Resolution-robust Large Mask Inpainting with Fourier Convolutions

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Image Inpainting

Simple task of filling in missing (masked) areas.

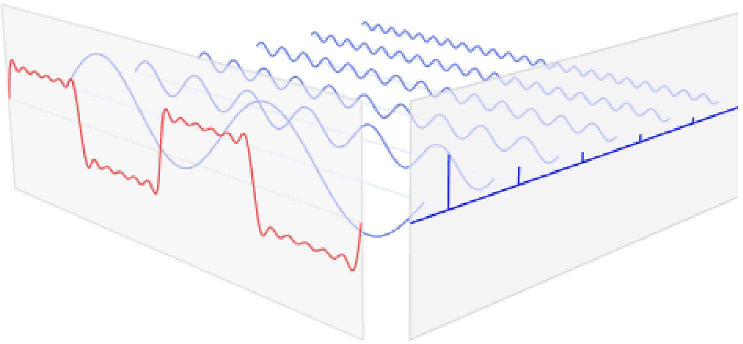
Can be used for image completion or image editing.

Requires a large receptive field when handling large masks.

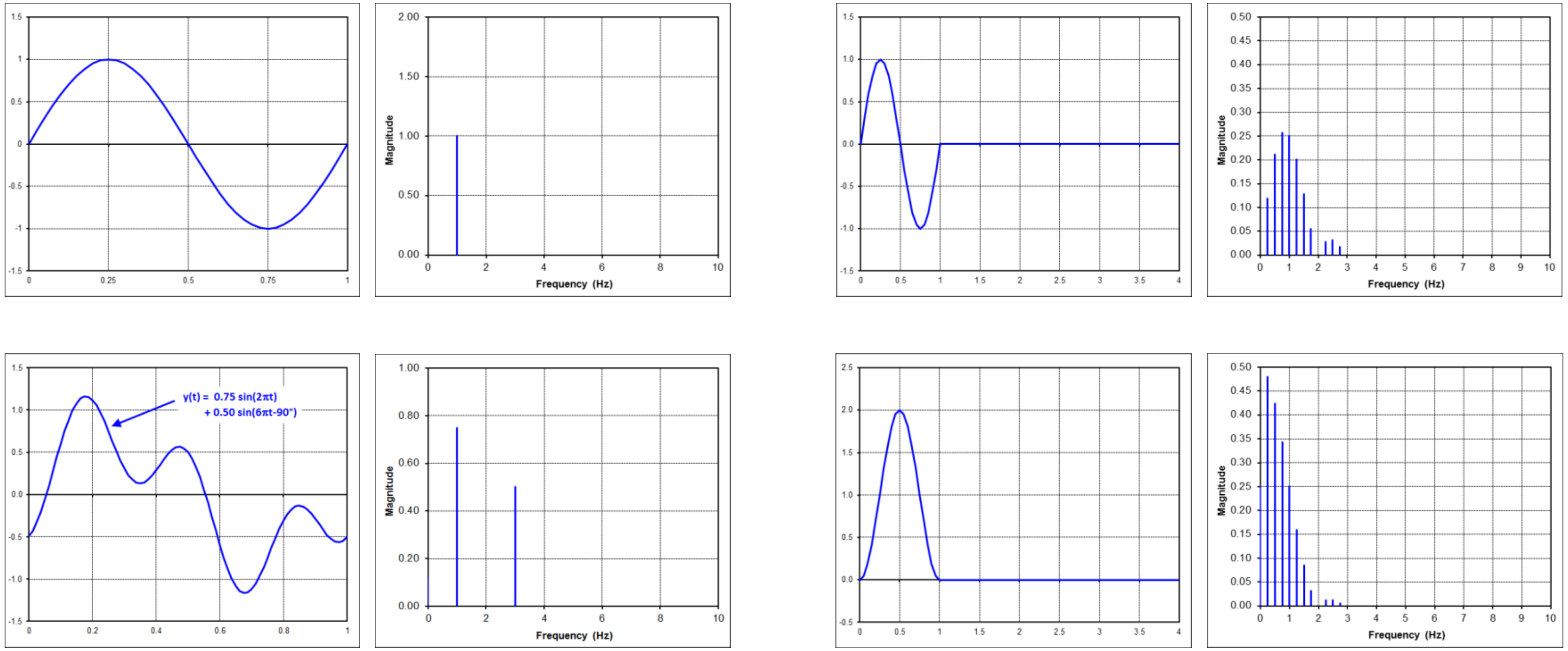
Fourier Transform

Changing the basis of signals (temporal → frequency)

- Decompose a periodic signal into a weighted sum of sinusoidal signals.
- Red signal = $1 \times \sin(\omega t) + 0.5 \times \sin(2\omega t) + 0.1 \times \sin(3\omega t) + \ \ldots$



Inverse Fourier Transform is also a straight forward operation.

