Image Inpainting via Conditional Texture and Structure Dual Generation

(ICCV 2021)

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Image Inpainting

Image Inpainting

Image inpainting is the process of genarating or reconstructing distorted regions of an Image.

Challenges : (Previous methods)

- The cases with large corruptions, generally suffer from distorted results.
- Previous methods have a common drawback in recovering the global structure of the image.
- Previous methods involving structures are sensitive to the accuracy of structures (e.g. edges and contours) which is not easy to guarantee.

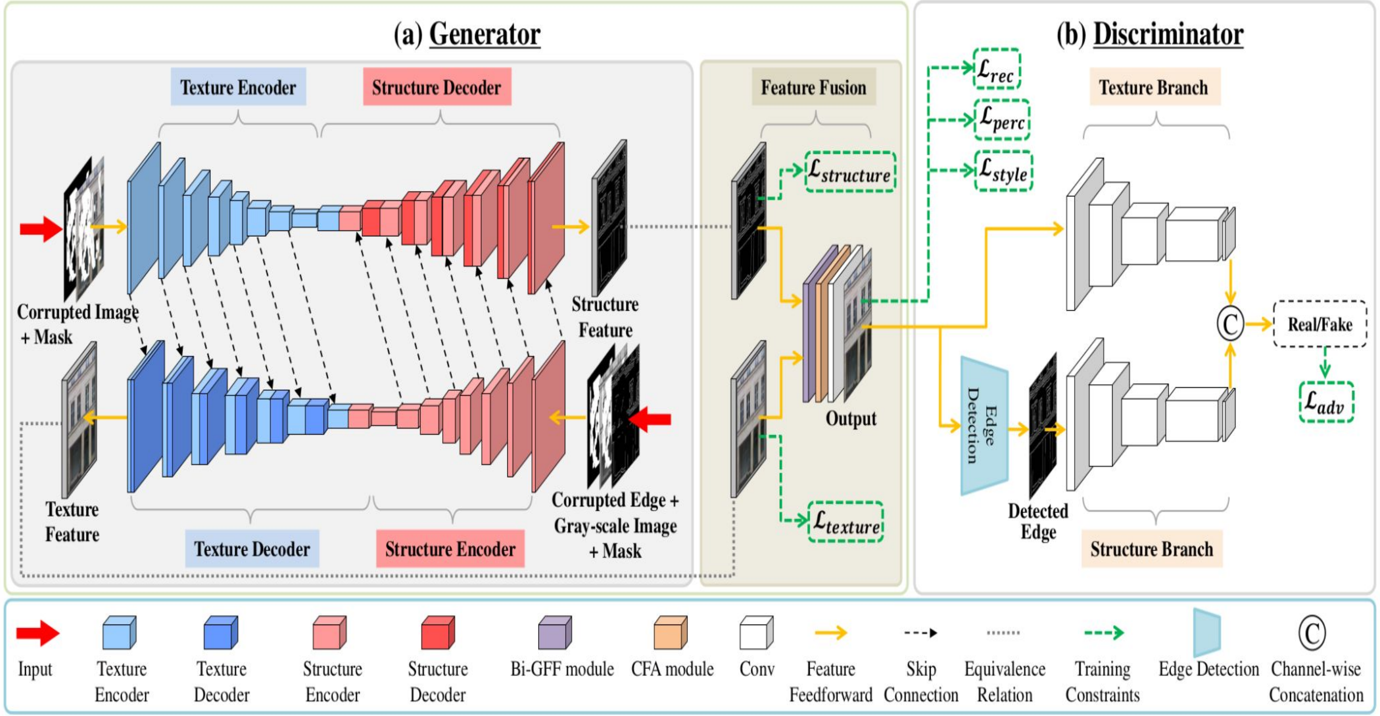
Architecture

