Bridging Global Context Interactions for High-Fidelity Image Completion

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Figure 1. Example completion results of our method on different sceneries with various masks (missing regions shown in white, a transparency ratio is set for better visualization). Our TFill model not only effectively removes large objects (left), but also infers reasonable contents and plausible appearances for semantical image completion on various settings (right). (Zoom in to see the details.)

Abstract

Bridging global context interactions correctly is important for high-fidelity image completion with large masks. Previous methods attempting this via deep or large receptive field (RF) convolutions cannot escape from the dominance of nearby interactions, which may be inferior. In this paper, we propose to treat image completion as a directionless sequence-to-sequence prediction task, and deploy a transformer to directly capture long-range dependence. Crucially, we employ a restrictive CNN with small and non-overlapping RF for weighted token representation, which allows the transformer to explicitly model the long-range visible context relations with equal importance in all layers, without implicitly confounding neighboring tokens when larger RFs are used. To improve appearance consistency between visible and generated regions, a novel attention-aware layer (AAL) is introduced to better exploit distantly related high-frequency features. Overall, extensive experiments demonstrate superior performance compared to state-of-the-art methods on several datasets. Code is available at https://github.com/lyndonzheng/TFill.

1. Introduction

Image completion refers to the task of filling reasonable content with photorealistic appearance into missing regions, conditioned on partially visible information (as shown in Fig. 1). Earlier methods infer the pixels of missing regions by propagating pieces from neighboring visible regions [1–3,9], while more recent ones directly learn to generate content and appearance using deep neural networks [17, 28, 29, 35–37, 47, 51, 52, 54, 60].

A main challenge in this task is the requirement of bridging and exploiting visible information globally, after it had been degraded by arbitrary masks. As depicted on the left of Fig. 1, when the entire person is masked, the natural expectation is to complete the masked area based on the visible background context. In contrast, on the right of Fig. 1, when large free-form irregular masks cover the main parts but leave the partial information visible, it is necessary but highly challenging to correctly capture long-range depen-
dencies between the separated foreground regions, so that the masked area can be completed in not just a photorealistic, but also semantically correct, manner.

To achieve this goal, several two-stage approaches [35, 37, 51, 52, 54] have been proposed, consisting of a content inference network and an appearance refinement network. They typically infer a coarse image/edge/semantic map based on globally visible context in a first phase, and then fill in visually realistic appearances in a second phase. However, this global perception is achieved by repeating local convolutional operations, which have several limitations. First, due to the translation equivariance, the information flow tends to be predominantly local, with global information only shared gradually through heat-like propagation across multiple layers. Second, during inference, the elements between adjacent layers are connected via learned but fixed weights, rather than input-dependent adaptive weightings. These issues mean long-distance messages are only delivered inefficiently in a very deep layer, resulting in a strong inclination for the network to fill holes based on nearby rather than distant visible pixels (cf. Fig. 1).

In this paper, we propose an alternative perspective by treating image completion as a directionless sequence-to-sequence prediction task. In particular, instead of modeling the global context using deeply stacked convolutional layers, we design a new content inference model, called TF Fill, that uses a transformer-based architecture to fill reasonable content into the missing holes. An important insight here is that a transformer directly exploits long-range dependencies at every encoder layer through an equal flowing opportunity for all visible pixels, regardless of their relative spatial positions (Fig. 4(c)). This reduces the proximity-dominant influence that can lead to semantically incoherent results.

However, it remains a challenge to directly apply these transformer models to visual generation tasks. In particular, unlike in NLP where each word is naturally treated as a vector for token embedding [10, 39, 40, 46], it is unclear what a good token representation should be for a visual task. If we use every pixel as a token, the memory cost will make this infeasible except for very small downsampled images [8, 47]. To mitigate this issue, our model embeds the masked image into an intermediate latent space for token representation, an approach also broadly taken by recent vision transformers [6, 12, 49, 62, 64]. However, unlike these models that use conventional CNN-based encoders to embed the tokens, we propose a restrictive CNN for token representation, which has a profound influence on how the visible information is connected in the network. To do so, we ensure the individual tokens represent visible information independently, each within a small and non-overlapping patch, and forces the long-range context relationships between tokens to be explicitly and co-equally perceived in every transformer encoder layer. As a result, each masked pixel will not be gradually affected by neighboring visible pixels.

