WaveFill: A Wavelet-based Generation Network for Image Inpainting

1. Appendix Outline

We provide more details on experimental settings, detailed WaveFill network architecture, more experimental results, and more ablation studies in the ensuing 4 sections.

2. Detailed Experimental Settings

Image Processing: We fix the image resolution at $256 \times 256$. Specifically, we use small images ($256 \times 256$) of Places2 [13] and resize CelebA-HQ [2] images to $256 \times 256$. For Paris StreetView [7] images ($936 \times 537$), we crop patches of $537 \times 537$ from the image center and then resize the cropped patches to $256 \times 256$. Given a raw image $I_{gt}$ and its mask $M$ (0 for valid pixels and 1 for invalid) of the target size, the input image is obtained by $I_{in} = I_{gt} \odot (1 - M)$, where $\odot$ is element-wise product. The WaveFill generator takes $[I_{in}, M]$ as inputs and produces the prediction $I_{pred}$ in the spatial domain. The final output is $I_{out} = I_{in} + I_{pred} \odot M$.

Ablation Study Settings: In the ablation studies presented in the submitted manuscript, the baseline adopts a U-Net-like architecture [8] for image inpainting in spatial domain. It uses multiple residual blocks (as in the low-frequency branch of WaveFill generator) between the CNN encoder and decoder, and replaces all vanilla convolution by gated convolution [11]. For a fair comparison, it also performs feature fusion by concatenating low-level features from encoder with up-sampled high-level features from decoder followed by a gated convolution.

For DCT-based model, we apply Discrete Cosine Transform (DCT) to the entire image. As illustrated in Fig. 1, we split frequency bands into one low-frequency band and two high-frequency bands. We then concatenate the 3 square patches of high-frequency bands in the channel dimension, and obtain similar inputs as the wavelet-based model. With the frequency domain inputs, we adopt the same network structure of WaveFill to train the DCT-based model.

3. Detailed Network Architectures

The discriminators $D_1$ and $D_2$ share the same structure for the predictions of $Lv1-HighFreq$ and $Lv2-HighFreq$. Fig. 4 shows detailed discriminator structure. For the generator in WaveFill, Fig. 5 shows it detailed architecture where the IDWT part is not included for brevity.

4. More Experimental Results

Inter-Frequency Conflicts: As most state-of-the-art (SOTA) inpainting methods optimize different objectives in spatial domain concurrently, which often leads to inter-frequency conflicts and compromised inpainting. To visualize and quantify the inter-frequency conflicts, we compute the histogram of low-frequency and high-frequency components of SOTA predictions (as illustrated in Fig. 1 of the submitted manuscript) and measure their differences with that of ground truth via Earth Mover’s Distance (EMD) [9]. In particular, the inpainting prediction is decomposed into $LL, LH, HL$, and $HH$ with 1-level wavelet decomposition where $LL$ is treated as low-frequency bands and the rest are assembled and treated as high-frequency bands. Table 1 shows the EMD over the validation set of CelebA-HQ [2]. It can be found that WaveFill achieves comparable EMD on low-frequency bands but outperforms SOTAs significantly on high-frequency bands. The EMD statistics show that separate generation of different frequency bands with corresponding objectives helps to produce better high-frequency

| Frequency Bands | GMCNN [10] | EC* [6] | GC [11] | Ours |
|-----------------|------------|--------|--------|------|
| Low             | 9.03       | 9.97   | 8.99   | 9.76 |
| High            | 43.86      | 39.60  | 43.42  | 30.81 |

Table 1. Histogram differences as measured by Earth Mover’s Distance (EMD) between the prediction and ground truth (over CelebA-HQ [2] validation set with square masks).
Quantitative Results: Table 2 shows the quantitative results over the Paris StreetView [7] with irregular masks [4] (no space to report it in the submitted manuscript). For small masks with mask ratios of 10-20%, WaveFill achieves superior FID scores and fair $\ell_1$, PSNR, and SSIM as performance saturates over these three metrics. For larger and more challenging irregular masks, WaveFill outperforms the state-of-the-art [6, 5] consistently by large margins.

