Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks

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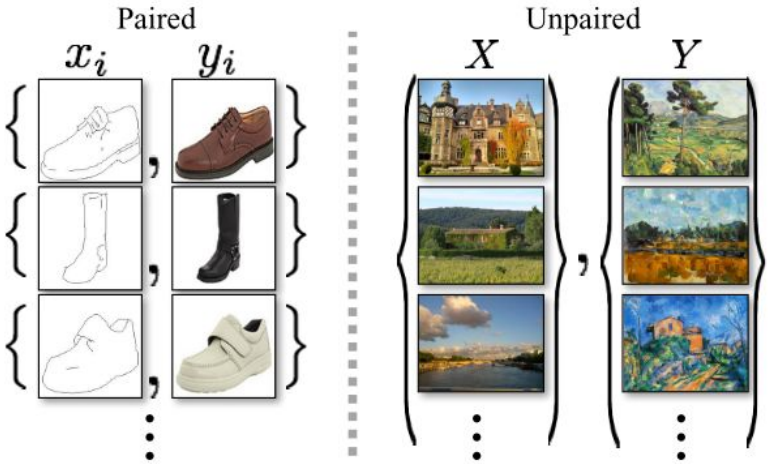
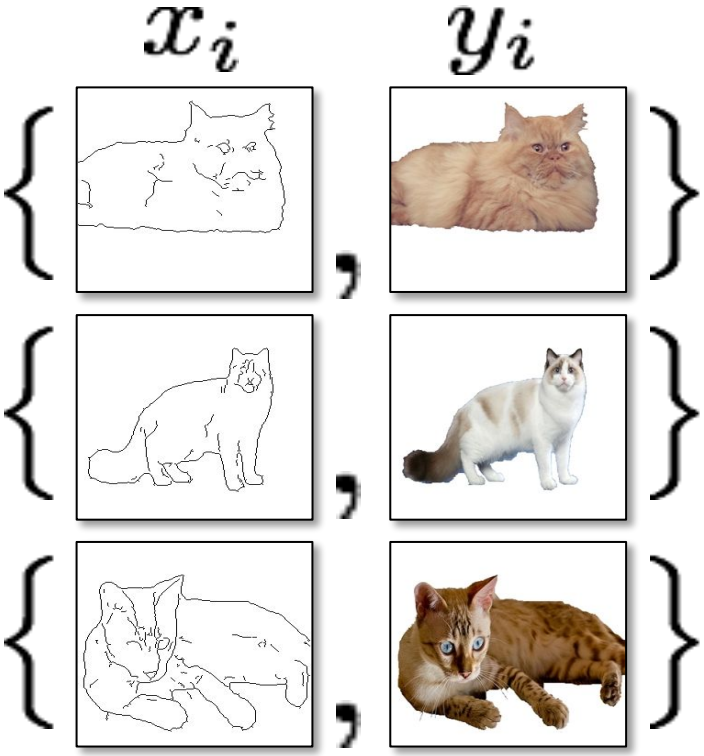
Presenter: Hai Nguyen

Introduction

- Focus on image-to-image translation when paired training data is not available
- Assumption: There is some underlying relationship between 2 domains e.g. two different renderings of the same underlying scene. Deterministic mapping
- Applications in style transfer, object transfiguration, season transfer, photo enhancement



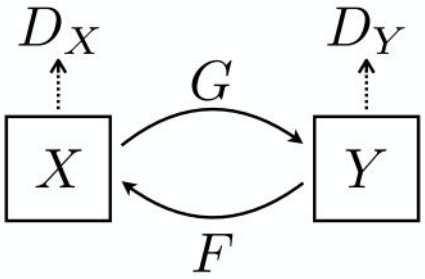
Paired



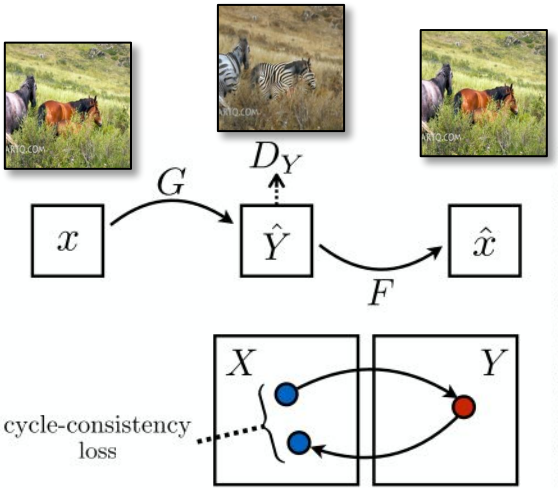
- Expensive to collect pairs.
- Impossible in many scenarios.