While the proposed transformer-based architecture can achieve better results than state-of-the-art methods [12, 51, 52, 60], by itself it only works for a fixed sequence length because of the position embedding (Fig. 2(a)). To allow our approach to flexibly scale to images of arbitrary sizes, especially at high resolution, a fully convolutional network (Fig. 2(b)) is subsequently applied to refine the visual appearance, building upon the coarse content previously inferred. A novel Attention-Aware Layer (AAL) is inserted between the encoder and decoder that adaptively balances the attention paid to visible and generated content, leading to semantically superior feature transfer (Figs. 5 and 9).

We highlight our main contributions as follows: 1) A restrictive CNN head is introduced for individual weighted token representation, which mitigates the proximity influence when propagating visible information to missing holes. 2) Through a transformer-based architecture, the long-range interactions between these tokens are explicitly modeled, in which the masked tokens are perceptive of other visible tokens with equal opportunity, regardless of their positions. 3) A novel attention-aware layer with adaptive attention balancing is introduced in a refined stage to obtain higher quality and resolution results. 4) Finally, extensive experiments demonstrate that the proposed model outperforms the existing state-of-the-art image completion models.

2. Related Work

Image Completion: Traditional image completion (also known as “image inpainting” [3]) methods, like diffusion-based [1, 4, 26] and patch-based [2, 9, 18], mainly focus on background completion, by directly copying and propagating the background pixels to masked regions.

Driven by the advances of GANs [13], CGANs [34] and VAEs [25], a series of CNN-based methods [17, 28, 35, 36, 44, 52, 59, 60] have been proposed to hallucinate semantic meaningful content. In particular, Pathak et al. [36] introduced GANs into image completion for large holes. Iizuka et al. [17] extended [36] to random regular mask. Yu et al. [52] combined the patch-based idea into learning-based architecture, which is followed by [42, 43, 51, 54, 55, 60]. Liu et al. [28] addressed random irregular masks. Zheng et al. [60, 61] introduced a pluralistic image completion task, aiming to generate multiple and diverse results, which is followed by [30, 37, 47, 58]. Nazeri et al. [35] brought the auxiliary edge information for image completion. Then, more auxiliary information were combined into this task, e.g. Faceshape [38]. DeepFill v2 [53], SC-FEGAN [20], SWAP [27], and MST [5]. Most of these models are built upon a CNN-based architecture, in which the masked re-
Visual Transformer: The Transformer was firstly proposed by Vaswani et al. [46] for machine translation. Inspired by the dramatic success of transformers in NLP [10, 40], recent works have explored applying a standard transformer for vision tasks [32], such as image classification [8, 11, 14], object detection [6, 64], semantic segmentation [48, 62], image generation and translation [8, 12, 16, 19], and completion [31, 47]. Many of these visual transformer-based works [6, 8, 11, 12, 16, 19, 47, 48, 62, 64], we discover how the token representation has a profound effect on the flow of visible information in image completion, in spite of the supposedly global reach of transformers. The latter network is designed to refine appearance by utilizing high-resolution visible features globally, and also frees the limitation to fixed sizes.

3. Methods

Given a masked image $I_{m}$, degraded from a real image $I$ by masks, our goal is to learn a model $\Phi$ to infer semantically reasonable content for missing regions, as well as filling in with visually realistic appearance.

To achieve this, our framework, illustrated in Fig. 2, consists of a content inference network (TFill-Coarse, Fig. 2(a)) and an appearance refinement network (TFill-Refined, Fig. 2(b)). The former is responsible for capturing the global context through a transformer encoder. The embedded tokens have small receptive fields (RF) and limited capacity, preventing masked pixels’ states from being implicitly dominated by visible pixels nearby than far. While similar transformer-based architectures have recently been explored for visual tasks [6–8, 11, 12, 16, 19, 47, 48, 62, 64], we discover how the token representation has a profound effect on the flow of visible information in image completion, in spite of the supposedly global reach of transformers. The latter network is designed to refine appearance by utilizing high-resolution visible features globally, and also frees the limitation to fixed sizes.