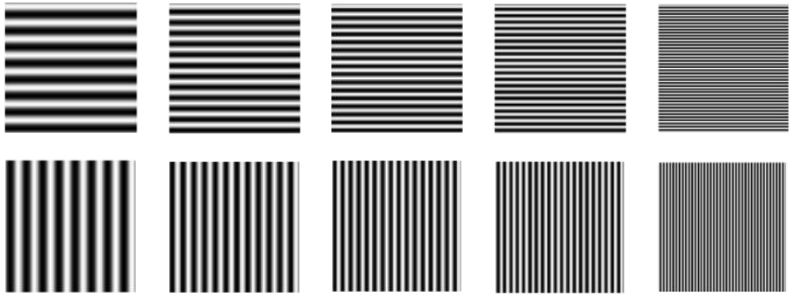


Fourier Transform

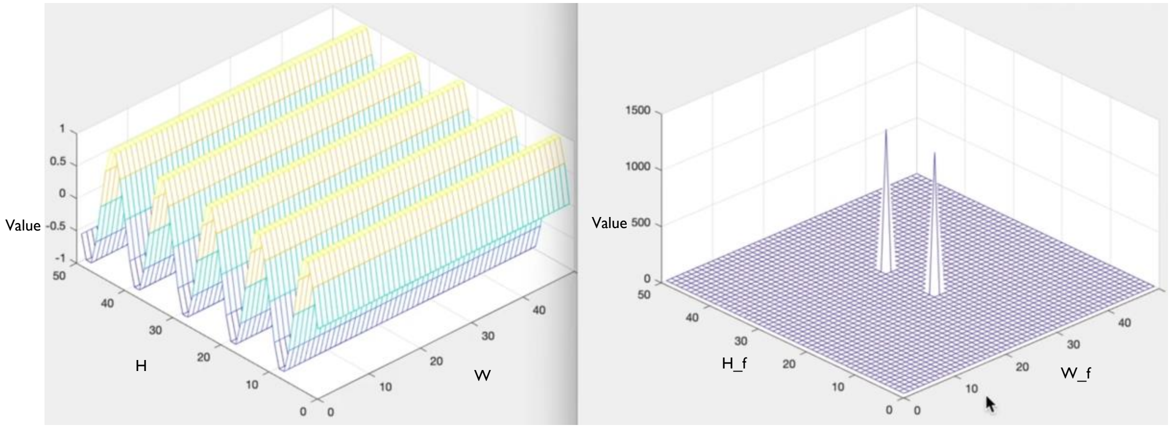
Changing the basis of signals (spatial → frequency)

- Extending to 2D signals (i.e., images)
- Summarize into a global information.