Structure-constrained texture synthesis

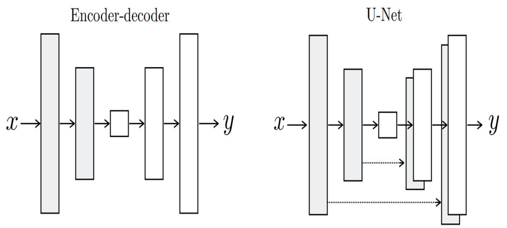
Texture-guided structure reconstruction

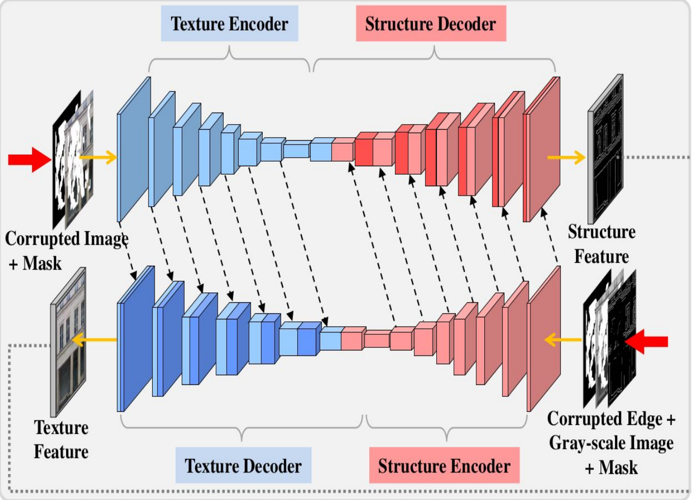
Bi-directional Gated Feature Fusion (Bi-GFF)

Contextual Feature Aggregation (CFA)



Generator :





Generator

Two-stream generator which jointly synthesizes image textures and structures.(Partial Convolutions)

U-Net Variant

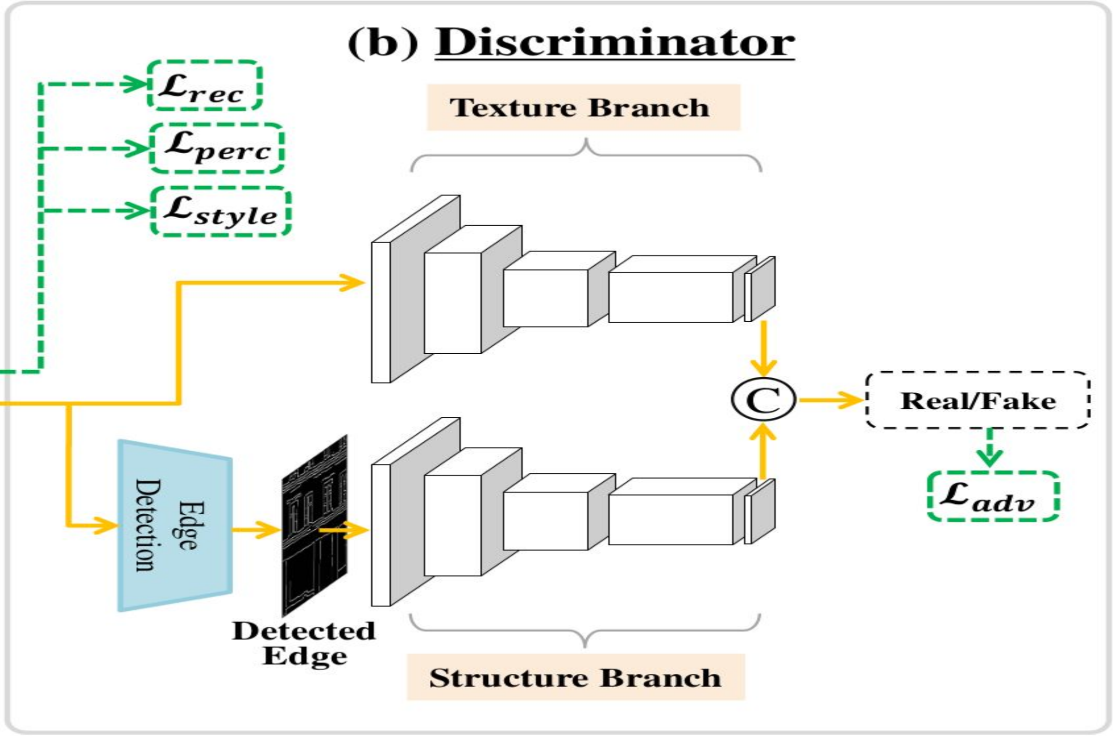
- Encoder-decoder
- Skip Connections

Input : The corrupted image and its corresponding edge map.
Output : Texture and structure Feature map.

Discriminator:

Discriminator

Two-stream discriminator to distinguish images by feature statistics of both texture and structure.

