OCONet: Image Extrapolation by Object Completion

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Outline

- Introduction
 - Outpainting task
 - Outpainting trend
- Background
 - GAN
 - PatchGAN Discriminator
 - Encoder Decoder
- OCONet: Image Extrapolation by Object Completion (CVPR 2021)





Introduction - outpainting task

- Generation of outer area of input image
- Major goal generation of perceptually natural image







Introduction - outpainting task

- Inpainting
 - generation/restoration of inner masked area of an input image
 - Relatively less difficult
- Inpainting
 - Sources from multiple directions



Input image

Output





- Outpainting
 - Sources from a single direction





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Output

Introduction - outpainting task

• 한계: Object 복원, bluriness







Introduction - Outpainting/Inpainting trend

- GAN based method
- provide additional information



Guided Image Outpainting via BidirectionalRearrangement with Progressive Step Learning (IEEE 2021)



EdgeConnect: Generative Image Inpainting with Adversarial Edge Learning (arXiv 2019)





Background - GAN (Generative Adversarial Networks)

- image generation model
- adversarial learning between Generator and Discriminator







Background - GAN (Generative Adversarial Networks)

• Objective function

 $\min_{G} \max_{D} V(D,G) = E_{x \sim p_{data}(x)}[\log D(x)] + E_{z \sim p_{z}(z)}[\log(1 - D(G(z))]]$

- Training Obejective
 - Generator의 분포가 training data의 분포를 근사







Background - PatchGAN Discriminator

• Whereas origianal discriminator does classification on a whole input image, PatchGAN discriminator does classification on patches of an input image



output: a matrix of values, each between one(Real) and zero(Fake)





Background - PatchGAN Discriminator

- L1, L2 loss의 한계점을 보완 → low frequency feature 학습 → blurry한 이미지 생성
- Whole image에서 general feature(low-frequency)가 아닌 n x n 으로 쪼갠 patch에 대하여 True/False를 예측
- 이를 통해 Generator가 High-frequency feature(detail)에 대하여 학습 가능







Background - Encoder Decoder

- composed of an Encoder(compresses input data) and a Decoder(reconstructs image)
- used for compressing data and extracting important features
- Latent Variable is usually in lower dimension than the input data







Background - Encoder Decoder with Skip Connection

- 단순 encoder-decoder architecture에서 image가 convolution을 거치며 low level feature가 누락
- Skip connection은 이러한 feature가 누락되기 전에 decoder 또는 뒤쪽의 layer에 전달될 수 있도록 함







OCONet - overview

- Major Contributions
 - Object completion network independent from the rest of the extrapolation problem
 - Signed Distance Field as mask representation







OCONet – step1 mask generation

- Mask Generation
 - Input: cropped color image I of size H*W*3
 - Output: cropped mask of size H*W*1
- Any instance segmentation method possible (in experiment shape mask)
- External masks can be used







OCONet – step2 Background extrapolation

• Input:

- 1) cropped color image I of size H*W*3
- 2) Input Mask
- zero out the foreground object in the generator's input using the object mask M.
- Output: background extrapolated image
- Any extrapolation method possible (in experiment Boundless GAN)







OCONet – step2 Background extrapolation

- Masking input image I
 - Pixels sometimes going beyond the extent of Completed Object
 - Better compositing result



Standard Boundless Boundless composite FG-masked Boundless

FG-masked composite





- Input: [I,M]
 - Input image I
 - Signed Distance Field (Input mask M)
- Output: [predicted texture, predicted mask]
 - Completed object pixels
 - Completed mask represented as Signed Distance Field







OCONet – Framework

- Generator: Encoder-Decoder with skip connections
- Discriminator: PatchGAN discriminator



Discriminator







OCONet – Framework

• Encoder-Decoder with skip connections







- Signed Distance Field (SDF)
 - Pixel의 위치를 boundary로부터 pixel거리로 측정하여 pixel 값으로 설정
 - Boundary에 해당하는 pixel들을 0, boundary 내의 pixel들은 +, 밖의 pixel들을 값을 가짐







- Signed Distance Field (SDF)
 - Signs indicate the segmentation (0 being the boundary and positive pixels indicating the object) → network is trained to learn the level sets for salient objects
 - Absolute values change gradually → network learns the gradual change around boundaries more naturally
 - Achieves sharpness by thresholding

