HUAZHONG UNIVERSITY OF SCIENCE AND TECHNOLOGY

LAB REPORT

High Resolution image transformation with Cycle-consistent Adversarial Networks

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Haoran YOU

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1 Metric

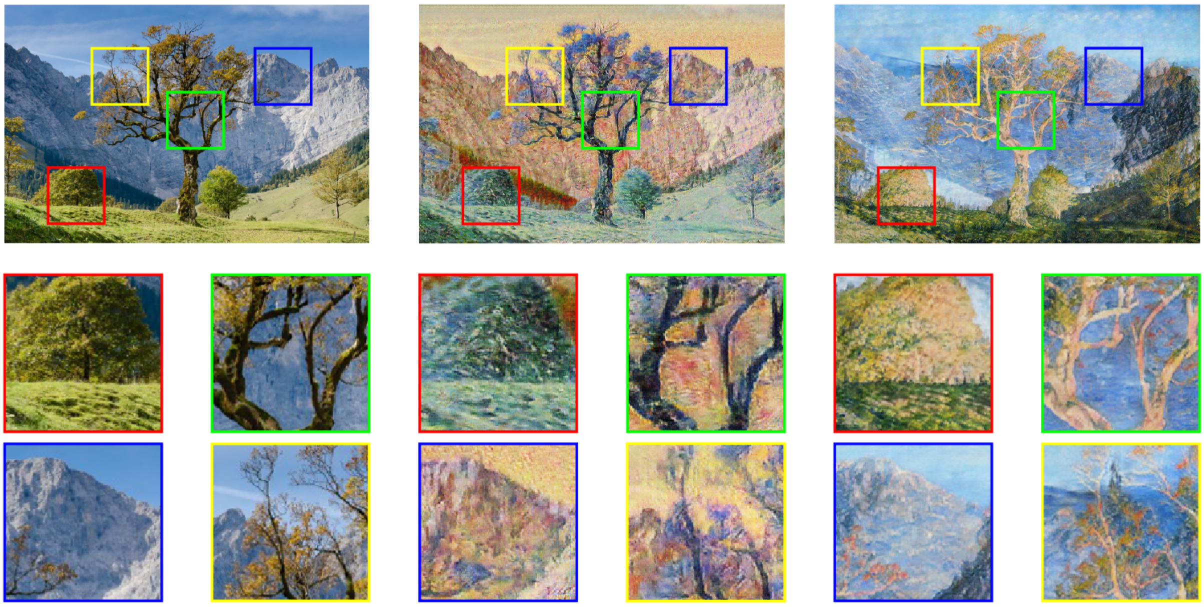

Figure 1: The left is original landscape, others are transfered to monet style with Cyclegan(the middle figure) and Ours network(right). Local image patches(128×128) extracted for quantitative comparisons. Shown in Table 1

Image Gradient Difference Loss We use gradient difference loss to evaluate the performance of *Cyclegan* and Our networks. Give the original image I^{ori}, stylized image $I^{sty} = G(I^{ori})$ and α which is an integer greater than or equal 1. Image Gradient Difference Loss can be expressed as [1]:

$$\ell_{GDL}(I^{ori}, I^{sty}) = \frac{\sum_{i,j}^{M,N} \left|\left|I^{ori}_{i,j} - I^{ori}_{i-1,j}\right| - \left|I^{sty}_{i,j} - I^{sty}_{i-1,j}\right|\right|^{\alpha} + \left|\left|I^{ori}_{i,j} - I^{ori}_{i,j-1}\right| - \left|I^{sty}_{i,j-1} - I^{sty}_{i,j-1}\right|\right|^{\alpha}}{M \times N} \tag{1.1}$$

We compare our artificial Monet-style landscape with what has been generated by *Cyclegan*. In particular, we choose local patches with size 128×128 and use the *GDL* from (eq:1) as a smoothing evaluation criteria. Obviously, lower GDL score means that the artifact performs better in detail and has a similar semantic expression with original picture. As seen in Table1, our networks get a lower score than *Cyclegan*, which is consistent with our visual experience.

2 Anime2Sketch

There are extensive applications for high resolution image transfer since extreme quality is what most of us pursue. For instance, many artists devote their intelligence and innovation for the animation industry development, most of the time it needs to be converted between anime characters and sketches. We use 583 sketch images and 300 anime images to train our networks, in order to implement the conversion between them automatically. The result can be seen in Figure1(anime2sketch),2(sketch2anime). Besides, we compare our result of transformation with *Cyclegan* and find that our networks perform better in detail and style construction.

