Pre-trained and Shared Encoder in Cycle-Consistent Adversarial Networks to Improve Image Quality

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1. Introduction

Images generated from CycleGAN become blurry especially in areas with complex edges.

Input Output

Fig.1. Problem in CycleGAN

To solve this problem, we design a new module called ED-Block to extract and project edges and boundaries information in advance and add them back to output to improve image quality.

Input Ours CylceGAN Unit DiscoGAN

Fig.2. Results comparison

2. Method

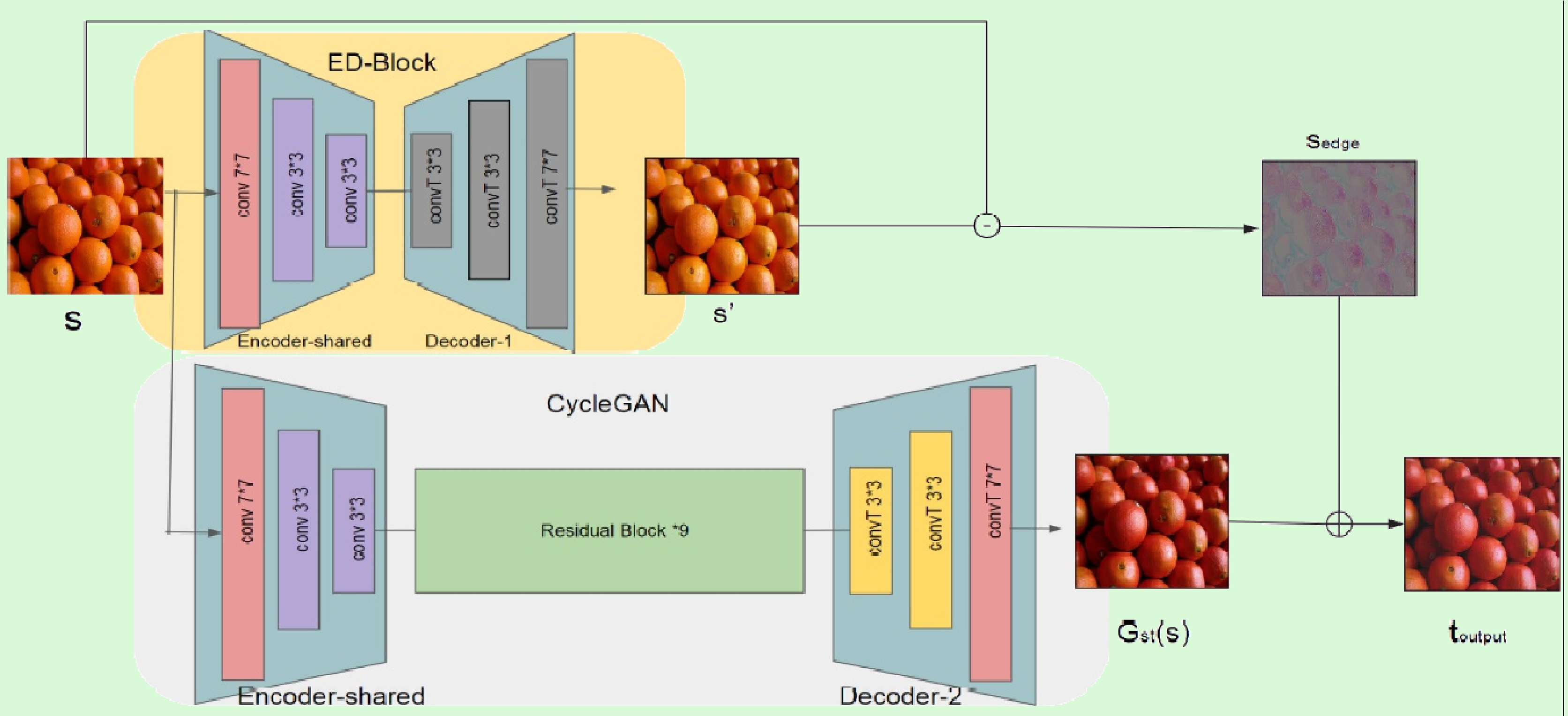

Fig.3. The structure of our proposed network.

ED-Block is trained in advance using Eq.1. Then, we subtract the output image to the original input, we can get difference map.

$$\mathcal{L}_{recover}(s, s') = ||s - s'||_1 \quad (1) \qquad s_{edge} = s - s' \quad (2)$$

ED-Block will be frozen before training CycleGAN part and its encoder will be shared with generators. We also did some changes on adversarial losses and cycle consistency loss to train CycleGAN part.

$$\mathcal{L}^{s}_{adv}(G_{st}, D_T) = \mathbb{E}_{t\sim P_T(t)}[\log D_T(t)] + \mathbb{E}_{s\sim P_S(s)}[\log(1 - D_T(G_{st}(s) + s_{edge}))] \quad (3)$$

$$s'' = G_{ts}\big(G_{st}(s) + s_{edge}\big) + s_{edge} \quad (4)$$

$$\mathcal{L}^{s}_{cyc}(s, s'') = ||s - s''||_1 \quad (5)$$

3. Experiment

The epoch of training ED-Block shoule be proper to reconstructed the input image. After many attempts, we set it to 200 epochs.