84.8	54.6	24.4	-5.8	-17.0	8.2	33.4	58.2	69.2	80.3	91.7	116.5
49.3	14.8	-15.4	-45.7	-60.2	-35.0	-9.8	9.4	20.5	31.6	46.2	85.5
39.2	-10.3	-55.3	-85.5	-103.4	-78.2	-53.0	-39.4	-28.3	-17.2	21.3	68.6
32.3	-17.2	-66.7	-116.3	-146.6	-121.4	-99.3	-88.1	-77.0	-42.3	5.0	52.3
25.4	-24.1	-73.7	-104.2	-132.7	-161.8	-148.0	-136.9	-105.8	-58.6	-11.3	36.0
24.3	-6.1	-34.6	-63.1	-91.7	-127.3	-170.1	-169.4	-120.5	-71.2	-22.0	27.2
63.5	35.0	6.4	-22.1	-58.4	-102.0	-133.5	-129.2	-111.8	-62.6	-13.3	35.9
104.6	76.0	47.5	9.7	-33.9	-77.5	-83.6	-80.1	-70.2	-53.9	-4.7	44.6
145.6	117.1	77.8	34.2	-9.4	-31.1	-33.6	-31.1	-21.2	-11.3	4.0	53.2
186.7	145.9	102.3	58.7	21.9	18.9	16.3	17.9	27.8	37.7	47.6	72.4
214.0	170.4	127.3	90.2	71.4	68.8	66.2	66.9	76.8	86.7	96.6	111.9

$$f(x) = \begin{cases} \min_{s \in S} d(x, s) & x \notin S \\ -\min_{s \notin S} d(x, s) & x \in S \end{cases}$$

- S = subset of pixels
- s = boundary
- d = Euclidean distance







• Comparison with other representations

L1 loss	• L1 encourages the model to output 1 or 0			
	• Sharp edges			
	 Fail on thin, ambiguous structures 			
Cross Entropy loss	 encourages the model, at each pixel, to output its estimate of the probability that that pixel is part of the mask. T Blurry mask 			





Network loss functions

 $\mathcal{L}_{\rm object} = \lambda_{\rm pixel} \mathcal{L}_{\rm pixel} + \lambda_{\rm mask} \mathcal{L}_{\rm mask}.$

• where, $\lambda_{\text{pixel}} = 1$ and $\lambda_{\text{mask}} = 0.1$

• Mask loss:
$$\mathcal{L}_m = \frac{1}{N_{pix}} \left\| M_{pred} - SDF(M_{GT}) \right\|_1$$

where, N_{pix} is the number of pixels, M_{GT} is the ground truth mask, and SDF is the signed distance function scaled to be between -1 and 1

• L2 reconstruction loss:
$$\mathcal{L}_{\text{pixel}} = \frac{(\sum M_{\text{GT}}(x, y)(I_{\text{pred}}(x, y) - I_{\text{GT}}(x, y))^2}{\sum M_{\text{GT}}(x, y)}$$





OCONet – step3 Generator

Generator loss functions

$$\mathcal{L}_{\text{gen}} = \lambda_{\text{adv}} \frac{1}{N_{\text{pix}}} \left(\sum_{(x,y)} -D(x,y) \right) + \mathcal{L}_{\text{object}} + \lambda_{\text{fm}} \mathcal{L}_{\text{fm}}$$

• where, $\lambda_{\text{perceptual}} = \lambda_{\text{pixel}} = 1$ and $\lambda_{\text{mask}} = 0.1$

• Reconstruction loss:
$$\mathcal{L}_{object} = \frac{1}{N_{pix}} \|M_{pred} - SDF(M_{GT})\|_{1}$$

where N_{pix} is the number of pixels, M_{GT} is the ground truth mask, and SDF is the signed distance function scaled to be between -1 and 1

• Feature Matching loss:
$$\mathcal{L}_{\text{fm}} = \sum_{i} \frac{1}{N_i} \sum_{x,y} \left(\hat{\phi}_i(I_{\text{real}}) - \hat{\phi}_i(I_{\text{gen}}) \right)^2$$

qi being features in the ith layer of the discriminator

• Gan loss:
$$\mathcal{L}_{GAN} = \frac{1}{N_{pix}} \left(\sum_{(x,y)} -D(x,y) \right)$$





OCONet – step4 composition

- composite foreground object onto an extrapolated background
 - Input: cropped color image I of size H*W*3
 - Output: mask indicating an object to be completed of size H*W*1
- Any instance segmentation method possible (in experiment shape mask)







OCONet – experiment results

• Qualitative



Input Ours Boundless SSSD

GT





OCONet – experiment results

• Quantitative

		FID (lower is better)			L1 (lower is better)			
Category	n	Ours	Boundless	SSSD	Ours	Boundless	SSSD	
Airplane	1256	34.15	57.33	56.61	11.2	11.4	18.7	
Apple	337	83.21	107.31	122.54	18.5	18.5	18.8	
Car	1396	44.00	63.48	68.41	21.3	22.2	22.8	
Cat	613	94.04	126.68	131.85	18.0	18.4	18.9	
Dog	840	74.93	89.15	92.11	17.9	18.6	19.0	
Horse	909	63.21	90.58	90.31	20.3	21.0	21.2	
Kite	104	136.60	148.99	141.61	6.46	6.44	6.58	
Person	802	107.36	112.08	112.46	19.8	20.2	20.4	
Train	261	65.08	114.44	111.36	20.6	21.3	21.8	
All	6518	20.82	30.67	32.02	17.9	18.4	18.8	