$$= \sum_{i=1} a_i$$



- Examples of 2D FFT



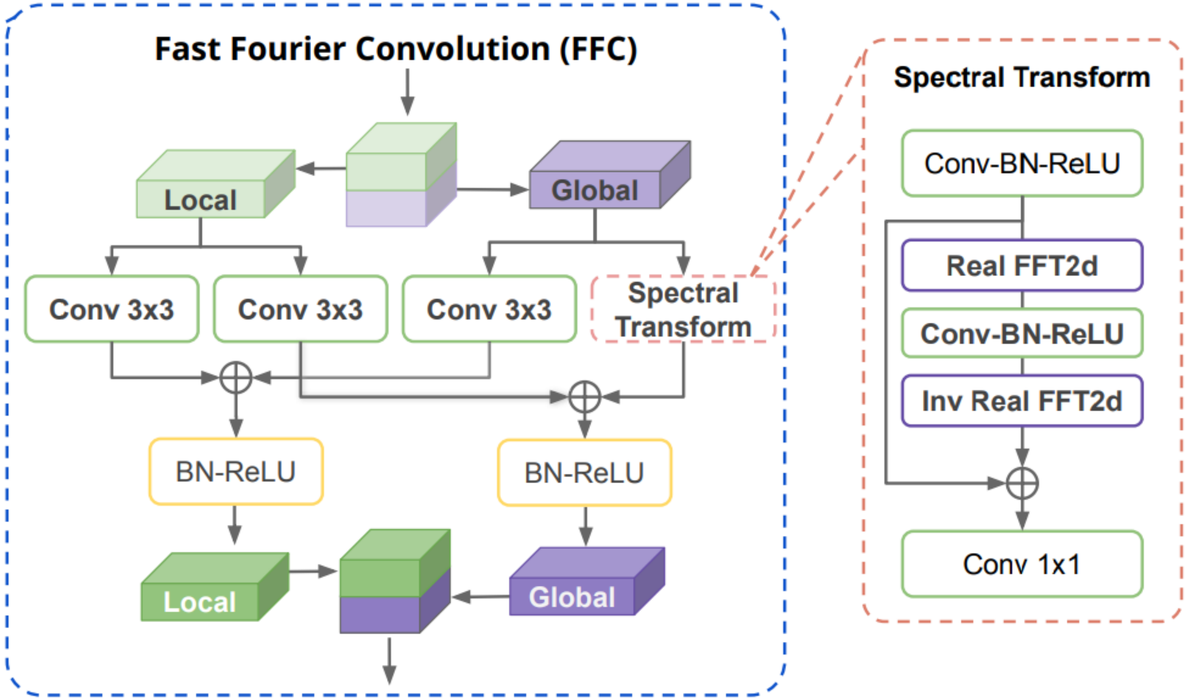
Fast Fourier Convolution (FFC)

Pass convolution filters through features in the frequency domain.

- Effectively obtain a global receptive field.
- Frequency-wise control of features.

Internally exchange local and global features.

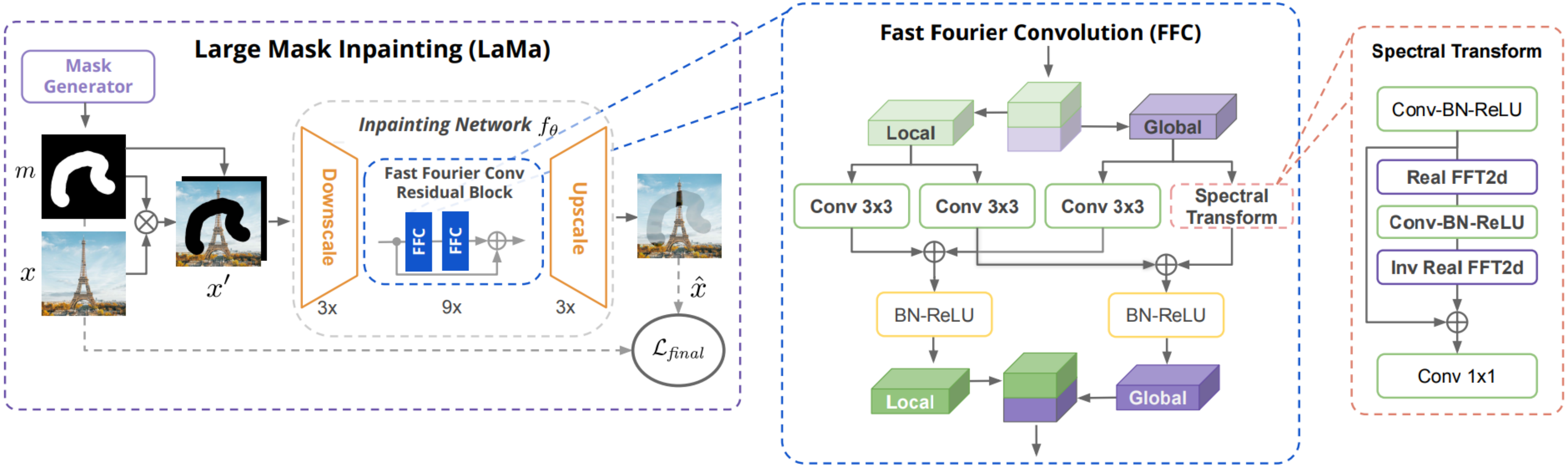
- Do not need to "wait" for local features to propagate to other regions.