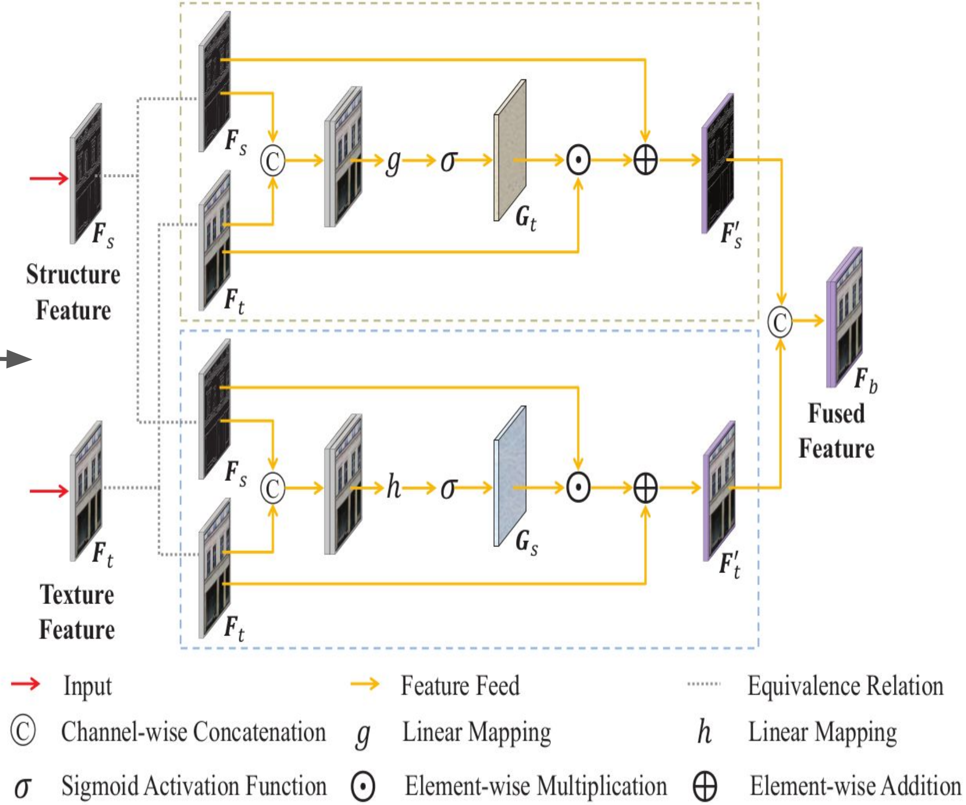


Input : Texture and structure Feature map.

Output : Real/Fake.

Bi-GFF :

Bi-directional Gated Feature Fusion (Bi-GFF)