Input 10 epochs 50 epochs 100 epochs 200 epochs 500 epochs

Fig.4. Results of ED-Block

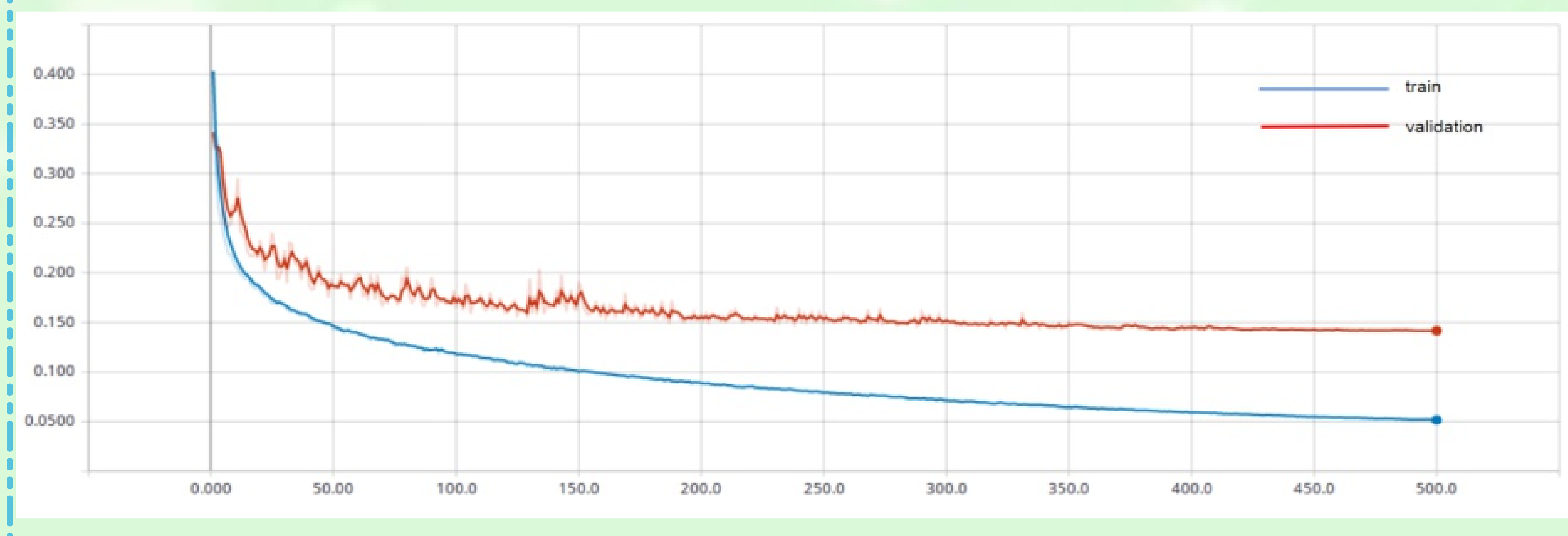

Fig.5. Loss values of ED-Block in 500 epochs

Model	Parameters (10^5)	Time expense (hours)
ED-Block	**7.56**	**1.533**
Our-CycleGAN	**275.30**	**16.898**
CycleGAN	**282.86**	**15.35**
Unit	**270.66**	**21.198**
Disco	**598.1**	**16.844**

Fig.6. Models Comparison

Our network achieves highest evaluation scores among CycleGAN, Unit and DiscoGAN.

Model	SSIM		PSNR(dB)	
	consistent-apple	consistent-orange	consistent-apple	consistent-orange
Ours	**0.8029**	**0.7503**	**19.266**	17.068
Ours (with t_{edge})	0.7535	0.7021	16.764	15.582
CycleGAN	0.7329	0.6927	19.035	17.985
CycleGAN-Skip	0.7412	0.7061	18.654	17.743
Unit	0.6948	0.6705	18.449	**18.297**
Disco	0.4403	0.4107	13.424	14.462

Fig.7. Evaluation Scores on Apple2Orange

4. Conclusion

- We designed a novel block, called ED-Block, to extract edge information and save it in difference map.
- We proposed ED-CycleGAN and by adding translated image to its difference map, we can get images with much better quality.
- Our model get notable evaluation scores compared with CycleGAN, Unit and DiscoGAN.

5. Reference

[1] Isola, P., Zhu, J.Y., Zhou, T., Efros, A.A.: Image-to-image translation with conditional adversarial networks. In: Computer Vision and Pattern Recognition (CVPR), 2017 IEEE Conference on (2017)
[2] Johnson, J., Alahi, A., Li, F.: Perceptual losses for real-time style transfer and super-resolution. ECCV abs/1603.08155 (2016)
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