3.1. Content Inference Network: TFill-Coarse

Our TFill-Coarse depends on the self-attention module in a transformer-encoder to equally perceiving global visible context for the completed content generation. Considering the fixed length position embedding and dramatically increased computational cost, we first downsample images with arbitrary sizes to a fixed size, e.g. $256 \times 256$. However, it is still not feasible to run a transformer model if we directly flatten image pixels into a 2D sequence.

To obtain a practicable number of visual tokens, different embedding methods (Fig. 3(a)-(c)) have been used in current visual transformer-based works [6, 8, 11, 12, 16, 19, 47, 48, 62, 64]. These visual tokens’ RF is either as small as a pixel (e.g. iGPT [8]) that loses important context details due to the large-scale downsampling, or is as large as the full image size (e.g. VQGAN [12]) that has firstly been gradually influenced by neighboring pixels in deep CNN...
layers. While patch embedding [11] achieves impressive performance in many tasks, one-layer linear projection is still not good enough [49].

**Restrictive CNN:** In contrast to these methods, our token representation is extracted using a restrictive CNN (Fig. 3(d)) in 4 blocks. In each block, the $1 \times 1$ filter and layernorm is applied for non-linear projection, followed by a partial convolution layer [28] that uses a $2 \times 2$ filter with stride 2 to extract visible information. In particular, if half of the regions in a window are masked, we only embed the other 50% comprising visible pixels as our token representation, and establish an initial weight of 0.5 for the next weighted self-attention layer. To do this, we ensure each token represents only the visible information in a local patch, leaving the long-range dependencies to be explicitly modeled by a transformer, without cross-contamination from implicit correlation due to larger CNN RF.

In fact, some latest works also begin to explore the influence of different token embeddings. Swin [32] used shifted windows to get multi-scales embedded features. ViT [49] demonstrated an early CNN token embedding is important for visual transformer. However, they do not consider information flowing from visible to masked regions. When a large RF is applied into a deep CNN embedding, the masked holes will be gradually determined by the neighboring visible pixels. In Fig. 4, we empirically show this is precisely the case for prior CNN-based models. Because masked regions originally hold zero values, they will take the neighboring visible pixels as a filled and reasonable value for the next layer. In contrast, as the small patch is directly embedded using local visible information with important weight, the proposed restrictive CNN is better suited for image completion task.

**Weighted Self-Attention Layer:** To further bias the important visible values, we replace the self-attention layer with a weighted self-attention layer, in which a weight is applied to scale the attention scores. The initial weight $w_i \in \{0.02, 1.0\}$ is obtained by calculating the fraction of visible pixels in a small patch, e.g. 192/(16 x 16) means 192 pixels in the 16 x 16 patch are visible. It will then be gradually amplified by updating $w_i^{t+1} \leftarrow w_i^t$ after every encoder layer, to reflect visible information flow. This initial ratio for each token is efficiently implemented in our restrictive CNN encoder.

**CNN-based Decoder:** Following existing works [51, 52, 60], a gradual upsampling decoder is implemented to generate photorealistic images. Instead of sequentially generating tokens, our model directly predict all tokens in one step, resulting in a much faster testing time than existing transformer-based generation networks [8, 12, 47] (Table 3).

3.2. Appearance Refinement Network: TFill-Refined

Although the proposed TFill-Coarse model correctly infers superiorly reasonable content (shown in Figs. A.1, A.2, and A.3) by equally utilizing the global visible context in every layer, two limitations remain. First, it is not suitable for high-resolution input due to the fixed length position embedding. Second, the realistic completed results may not be fully consistent with the original visible appearances, e.g. the completed eye in Fig. 5 (c).