Chi etal. "Fast fourier convolution." *NIPS* 2020

Large Mask Inpainting (LaMa)

Model architecture: Simple resblock-based architecture (e.g., MUNIT, FUNIT)



Loss function: $\mathcal{L}_{final} = \kappa L_{Adv} + \underbrace{\alpha \mathcal{L}_{HRFPL}}_{\text{Perceptual loss}} + \underbrace{\beta \mathcal{L}_{DiscPL}}_{\text{Feature matching loss}} + \gamma R_1$

High-receptive field Perceptual loss computed from a pre-trained ResNet

Large Mask Inpainting (LaMa)

Experiments

Method	# Params $\times 10^6$	Places (512 × 512)						CelebA-HQ (256 × 256)			
		Narrow masks		Wide masks		Segm. masks		Narrow masks		Wide masks	
		FID ↓	LPIPS ↓	FID ↓	LPIPS ↓	FID ↓	LPIPS ↓	FID ↓	LPIPS ↓	FID ↓	LPIPS ↓
LaMa-Fourier (ours)	27	0.63	0.090	2.21	0.135	5.35	0.058	7.26	0.085	6.96	0.098
CoModGAN [64]	109▲	0.82▲30%	0.111▲23%	1.82▼18%	0.147▲9%	6.40▲20%	0.066▲14%	16.8▲131%	0.079▼7%	24.4▲250%	0.102▲4%
MADF [67]	85▲	0.57▼10%	0.085▼5%	3.76▲70%	0.139▲3%	6.51▲22%	0.061▲5%	—	—	—	—
AOT GAN [60]	15▼	0.79▲25%	0.091▲1%	5.94▲169%	0.149▲11%	7.34▲37%	0.063▲10%	6.67▼8%	0.081▼4%	10.3▲48%	0.118▲20%
GCPR [17]	30▲	2.93▲363%	0.143▲59%	6.54▲196%	0.161▲19%	9.20▲72%	0.073▲27%	—	—	—	—
HiFill [54]	3▼	9.24▲1361%	0.218▲142%	12.8▲479%	0.180▲34%	12.7▲137%	0.085▲49%	—	—	—	—
RegionWise [30]	47▲	0.90▲42%	0.102▲14%	4.75▲115%	0.149▲11%	7.58▲42%	0.066▲14%	11.1▲53%	0.124▲46%	8.54▲23%	0.121▲23%
DeepFill v2 [57]	4▼	1.06▲68%	0.104▲16%	5.20▲135%	0.155▲15%	9.17▲71%	0.068▲18%	12.5▲73%	0.130▲53%	11.2▲61%	0.126▲28%
EdgeConnect [32]	22▼	1.33▲110%	0.111▲23%	8.37▲279%	0.160▲19%	9.44▲76%	0.073▲27%	9.61▲32%	0.099▲17%	9.02▲30%	0.120▲22%
RegionNorm [58]	12▼	2.13▲236%	0.120▲33%	15.7▲613%	0.176▲31%	13.7▲156%	0.082▲42%	—	—	—	—

Ablations Study

	Model	Pretext Problem	Dilation	Segmentation masks	
				FID ↓	LPIPS ↓
$\mathcal{L}_{HRFPL}$	RN50	Segm.	+	5.69	0.059
$\mathcal{L}_{ClfPL}$	RN50	Clf.	+	5.87▲3%	0.059
	RN50	Clf.	-	6.00▲5%	0.061▲3%
	VGG19	Clf.	-	6.29▲11%	0.063▲6%
$\cancel{\mathcal{L}_{PL}}$	-	-	-	6.46▲13%	0.065▲9%

