoupled probabilistic modeling (DPM), continuous sampling (CS), and uncertainty-guided attention (UGA) in models “D”, “E”, and “F”. Model “G” only adopts attention blocks at 16 × 16 resolution.

| Model | Iter. | DPM | CS | UGA | Att. Res. | FID↓ |
|-------|-------|-----|----|-----|-----------|------|
| A     | 3     | ✓   | ✓  | ✓   | 32,16     | 2.36 |
| B     | 1     | -   | -  | ✓   | 32,16     | 2.95 |
| C     | 2     | ✓   |    | ✓   | 32,16     | 2.55 |
| D     | 3     | ✓   |    | ✓   | 32,16     | 2.49 |
| E     | 3     | ✓   |    | ✓   | 32,16     | 2.45 |
| F     | 3     | ✓   |    | ✓   | 32,16     | 2.44 |
| G     | 3     | ✓   | ✓  | ✓   | 16        | 2.64 |

Table 2. Quantitative ablation study of the number of testing iterations. As the number of iterations increases, the FID↓ results get better and then saturate.

```
| Iter. | 4   | 5   | 6   | 7   | 8   | 9   | 10   |
|-------|-----|-----|-----|-----|-----|-----|------|
| Model A | 2.23 | 2.16 | 2.12 | 2.09 | 2.07 | 2.05 | 2.05 |
| Model B | 2.27 | 2.20 | 2.16 | 2.14 | 2.12 | 2.11 | 2.11 |
```

Based on experimental results. To generate 512 × 512 images, we iterate twice for training and four times for testing. The fact that previous work [34, 80] trains models on Places2 with 50M or more images – much more extensive data than ours – evidences the benefit of our method. It is found that additional training can further improve our approach, and yet 20M images currently already deliver cutting-edge performance.

### 4.3. Ablation Study

In this section, we conduct a comprehensive investigation of the proposed designs in our method. For quick evaluation, we train our models for 6M images at 256 × 256 resolution using Places365-Standard, a subset of Places2 [82]. We start with model “A”, which employs our full designs and adopts three iterations during training.

**Iterative number.** Our core idea is to employ iterative optimization to enhance the generation quality. We adjust the iteration number and maintain the same setup during training and testing. As illustrated in Table 1, models with one and two iterations, dubbed “B” and “C”, yield 0.59 and 0.19 FID decreases compared to model “A”. Additionally, as shown in Fig. 2, adopting more iterations is capable of producing more aesthetically pleasing content. The first and third cases exhibit obviously fewer artifacts, and the arch in the second example is successfully restored after three iterations. Both the quantitative and qualitative results manifest the importance of iterative generation.

It is noted that we can test the system with a different number of iterations from the training stage. Using more iterations results in higher FID performance, as demonstrated in Table 2, yet at the expense of longer inference time. Thus, there is a trade-off between inference speed and generation quality. Additionally, when comparing models “A” and “B”, it is clear that introducing more iterations in the training process is beneficial. But the number of iterations in the inference stage is more important.

**Decoupled probabilistic modeling.** To deliver accurate prediction while supporting the uncertainty measure for iterative inpainting, we propose decoupled probabilistic modeling. When putting all supervision on the sampled result, we observe the training diminishes the variance term (close to 0 for all pixels). It is because, unlike denoising diffusion models that precisely quantify the noise levels at each step, our GANs-based method no longer provides specific optimization targets for the mean and variance terms. The variance term is underestimated for trivial optimization in this case. It renders the picking process less effective.

As illustrated in Table 1, model “D” obtains an inferior FID result compared with the full model “A”. Besides, from the visual comparison in Fig. 5, it is observed that model “D” tends to generate blurry content, while model “A” produces sharper structures and fine-grained details. All these observations prove the effectiveness of this design.