Qualitative Results:
Fig. 2 illustrates our synthesized multi-frequency components and their histograms. In addition, we compare WaveFill with a number of state-of-the-art methods [10, 6, 11, 5] qualitatively. Figs. 6, 7 and 8 show the inpainting of a few more sample images from CelebA-HQ [2], Places2 [13] and Paris StreetView [7], respectively.

Failure Case Analysis: Similar to existing work like EC [6] and GC [11], our method sometimes fails to generate reasonable semantics while handling large corrupted regions as shown in Fig. 3. This happens more for Places2 dataset [13] that captures thousands of objects and scenes of different types. The failure is largely attributed to the insufficient contextual information (around the corrupted regions) with which the model cannot recognize the semantics and produce reasonable contents.

5. More Ablation Studies

Decomposition Levels: We studied different levels of wavelet decomposition over Paris StreetView [7] with irregular masks. As Table 3 shows, 2-level wavelet decomposition (ours) performs better than 1-level decomposition in most metrics except PSNR, which could be because 1-level decomposition does not disentangle low and high-frequency information sufficiently and so may still suffer from inter-frequency conflicts. 3-level decomposition performs worse than 2-level decomposition as well largely due to the increased complexity in generation. As we adopt the image size $256 \times 256$, the size of low-frequency bands is only $32 \times 32$ (in 3-level decomposition) which contains very limited information for guiding the generation of high-frequency contents.

Wavelet Filters: We adopted the Haar wavelet filter as the basis for the wavelet transform. To investigate the effects of wavelet filters over the inpainting performance, we

| Mask | EC [6] | MEDFE [5] | Ours |
|------|--------|-----------|------|
| 10-20% | 20.46 | 14.79 | **12.22** |
| 20-30% | 35.09 | 27.77 | **21.98** |
| 30-40% | 49.43 | 43.02 | **34.02** |
| 40-50% | 62.03 | 64.98 | **46.50** |

| $\ell_1$ (%) | EC [6] | MEDFE [5] | Ours |
|--------------|--------|-----------|------|
| 10-20% | 1.16 | **1.02** | 1.04 |
| 20-30% | 2.01 | 1.78 | **1.63** |
| 30-40% | 2.94 | 2.76 | **2.37** |
| 40-50% | 4.10 | 4.14 | **3.34** |

| PSNR | EC [6] | MEDFE [5] | Ours |
|------|--------|-----------|------|
| 10-20% | 30.81 | **32.80** | 32.79 |
| 20-30% | 27.87 | 29.07 | **29.86** |
| 30-40% | 25.76 | 26.31 | **27.72** |
| 40-50% | 24.09 | 23.73 | **25.78** |

| SSIM | EC [6] | MEDFE [5] | Ours |
|------|--------|-----------|------|
| 10-20% | 0.948 | 0.965 | **0.966** |
| 20-30% | 0.905 | 0.929 | **0.938** |
| 30-40% | 0.848 | 0.869 | **0.894** |
| 40-50% | 0.778 | 0.790 | **0.839** |

Table 2. Quantitative experimental results over Paris StreetView [7] validation images (100) with irregular masks [4].
Table 3. Ablation study of different wavelet decomposition levels over Paris StreetView [7] validation images (100) with irregular masks [4].

| Filter       | FID | $\ell_1$ (%) | PSNR | SSIM |
|--------------|-----|--------------|------|------|
| Lv1 Wavelet  | 33.23 | 2.41     | **29.04** | 0.900 |
| Lv3 Wavelet  | 34.36 | 2.48     | 28.49 | 0.898 |
| Lv2 Wavelet  | 31.02 | 2.34     | 28.94 | **0.904** |

Table 4. Ablation study of frequency component over Paris StreetView [7] validation images (100) with irregular masks [4].

| Component     | FID | $\ell_1$ (%) | PSNR | SSIM |
|---------------|-----|--------------|------|------|
| only LowFreq  | 62.32 | 3.77     | 25.84 | 0.820 |
| w/o Lv2-HighFreq | 54.48 | 4.18     | 23.26 | 0.784 |
| w/o Lv1-HighFreq | 42.25 | 2.80     | 27.87 | 0.882 |
| Full          | 31.02 | 2.34     | 28.94 | **0.904** |