$$F'_t = \beta(G_s \odot F_s) \oplus F_t,$$

$$F'_s = \alpha(G_t \odot F_t) \oplus F_s,$$

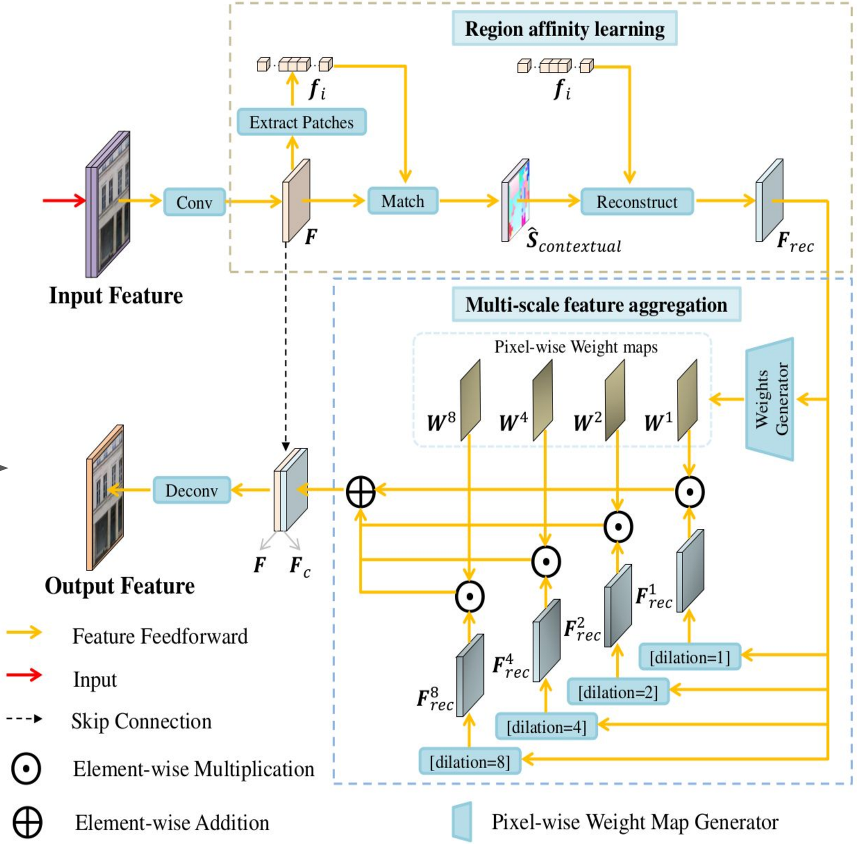
$$F_b = \text{Concat}(F'_s, F'_t).$$

CFA :

$$S_{contextual}^{i,j} = \left\langle \frac{\boldsymbol{f}_i}{\|\boldsymbol{f}_i\|_2}, \frac{\boldsymbol{f}_j}{\|\boldsymbol{f}_j\|_2} \right\rangle, \quad \hat{S}_{contextual}^{i,j} = \frac{\exp\left(S_{contextual}^{i,j}\right)}{\sum_{j=1}^{N} \exp\left(S_{contextual}^{i,j}\right)}.$$

$$\tilde{\boldsymbol{f}}_i = \sum_{j=1}^{N} \boldsymbol{f}_j \cdot \hat{S}_{contextual}^{i,j}, \qquad \boldsymbol{F}_{rec}^{k} = \mathrm{Conv}_k\left(\boldsymbol{F}_{rec}\right),$$

Contextual Feature Aggregation (CFA)



$$\boldsymbol{W} = \mathrm{Softmax}\left(G_w\left(\boldsymbol{F}_{rec}\right)\right),$$
$$\boldsymbol{W}^1, \boldsymbol{W}^2, \boldsymbol{W}^4, \boldsymbol{W}^8 = \mathrm{Slice}(\boldsymbol{W}),$$

$$\boldsymbol{F}_c = \left(\boldsymbol{F}_{rec}^1 \odot \boldsymbol{W}^1\right) \oplus \left(\boldsymbol{F}_{rec}^2 \odot \boldsymbol{W}^2\right) \oplus \left(\boldsymbol{F}_{rec}^4 \odot \boldsymbol{W}^4\right) \oplus \left(\boldsymbol{F}_{rec}^8 \odot \boldsymbol{W}^8\right).$$

Loss Functions

- **Reconstruction Loss :** $\mathcal{L}_{rec} = \mathbb{E}\left[\|\boldsymbol{I}_{out} - \boldsymbol{I}_{gt}\|_1\right].$

- **Perceptual Loss :** $\mathcal{L}_{perc} = \mathbb{E}\left[\sum_i \|\phi_i(\boldsymbol{I}_{out}) - \phi_i(\boldsymbol{I}_{gt})\|_1\right],$

- **Style Loss :** $\mathcal{L}_{style} = \mathbb{E}\left[\sum_i \|(\psi_i(\boldsymbol{I}_{out}) - \psi_i(\boldsymbol{I}_{gt}))\|_1\right],$

- **Adversarial Loss :** $$\mathcal{L}_{adv} = \min_G \max_D \mathbb{E}_{\boldsymbol{I}_{gt}, \boldsymbol{E}_{gt}}\left[\log D(\boldsymbol{I}_{gt}, \boldsymbol{E}_{gt})\right] + \mathbb{E}_{\boldsymbol{I}_{out}, \boldsymbol{E}_{out}} \log\left[1 - D(\boldsymbol{I}_{out}, \boldsymbol{E}_{out})\right].$$

- **Intermediate Loss :** $$\mathcal{L}_{inter} = \mathcal{L}_{structure} + \mathcal{L}_{texture} = \mathrm{BCE}(\boldsymbol{E}_{gt}, \mathcal{P}_s(\boldsymbol{F}_s)) + \ell_1(\boldsymbol{I}_{gt}, \mathcal{P}_t(\boldsymbol{F}_t)),$$

- **Joint Loss :** $$\mathcal{L}_{joint} = \lambda_{rec}\mathcal{L}_{rec} + \lambda_{perc}\mathcal{L}_{perc} + \lambda_{style}\mathcal{L}_{style} + \lambda_{adv}\mathcal{L}_{adv} + \lambda_{inter}\mathcal{L}_{inter},$$