**Continuous sampling.** Our approach may use the estimated variance to perform continuous sampling. Table 1
Table 3. Quantitative comparisons on Places [82] and CelebA-HQ [23]. “†”: the officially released Stable Diffusion inpainting model trained on a large-scale high-quality dataset LAION-Aesthetics V2 5+. Our method achieves the best performance under both large and small mask settings. The best and second best results are in red and blue.

Table 4. Ablation study of mask schedule functions.

Figure 7. Visualization of mask schedule functions.

Besides, as aforementioned in Sec. 3.2, the conventional attention mechanism may result in color consistency and blurriness. To support this claim, we tease apart the uncertainty guidance and notice a minor performance drop in Table 1. Also, we provide a visual comparison in Fig. 5. We observe that model “A” produces more visually appealing window details than model “F”.

**Uncertainty-guided attention.** To fully exploit distant context, we add attention blocks to our framework. We first compare using attention at $32 \times 32$, $16 \times 16$ (model “A”) and only at $16 \times 16$ (model “G”). We discover a 0.28 FID drop in model “G” from the quantitative comparison in Table 1, demonstrating the significance of long-range interaction in large-hole image inpainting.

**Mask schedule.** As illustrated in Table 4 and Fig. 7, we analyze various mask schedule strategies and discover that the uniform strategy achieves the best FID. We argue that this is because the mask ratios of input images vary widely, and uniform schedule results in more stable training for different iterations.

### 4.4. Comparisons to State-of-the-Art Methods

We thoroughly compare the proposed spatial diffusion model (SDM) with GANs-based models [34, 56, 70, 72, 76, 80, 83], autoregressive models [62], and denoising diffusion models [46] in Table 3. Although the last two lines have lately made notable progress even for commercial use, the majority of off-the-shelf techniques can only handle images with up to $256 \times 256$ resolution. We use publicly accessible
models for $512 \times 512$ resolution and test them on the same masks to make a fair comparison.

As shown in Table 3, our SDM achieves the state-of-the-art performance on Places2 and CelebA-HQ benchmarks under both large and small mask settings. It can be seen that our method significantly performs better than the existing GANs-based models. Besides, even with only 20% of the parameters of strong denoising diffusion model LDM [46], our method delivers superior results in terms of all metrics. For example, on the Places2 benchmark, our SDM brings about 1.1 improvement on FID and larger gains on P-IDS and U-ID under the large mask setup. As for the inference speed, our SDM costs nearly 250ms to obtain a $512 \times 512$ image, which is $10 \times$ faster than LDM ($\sim$3s). Notably, our model is trained using far fewer samples (our 20M images vs. CoModGAN’s [80] 50M images). We observe that more extended training can further boost performance. All these results demonstrate the effectiveness of our method.

We also provide visual comparisons in Fig. 8. In a variety of scenes, our method generates more aesthetically pleasing textures with fewer artifacts when compared to existing methods. For instance, room layouts and building structures are better inpainted by our approach. More examples are provided in the supplementary materials.

5. Conclusion

We have proposed a new spatial diffusion model for large-hole image inpainting. Utilizing the proposed decoupled probabilistic modeling and spatial diffusion scheme, our method can assess the prediction accuracy and retain the pixels with the lowest uncertainty as hints for subsequent processing, yielding high-quality completion. The state-of-the-art results on multiple benchmarks demonstrate the effectiveness of our method.

Limitation analysis. Despite the fact that our method can generate diverse content in missing areas, we observe it tends to deliver more changes in small details rather than in large structures. We will further improve the diversity of our generation. Besides, our method occasionally has trouble understanding objects when only a few hints are given. In the supplemental materials, we display a few failure cases.
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SDM: Spatial Diffusion Model for Large Hole Image Inpainting
(Supplementary Material)

A. Architecture Details

Apart from the descriptions in Sec. 3.2 and Sec. 4.2, we here provide a more through illustration of architecture details. We adopt a U-Net architecture with skip connections, where the encoder downsamples the size of an $H \times W$ input to $\frac{H}{2^n} \times \frac{W}{2^n}$ and the decoder upsamples it back to $H \times W$. At each resolution, there is just one residual block made up of two $3 \times 3$ convolutional layers, unless otherwise stated. Both the encoder and the decoder employ attention blocks at feature sizes of $\frac{H}{16} \times \frac{W}{16}$ and $\frac{H}{32} \times \frac{W}{32}$, and an early convolutional block is also introduced at these scales. Different attention blocks use adaptive mapping functions in Fig. 4, each of which is composed of 4 convolutional layers with a kernel size of $3 \times 3$.