Slide from the authors

Formulation

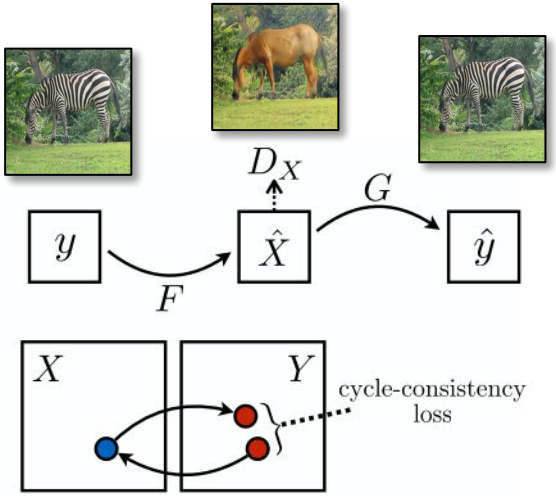


$$\mathcal{L}_{\text{GAN}}(G, D_Y, X, Y)$$
$$\mathcal{L}_{\text{GAN}}(F, D_X, Y, X)$$



Forward cycle-consistency loss

$$\|F(G(x)) - x\|_1$$



Forward cycle-consistency loss

$$\|G(F(y)) - y\|_1$$

$$\mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) = \mathbb{E}_{y \sim p_{\text{data}}(y)}[\log D_Y(y)] + \mathbb{E}_{x \sim p_{\text{data}}(x)}[\log(1 - D_Y(G(x))]$$

Full objective

$$\mathcal{L}(G, F, D_X, D_Y) = \mathcal{L}_{\text{GAN}}(G, D_Y, X, Y) + \mathcal{L}_{\text{GAN}}(F, D_X, Y, X) + \lambda \mathcal{L}_{\text{cyc}}(G, F),$$

Slide from the authors

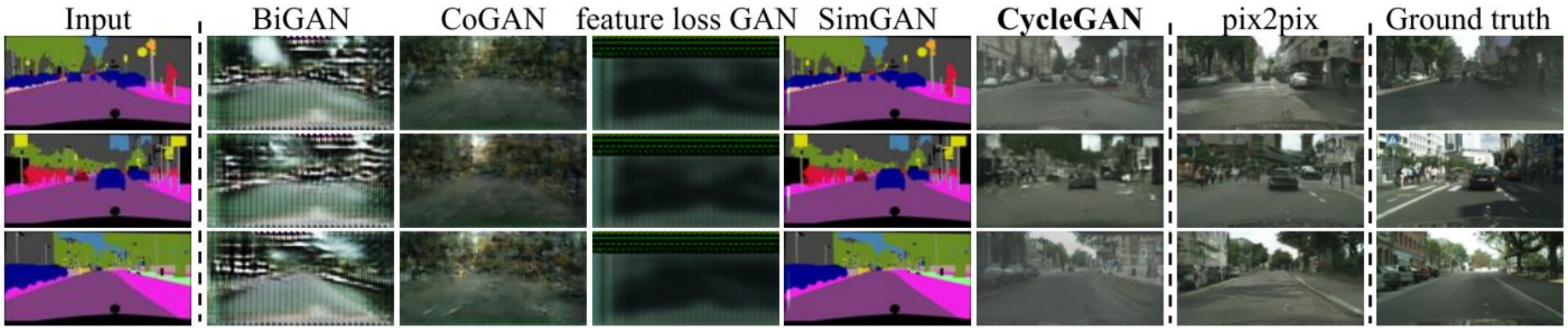
GAN does not force output to correspond to input

The generator can output the same input with different inputs as long as the discriminator cannot distinguish fake images from real ones