G : Generator
D : Discriminator
I_{gt} : Ground-truth image
E_{gt} : Complete Edge Map
Y_{gt} : Gray-scale image
M_{in} : Initial binary mask
I_{in} : $I_{gt} \odot M_{in}$ (damaged image)
E_{in} : $E_{gt} \odot M_{in}$ (damaged edge map)
Y_{in} : Y_{gt} M_{in} (damaged gray image)
I_{out}, E_{out} = $G(I_{in}, E_{in}, Y_{in}, M_{in})$
$\bigcirc$: element-wise multiplication

Training : Experimental Settings

- CelebA, ParisStreetView and Places2 with their original training, testing and validation split.
- All the images and corresponding masks are resized to 256 X 256 pixels.
- The model is implemented in PyTorch. Training is launched on a single NVIDIA 1080TI GPU (11GB) with batch size of 6.
- we first use a learning rate of 2×10^{-4} initial training, then finetune the model with a learning rate of 5×10^{-5}.
- The discriminator is trained with a learning rate of 1/10 of the generator.
- It takes around 4 days to train the models on CelebA and Paris StreetView and 10 days on Places2.

Results

- Qualitative and quantitative experiments on the CelebA, ParisStreetView and Places2.

Metrics	LPIPS†			PSNR¶			SSIM¶			User Study¶
Mask Ratio	0-20%	20-40%	40-60%	0-20%	20-40%	40-60%	0-20%	20-40%	40-60%	0-60%
PatchMatch [2]	0.074	0.183	0.332	30.02	24.77	20.51	0.864	0.680	0.487	2.7%
PConv [13]	0.065	0.134	0.283	30.19	25.18	21.20	0.885	0.730	0.527	4.0%
DeepFillv2 [36]	0.056	0.123	0.266	30.32	25.34	21.48	0.889	0.735	0.531	14.0%
RFR [11]	0.048	0.101	0.239	30.74	25.80	21.99	0.899	0.750	0.553	23.3%
EdgeConnect [18]	0.061	0.131	0.268	30.28	25.30	21.39	0.886	0.737	0.535	4.7%
PRVS [10]	0.057	0.124	0.257	30.30	25.39	21.50	0.893	0.742	0.541	5.3%
MED [14]	0.053	0.120	0.248	30.41	25.45	21.63	0.895	0.745	0.547	6.0%
Ours	**0.042**	**0.095**	**0.227**	**30.81**	**25.97**	**22.23**	**0.904**	**0.759**	**0.561**	**40.0%**

Table 1: Objective quantitative comparison and user study on Places2 (†Lower is better; ¶Higher is better).

Results

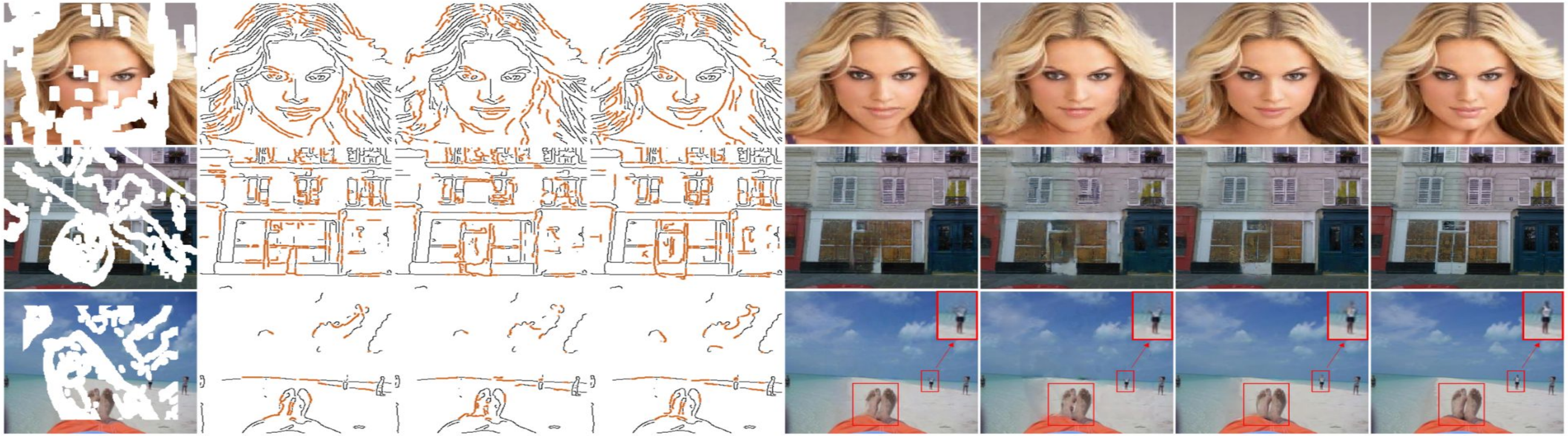
Metrics	LPIPS†			PSNR¶			SSIM¶		
Mask Ratio	0-20%	20-40%	40-60%	0-20%	20-40%	40-60%	0-20%	20-40%	40-60%
PatchMatch [1]	0.059	0.202	0.371	29.81	23.49	18.77	0.878	0.704	0.516
PConv [4]	0.046	0.122	0.221	31.89	26.48	21.32	0.899	0.750	0.558
DeepFillv2 [7]	0.040	0.107	0.214	32.48	26.93	21.70	0.906	0.757	0.569
RFR [3]	0.031	0.090	0.185	33.50	27.63	22.69	0.916	0.780	0.603
EdgeConnect [6]	0.042	0.117	0.215	32.12	26.79	21.66	0.904	0.758	0.566
PRVS [2]	0.039	0.112	0.209	32.34	26.89	21.78	0.908	0.762	0.573
MED [5]	0.037	0.106	0.203	32.68	27.01	21.86	0.907	0.763	0.575
Ours	**0.028**	**0.081**	**0.179**	**33.91**	**27.73**	**22.70**	**0.920**	**0.788**	**0.609**