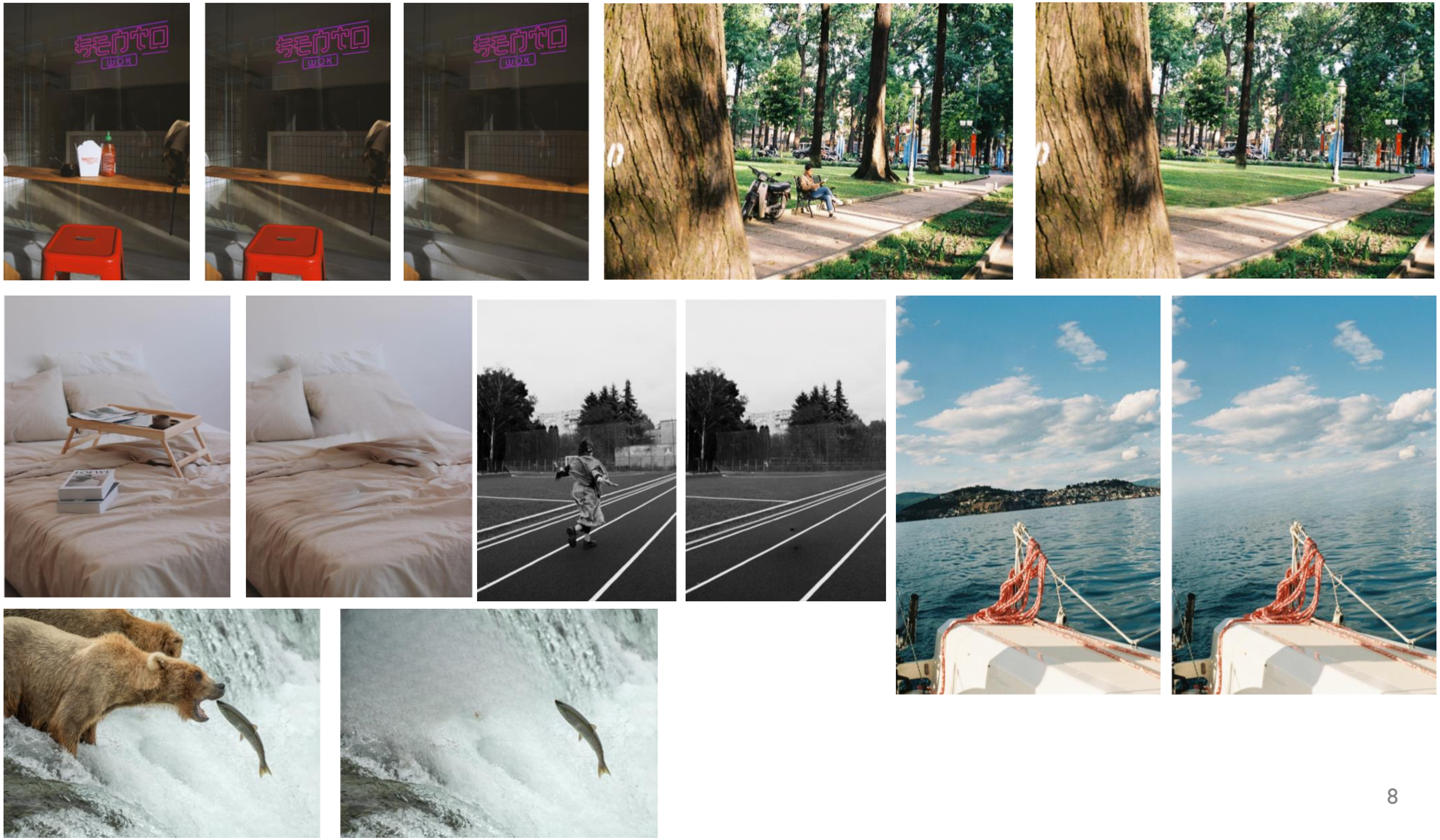
Table 3: Comparison of LaMa-Regular trained with different perceptual losses. The ▲ denotes deterioration, and ▼ denotes improvement of a score compared to the model trained with *HRF* perceptual loss based on segmentation ResNet50 with dilated convolutions (presented in the first row). Both dilated convolutions and pretext problem improved the scores.

Model	Convs	# Params	# Blocks	Narrow masks		Wide masks	
				FID ↓	LPIPS ↓	FID ↓	LPIPS ↓
Base	Fourier	27	9	0.63	0.090	2.21	0.135
Base	Dilated	46	9	0.66▲4%	0.089▼1%	2.30▲4%	0.136▲1%
Base	Regular	46	9	0.60▼5%	0.089▼1%	3.51▲59%	0.139▲3%
Shallow	Fourier	19	6	0.72▲13%	0.094▲4%	2.31▲5%	0.138▲2%
Deep	Regular	74	15	0.63	0.090	2.62▲18%	0.137▲2%

Table 2: The table demonstrates performance of different LaMa architectures while leaving the other components the same. The ▲ denotes deterioration, and ▼ denotes improvement compared to the Base-Fourier model (presented in the first row). The FFC-based models may sacrifice a little performance on narrow masks, but significantly outperform bigger models with regular convolutions on wide masks. Visually, the FFC-based models recover complex visual structures significantly better, as shown in Figure 4.