The input consists of 7 channels: 3 for color images, 1 for the initial mask, 1 for the updated mask, 1 for the uncertainty map, and 1 for the time step. The number of channels is initially converted to 64, then doubled after each downsampling, up to a maximum of 512, and the decoder employs a symmetrical setup. The output contains 6 channels: 3 for the mean term and 3 for the log variance term.

We use a weight modulation technique, where the style representation is derived from an image global feature and a random latent code. As for the global feature, we employ convolutional layers to further downsample the feature size from $\frac{H}{2^n} \times \frac{W}{2^n}$ to $\frac{H}{2^{n+1}} \times \frac{W}{2^{n+1}}$ and a global pooling layer to obtain 1/d representation. The random latent code is mapped from Gaussian noise by 8 fully connected layers.

B. Generalization to $1024 \times 1024$ Resolution

To evaluate the generalization ability of models, we compare our spatial diffusion model (SDM), MAT [34] and LaMa [56] trained on $512 \times 512$ Places2 [82] at the $1024 \times 1024$ resolution. As illustrated in Table B.1, our SDM performs significantly better than MAT and LaMa on all metrics, despite using fewer training samples. Remarkably, our approach results in an approximately 1.9 FID improvement. We do not involve denoising diffusion models (e.g., LDM) and other GANs-based models (e.g., CoModGAN) for comparisons because scaling them up to the $1024 \times 1024$ resolution is impractical.

C. $512 \times 512$ LPIPS Results

LPIPS [79] is also a widely used perceptual metric in image inpainting. For a comprehensive comparison with state-of-the-art methods, we provide LPIPS results in Table C.2. We argue that LPIPS may not be suitable for large-hole image inpainting because it is calculated pixel-by-pixel. This measure is for reference only.

D. $256 \times 256$ CelebA-HQ Results

We also conduct quantitative comparisons on $256 \times 256$ CelebA-HQ [23] dataset. As shown in Table D.3, our method achieves the best performance among all methods.

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| Method          | #Param. $\times 10^6$ | Places   | CelebA-HQ |
|-----------------|-----------------------|----------|-----------|
| SDM (Ours)      | 74                    | 0.084    | 0.161     | 0.052     | 0.099     |
| Stable Diffusion | 860                   | 0.148    | 0.220     | -         | -         |
| LDM [46]        | 387                   | 0.100    | 0.190     | -         | -         |
| MAT [34]        | 62                    | 0.099    | 0.189     | 0.065     | 0.125     |
| CoModGAN [80]   | 109                   | 0.101    | 0.192     | 0.073     | 0.140     |
| LaMa [56]       | 51/27                 | 0.086    | 0.166     | 0.075     | 0.143     |
| ICT [62]        | 150                   | -        | -         | 0.105     | 0.195     |
| MADF [83]       | 85                    | 0.095    | 0.181     | 0.068     | 0.130     |
| AOT GAN [76]    | 15                    | 0.101    | 0.195     | 0.074     | 0.145     |
| HFill [70]      | 3                     | 0.148    | 0.284     | -         | -         |
| DeepFill v2 [72]| 4                     | 0.113    | 0.213     | 0.117     | 0.221     |
| EdgeConnect [40]| 22                    | 0.114    | 0.275     | 0.101     | 0.208     |