Table 5. Ablation study of wavelet filters over Paris StreetView [7] validation images (100) with irregular masks [4].

| Filter       | FID | $\ell_1$ (%) | PSNR | SSIM |
|--------------|-----|--------------|------|------|
| db2          | 32.12 | 2.35     | 28.96 | **0.904** |
| bior2.2      | 31.18 | 2.36     | **29.06** | 0.903 |
| haar         | 31.02 | 2.34     | 28.94 | **0.904** |

Table 6. Ablation study of loss terms over Paris StreetView [7] validation images (100) with irregular masks [4]. $L_{LF}$ denotes the low-frequency $L_1$ loss, and $L_G$ is the adversarial loss for high-frequency bands. $L_{FM}$ and $L_{perc}$ denote feature matching loss and perceptual loss respectively.

Evaluating another two types of wavelet filters including $db2$ from the Daubechies wavelet family and $bior2.2$ from the biororthogonal wavelet family. Table 5 shows experimental results. It can be seen that the three types of wavelet filters achieve comparable inpainting performance under different evaluation metrics.

**Frequency Component:** The WaveFill generator consists of three branches for processing 3 frequency bands $LowFreq$, $Lv2-HighFreq$ and $Lv1-HighFreq$. We trained three models to study the effects of the three branches: 1) Removing both high-frequency branches with only $LowFreq$; 2) Removing intermediate-frequency branch $Lv2-HighFreq$; 3) Removing high-frequency branch $Lv1-HighFreq$. As shown in Table 4, removing lower frequency bands $Lv2-HighFreq$ leads to more FID drops as compared with removing $Lv1-HighFreq$, and the model with only $LowFreq$ obtains the lowest FID. But for $\ell_1$, PSNR and SSIM, removing $Lv2-HighFreq$ affects more as compared with using $LowFreq$ only. We conjecture that $Lv1-HighFreq$ will be like noise when directly adding to $LowFreq$ without the support of intermediate-frequency bands $Lv2-HighFreq$.

**Loss Term Sensitivity:** The complete WaveFill involves 4 losses in training. We performed ablation studies to examine the contribution of each loss by removing it from the full objectives. As shown in Table 6, each loss has its contribution to the overall performance, and $L_{perc}$ contributes the most.

**Discriminator**

![Discriminator Network Diagram]

Figure 4. Detailed structures of WaveFill Discriminator: Conv-$(k, c, d)$ denotes the vanilla convolution with kernel size of $k \times k$, number of output channel $c$ and dilation rate $d$, $d$ is neglected when $d = 1$; LReLU denotes the Leaky ReLU with a slope of 0.2; SN refers to Spectral & Instance Normalization; Self-Attention denotes the Self-Attention module used in [12].
Figure 5. Detailed structures of WaveFill generator: DWT stands for Discrete Wavelet Transform; FRAN denotes the proposed Frequency Region Attention Normalization; GC/Conv-(k, c, d) denotes the gated convolution [11] or vanilla convolution with kernel size of \( k \times k \), number of output channel \( c \) and dilation rate \( d \), \( d \) is neglected when \( d = 1 \); Resblk is the abbreviation of Residual Block [1]; SN refers to Spectral & Instance Normalization; Positional Norm denotes Positional Normalization [3]; Self-Attention refers to the Self-Attention module used in [12].
Figure 6. Qualitative comparisons of our WaveFill with several state-of-the-art inpainting methods [10, 6, 11] over the CelebA-HQ [2] validation set with central square masks.
Figure 7. Qualitative comparisons of our WaveFill with several state-of-the-art inpainting methods [6, 11, 5] over the Places2 [13] validation set with irregular masks [4].
Figure 8. Qualitative comparisons of our WaveFill with several state-of-the-art inpainting methods [6, 5] over the Paris StreetView [7] validation set with irregular masks [4]. The red boxes are used to highlight the main differences across different approaches.
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