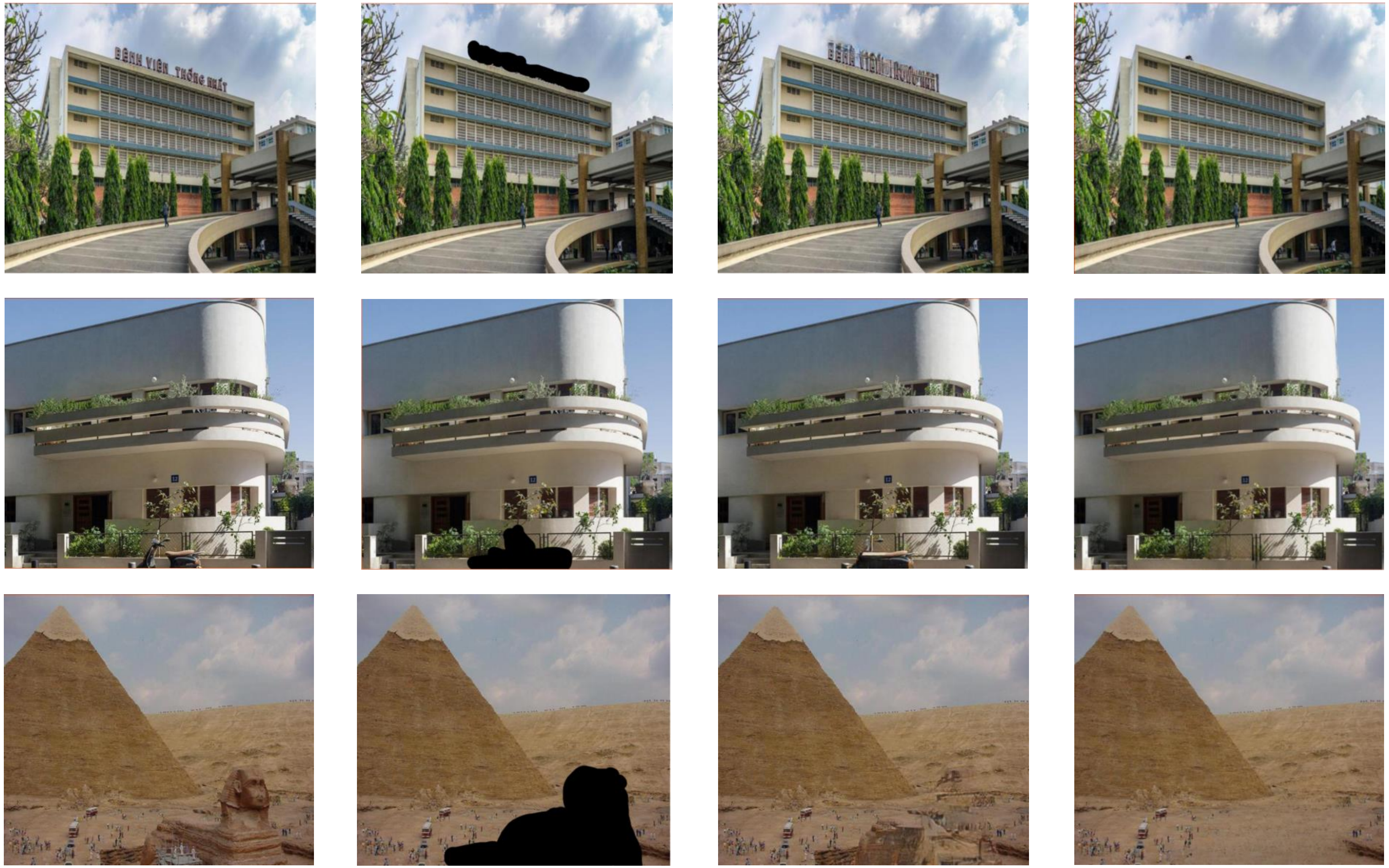
Large Mask Inpainting (LaMa)

Results



Large Mask Inpainting (LaMa)

Demo



Original Image | Masked Image | CoModGAN | LaMa