Table C.2. LPIPS↓ results on $512 \times 512$ Places2 [82] and CelebA-HQ [23] datasets. “↑”: our models are trained with 20M samples, much less than other methods (e.g., MAT uses 50M samples on Places2 and 25M samples on CelebA-HQ). We use a single model for both the small and large mask setups. "↓": the official Stable Diffusion inpainting model is trained on a large-scale high-quality dataset LAION-Aesthetics V2 5+. The best and second best results are in red and blue.
### Table D.3. Quantitative comparisons on 256 × 256 CelebA-HQ [23] dataset. The P-IDS and U-IDS results are shown in percentage (%). “†”: our model is trained with 12M samples, far less than other methods (e.g., MAT uses 25M samples). We use a single model for both the small and large mask setups. The best and second best results are in red and blue.

| Method        | Small Mask |         | Large Mask |         |
|---------------|------------|---------|------------|---------|
|               | FID↓       | P-IDS↑  | U-IDS↑     | FID↓   | P-IDS↑  | U-IDS↑     |
| SDM (Ours)†   | 2.58 21.35 | 33.70   | 4.57 14.07 | 25.28  |
| MAT [34]      | 2.94 20.88 | 32.01   | 5.16 13.90 | 25.13  |
| LaMa [56]     | 3.98 8.82  | 22.57   | 8.75 2.34  | 8.77   |
| ICT [62]      | 5.24 4.51  | 17.39   | 10.92 0.90 | 5.23   |
| MADF [83]     | 10.43 6.25 | 14.62   | 23.59 0.50 | 1.44   |
| AOT GAN [76]  | 9.64 5.61  | 14.62   | 22.91 0.47 | 1.65   |
| DeepFill v2 [72] | 5.69 6.62 | 16.82   | 13.23 0.84 | 2.62   |
| EdgeConnect [40] | 5.24 5.61 | 15.65   | 12.16 0.84 | 2.31   |

Figure E.1. Visual examples of diverse generation for our method.

**E. Additional Pluralistic Generation**

As shown in Fig. 6 and Sec. 5, our method also supports pluralistic generation. From the visual examples in Fig. E.1, we see that the differences mainly lie in the fine-grained details. We will work on improving the generating diversity.

**F. Failure Cases**

As discussed in Sec. 5, our model sometimes fails to recover the damaged objects when limited clues are provided. We show some failure cases in Fig. F.2. For instance, the missing part of the notebook is filled with the background, and the recovered bus structure is incomplete. We attribute one of the reasons to the lack of high-level semantic understanding. We will further improve the generative capability of our model.

**G. Additional Qualitative Comparisons**

We provide more visual examples on 512 × 512 Places2 [82] and CelebA-HQ [23] in Fig. G.3, Fig. G.4, Fig. G.5, Fig. G.6, and Fig. G.7. Compared to other methods, our SDM generates more photo-realistic and semantically consistent content. For example, our method successfully recovers human legs, airplane structures, and more realistic indoor and outdoor scenes.
Figure G.3. Qualitative side-by-side comparisons of state-of-the-art methods on $512 \times 512$ Places2 dataset. Please zoom in for a better view. Our SDM produces structures and details that are more realistic and reasonable.
Figure G.4. Qualitative side-by-side comparisons of state-of-the-art methods on 512 × 512 Places2 dataset. Please zoom in for a better view. Our SDM produces structures and details that are more realistic and reasonable.
Figure G.5. Qualitative side-by-side comparisons of state-of-the-art methods on $512 \times 512$ Places2 dataset. Please zoom in for a better view. Our SDM produces structures and details that are more realistic and reasonable.
Figure G.6. Qualitative side-by-side comparisons of state-of-the-art methods on $512 \times 512$ CelebA-HQ dataset. Please zoom in for a better view. Our SDM produces face outlines and details that are more realistic and reasonable.
Figure G.7. Qualitative side-by-side comparisons of state-of-the-art methods on 512 × 512 CelebA-HQ dataset. Please zoom in for a better view. Our SDM produces face outlines and details that are more realistic and reasonable.