**Attention-Aware Layer (AAL):** To mitigate these issues, a refinement network, trained on high-resolution images, is proposed (Fig. 2 (b)). In particular, to further utilize the visible high-frequency details in global, an Attention-
Aware Layer (AAL) is designed to copy long-range information from both encoded and decoded features.

As depicted in Fig. 6, given a decoded feature \( x_d \), we first calculate the attention score of:

\[
A = \phi(x_d)^T \theta(x_d),
\]

where \( A_{ij} \) represents the similarity of the \( j \)th feature to the \( i \)th feature, and \( \phi, \theta \) are 1×1 convolution filters.

Interestingly, we discover that using \( A \) directly in a standard self-attention layer is suboptimal, because the \( x_d \) features for visible regions are generally distinct from those generated for masked regions. Consequently, the attention tends to be insular, with masked regions preferentially attending to masked regions, and vice versa. To avoid this problem, we explicitly handled the attention to visible regions separately from masked regions. So before softmax normalization, \( A \) is split into two parts: \( A_v \) — similarity to visible regions, and \( A_m \) — similarity to generated masked regions. Next, we get long-range dependencies via:

\[
z_v = \text{softmax}(A_v)x_v, \quad z_m = \text{softmax}(A_m)x_d
\]

where \( z_v \) contains features of contextual flow [52] for copying high-frequency details from the encoded high-resolution features \( x_v \) to masked regions, while \( z_m \) has features from the self-attention that is used in SAGAN [56] for high-quality image generation.

Instead of learning fixed weights [60] to combine \( z_v \) and \( z_m \), we learn the weights mapping based on the largest attention score in each position. Specifically, we first obtain the largest attention score of \( A_v \) and \( A_m \), respectively. Then, we use the 1×1 filter \( \gamma \) and \( \alpha \) to modulate the ratio of the weights. Softmax normalization is applied to ensure \( w_v + w_m = 1 \) in every spatial position:

\[
[w_v, w_w] = \text{softmax}([\gamma(\text{max}(A_v)), \alpha(\text{max}(A_m))])
\]

where \( \text{max} \) is executed on the attention score channel. Finally, an attention-balanced output \( z \) is obtained by:

\[
z = w_v \cdot z_v + w_m \cdot z_m
\]

where \( w_v, w_m \in \mathbb{R}^{B \times 1 \times H \times W} \) hold different values for various positions, dependent on the largest attention scores in the visible and masked regions, respectively.

4. Experiments

4.1. Experimental Details

Datasets: We evaluated the proposed TFill model with arbitrary mask types on various datasets, including CelebA-HQ [22, 33], FFHQ [23], Places2 [63], and ImageNet [41].

Metrics: Following existing works [35, 47, 61], we mainly reported the traditional patch-level image quality metrics, including peak signal-to-noise ratio (PSNR) and structure similarity index (SSIM), and the latest learned feature-level LPIPS [57] and FID [15] metrics.

Implementation Details: Our model is trained in two stages: 1) the TFill-Course is first trained for 256×256 resolution; and 2) the TFill-Refined is then trained for 512×512 resolution. Unless other noted, TFill indicates the whole model in the paper. Both networks are optimized using the loss \( L = L_{\text{pixel}} + L_{\text{per}} + L_{\text{GAN}} \), where \( L_{\text{pixel}} \) is the \( \ell_1 \) reconstruction loss, \( L_{\text{per}} \) is the perceptual loss [21], and \( L_{\text{GAN}} \) is the discriminator loss [13]. More implementation details are provided in Appendix C.
4.2. Main Results

We firstly compared with the following state-of-the-art image completion methods: GL [17]SIGGRAPH’2017, DeepFillv2 [53]ICCV’2019, PIC [60]CVPR’2019, HiFill [51]CVPR’2020, CRFill [54]ICCV’2021, and ICT [47]ICCV’2021 using their publicly released codes and models.