Table 1: Gradient Difference Loss

α	Row/Method	RGB	CycleGAN	Ours
1	A	R	31.35	24.37
		G	31.48	24.58
		B	28.94	24.57
	B	R	27.77	19.15
		G	28.61	19.22
		B	29.17	23.44
	C	R	20.93	14.56
		G	23.36	13.27
		B	23.31	13.45
	D	R	24.98	21.77
		G	26.07	21.36
		B	28.43	24.76
	Mean	R	26.26	19.96
		G	27.38	19.61
		B	27.46	21.56
2	A	R	918.69	570.65
		G	930.61	580.84
		B	783.79	581.01
	B	R	789.59	366.97
		G	783.77	388.21
		B	809.21	626.73
	C	R	432.39	214.19
		G	511.26	191.85
		B	503.36	214.7
	D	R	639.02	463.83
		G	652.69	466.35
		B	772.86	658.41
	Mean	R	694.92	403.91
		G	719.58	406.81
		B	717.31	520.21

Figure 2: Anime2Sketch

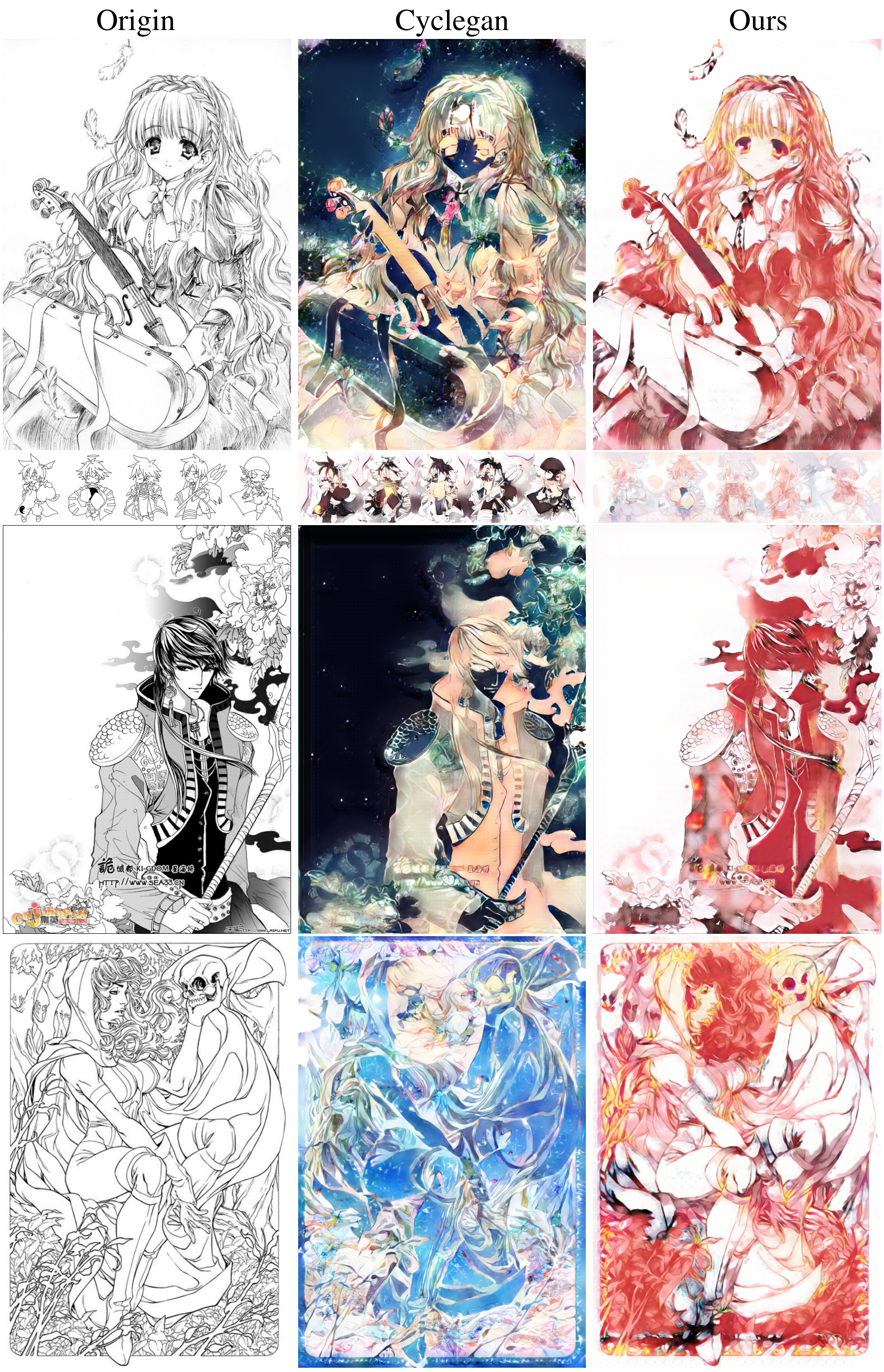

Figure 3: Sketch2Anime

References

[1] Md Jahidul Islam Gameron Fabbri and Junaed Sattar. Enhancing underwater imagery using generative adversarial networks. In *Computer Vision and Pattern Recognition (CVPR), 2018 IEEE International Conference on*, 2018.