Table 2: Objective quantitative comparison on CelebA (†Lower is better; ¶Higher is better).

Metrics	LPIPS†			PSNR¶			SSIM¶		
Mask Ratio	0-20%	20-40%	40-60%	0-20%	20-40%	40-60%	0-20%	20-40%	40-60%
PatchMatch [1]	0.078	0.195	0.362	30.70	25.31	20.59	0.881	0.689	0.499
PConv [4]	0.058	0.133	0.273	32.05	26.66	22.17	0.898	0.741	0.538
DeepFillv2 [7]	0.050	0.128	0.269	32.31	26.92	22.48	0.905	0.752	0.551
RFR [3]	0.041	0.112	0.234	32.69	27.33	22.76	0.919	0.772	0.568
EdgeConnect [6]	0.053	0.129	0.262	31.98	26.70	22.39	0.903	0.757	0.554
PRVS [2]	0.051	0.125	0.254	32.23	26.89	22.50	0.910	0.762	0.563
MED [5]	0.050	0.122	0.248	32.36	26.97	22.44	0.915	0.760	0.559
Ours	**0.039**	**0.107**	**0.226**	**32.93**	**27.48**	**22.89**	**0.923**	**0.777**	**0.573**

Table 3: Objective quantitative comparison on Paris StreetView (†Lower is better; ¶Higher is better).

Comparisons



(a) Input (b) EdgeConnect (c) PRVS (d) Ours (e) EdgeConnect (f) PRVS (g) Ours (h) Ground-truth

(a) Input (b) Ours (c) G_t (d) G_s (e) attention map (f) W^1 (g) W^2 (h) W^4 (i) W^8

Figure 1: Visualization of the feature maps learned by the network.

Comparisons

(a) Input (b) w/o structure (c) single stream (d) w/o Bi-GFF (e) w/o CFA (f) w/ CA (g) Ours (h) Ground-truth

Figure 7: Visualization of the effects of network architecture and individual modules on Paris StreetView.

Metrics	LPIPS†			PSNR¶			SSIM¶		
Mask Ratio	0-20%	20-40%	40-60%	0-20%	20-40%	40-60%	0-20%	20-40%	40-60%
w/o structure priors	0.054	0.129	0.251	31.72	26.71	22.22	0.909	0.755	0.550
single-stream	0.051	0.122	0.245	32.27	27.03	22.59	0.913	0.764	0.558
w/o Bi-GFF	0.045	0.114	0.236	32.61	27.20	22.75	0.919	0.772	0.567
w/o CFA	0.049	0.119	0.243	32.34	27.09	22.64	0.914	0.766	0.561
w/ CA	0.043	0.115	0.240	32.54	27.15	22.69	0.920	0.769	0.566
Ours	**0.039**	**0.107**	**0.226**	**32.93**	**27.48**	**22.89**	**0.923**	**0.777**	**0.573**

Table 2: Quantitative ablation study on Paris StreetView.

Thank You