Quantitative Results: Table 1 shows quantitative evaluation results on Places2 [63], in which the images were degraded by free-form masks provided in the PConv [28] testing set. The mask ratio denotes the range of masking proportion applied to the images. The original mask ratios hold six levels, from 0 to 60%, increasing 10% for each level. Here, following ICT [47], we only compare the results on middle-level mask ratios. As can be seen, the proposed TFill model outperformed the CNN-based state-of-the-art models in all mask scales. Specifically, it achieves averaging relative 18.8% and 13.3% improvements for LPIPS and FID scores, respectively. While the latest ICT [47] utilized the transformer architecture with much more blocks and more expensive computer cost, they downsampled the original image into $32 \times 32$, or $48 \times 48$ resolution, and then embedded each pixel as a token, resulting in important information is lost during such large-scale downsampling.

Qualitative Results: The qualitative comparisons are visualized in Figs. 7 and 9. The proposed TFill achieved superior visual results even under challenging conditions. In Fig. 9, we compared with CA [52], PIC [60], and CRFill [54] on Celeba-HQ dataset. Our TFill generates photorealistic high-resolution ($512 \times 512$) results, even when significant semantic information is missing.

Fig. 7 shows visual results on natural images that were degraded by random masks. Here, we mainly compared...
the results for semantic content completion, while visualizing the easily traditional object removal results in Appendix A.3 (Figs. A.7, A.8, and A.9). GL [17], DeepFillv2 [53], and HiFill [51], while good at object removal, failed to infer shapes needed for object completion, e.g., the content for animals. CRFill [54] provided plausible appearance, yet the animals’ shapes are unaligned, e.g., malformed leg and body of the dog. Our TFill inferred the correct shapes for even heavily masked objects in ImageNet, e.g., the fish even with head and tail separated by a large mask. It also outperformed all previous methods on high-resolution masked images in Places2, especially for some large masked regions. More comparisons are presented in Appendix A.2 (Figs. A.4, A.5, A.6). Please zoom in to see the details.

4.3. Ablation Experiments

We ran a number of ablations to analyze the effectiveness of each component in our TFill. Results are shown in Tables 2, 3, and 4, and Figs. 8 and 9.

TFill Architecture: We first evaluated components in the redesigned image completion architecture in Table 2, which experimentally demonstrates that the new architecture considerably improves the performance. Our baseline configuration (A) used an encoder-decoder structure derived from VQGAN [12], except here attention layers were removed in advance for a pure CNN-baseline. When combined with the powerful discriminator of StyleGANv2 [24], the performance was comparable to previous state-of-the-art CNN-based PIC [60, 61]. We first added the self-attention layer [56], not context mapping from the encoder [52, 60], to the decoder (Generator, G) in (B), but the performance remained similar to baseline (A). Interestingly, when we use the proposed restrictive CNN in (C) to embed information in the local patch, the performance improved substantially, especially for FID (relative 20.2% on CelebA-HQ). This suggests that the input feature representation is significant for the attention layer to equally deliver all messages, as explained in Fig. 4. We then improved this new baseline by adding the transformer encoder (D), which benefits from globally delivered messages at multiple layers. Finally, we introduced masked weights to each attention layer of the transformer (E), improving results further.

Token Representation: Tables 2 and 3 report the influence of the token representation. Our TFill achieved much better performance when using the restrictive-CNN. iGPT [8] downsamples the image to a fixed scale, e.g., $32 \times 32$, and embeds each pixel to a token. While this may not impact the classification [45], it has a large negative effect on generating high-quality images. Furthermore, the autoregressive form results in the completed image being inconsistent with the bottom-right visible region (Fig. 8 (b)), and each image runs an average of 26.45s on an NVIDIA 1080Ti GPU. ICT [47] improved iGPT by using bidirectional attention and adding a guided upsampling network. While the refined performance can almost match our coarse results, the running time is ruinously expensive (average 152.48s/img) and the content is not aligned well in Figs. 1 and 7. In contrast, VIT [11] embeds each patch to a token. As shown in Table 3 and Fig. 8, it can achieve relatively good quantitative and qualitative results. However, some details are perceptually poor, e.g., the strange eyes in Fig. 8. Finally, VQGAN [12] employs a large RF CNN to embed the image. It generates a visually realistic completion (Fig. 8 (d)), but when pasted to the original input (Fig. 8 (e)), there is an obvious gap between generated and visible pixels. When we used large convolutional kernels for large RF (229), the

| Method | CelebA-HQ | FFHQ |
|--------|----------|------|
|        | LPIPS↓  | FID↓ | LPIPS↓  | FID↓ |
| CA [52] | 0.104 | 9.53 | 0.127 | 8.78 |
| PIC [60] | 0.061 | 6.43 | 0.068 | 4.61 |
| MEDFE [29] | 0.067 | 7.01 | - | - |
| A | Traditional Conv | 0.060 | 6.29 | 0.066 | 4.12 |
| B | + Attention in G | 0.059 | 6.34 | 0.064 | 4.01 |
| C | + Restrictive Conv | 0.056 | 4.68 | 0.060 | 3.87 |
| D | + Transformer | 0.051 | 4.02 | 0.057 | 3.66 |
| E | + Masked Attention | 0.050 | 3.92 | 0.057 | 3.63 |
| F | + Refine Network | **0.048** | **3.86** | **0.053** | **3.50** |

Table 2. Learned Perceptual Image Patch Similarity (LPIPS) and Fréchet Inception Distance (FID) for various completion networks on center masked images. In this paper, we calculate the LPIPS and FID using all images in the corresponding test sets.
holes will firstly be filled in with neighboring visible pixels, resulting in worse results.

**AAL vs. Others Context Attention Modules:** An evaluation of our proposed AAL is shown in Table 4. For this quantitative experiment we used the same content generator (our TFill-Course), but different attention modules in the refinement network. As can be seen, even using the same content, the proposed AAL reduces LPIPS and FID scores by averaging relative 6.0% and 2.8%, over the existing works [52,56,60]. This is likely due to our AAL selects features based on the largest attention scores, using weights dynamically mapped during inference, instead of depending on fixed weights to copy features as in PIC [60].

The qualitative comparison is visualized in Fig. 9. CA [52], PIC [60], and CRFill [54] used different context attention in image completion. Here, we directly use their publicly models for visualization. As can be seen in the Fig. 9, these state-of-the-art methods cannot handle large holes. While TFill-SA used the good but lower-resolution (256 × 256) coarse content from TFill-Course, the mouth exhibits artifacts with inconsistent color. Our TFill-AAL (TFill-Refined) shows no such artifacts.

### Limitations:
Although our TFill model outperformed existing state-of-the-art methods on various images that were degraded by random irregular masks, the model is still not able to reason about high-level semantic knowledge. For instance, while our TFill model provided better plausible results in the third row of Fig. 7, it directly redesigned windows based on the visible windows, without understanding the physical world, that a door is necessary for a house. Therefore, a full understanding and imagination of semantic content in an image still needs to be further explored.

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#### Table 3. The effect of restrictive token representation on FFHQ dataset.

| Mask Type | LPIPS↓ | FID↓ | Mem↓ | Time↓ |
|-----------|--------|------|------|-------|
| SA [50]ICML’19 | 0.0584 | 0.0469 | 3.62 | 2.69 |
| CA [52]CVPR’18 | 0.0608 | 0.0443 | 3.86 | 2.66 |
| SLTA [60]CVPR’19 | 0.0561 | 0.0452 | 3.61 | 2.64 |
| Ours-AAL | **0.0533** | **0.0412** | **3.50** | **2.57** |

#### Table 4. The effect of various attention layers on FFHQ dataset.

| Mask Type | LPIPS↓ | FID↓ |
|-----------|--------|------|
| SA [50]ICML’19 | 0.0584 | 0.0469 |
| CA [52]CVPR’18 | 0.0608 | 0.0443 |
| SLTA [60]CVPR’19 | 0.0561 | 0.0452 |
| Ours-AAL | **0.0533** | **0.0412** |

#### Figure 9. Results with different attention modules in various methods. Our attention-aware layer is able to adaptively select the features from both visible and generated content.
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