Mode collapse

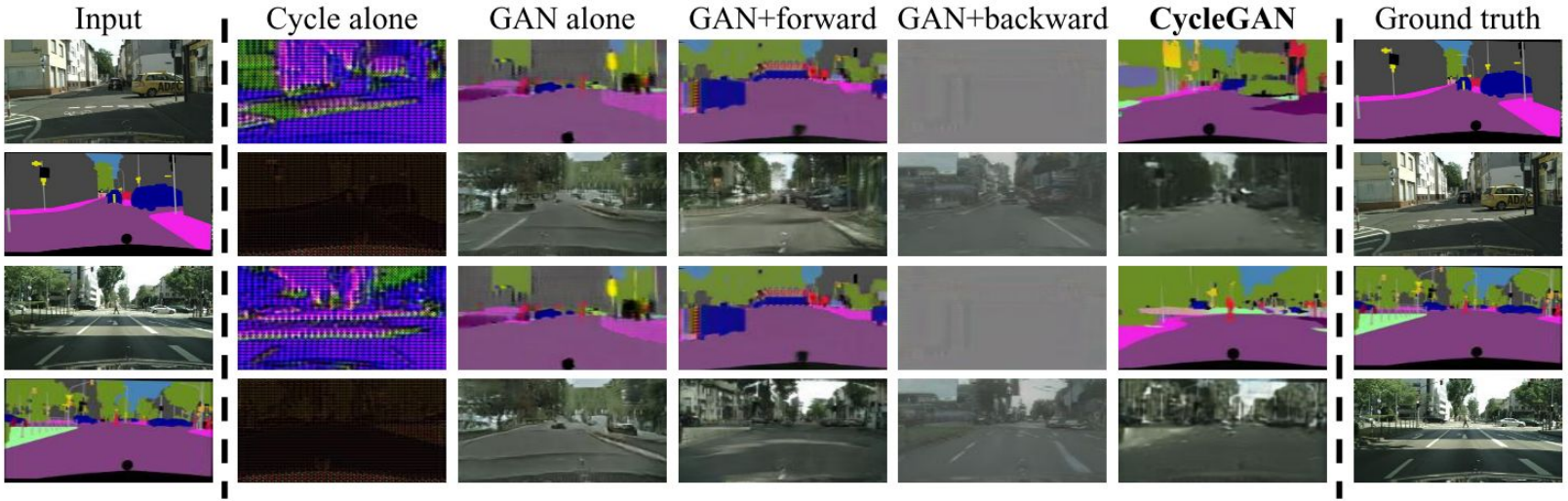
Slide from the authors

Results



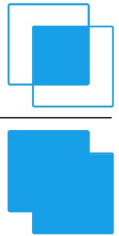
- BiGAN: GAN + learn the inverse mapping from X → Z
- CoGAN: G_X and G_Y have weights tied on the first few layers
- SimGAN: GAN + a non-cycle regularization term on pixels
- Feature Loss GAN: Like SimGAN but the regularization is computed over deep image features using a VGG-16
- Pix2Pix: Train on paired data - upper bound

Ablation Study



Loss	Per-pixel acc.	Per-class acc.	Class IOU
Cycle alone	0.22	0.07	0.02
GAN alone	0.51	0.11	0.08
GAN + forward cycle	**0.55**	**0.18**	**0.12**
GAN + backward cycle	0.39	0.14	0.06
CycleGAN (ours)	0.52	0.17	0.11

$$\text{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$



Style Transfer

Photograph
@ Alexei Efros

Monet

Van Gogh

Cezanne

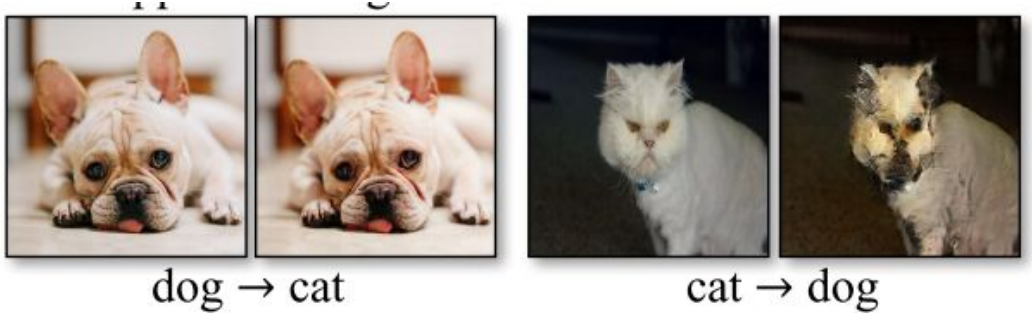
Ukiyo-e

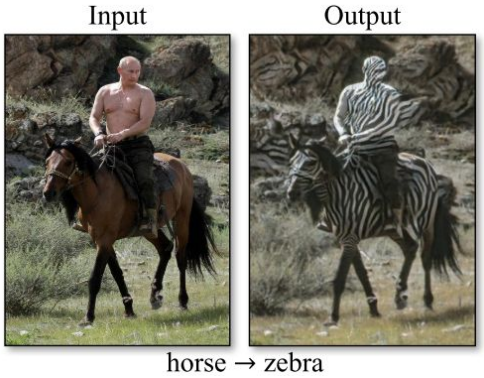
Slide from the authors


Input
Monet
Van Gogh
Cezanne
Ukiyo-e

Failure Cases

- Geometric changes, possibly due to the tailored generator that works well with appearance changes
- With unseen data during training i.e. human riding a horse





Thoughts

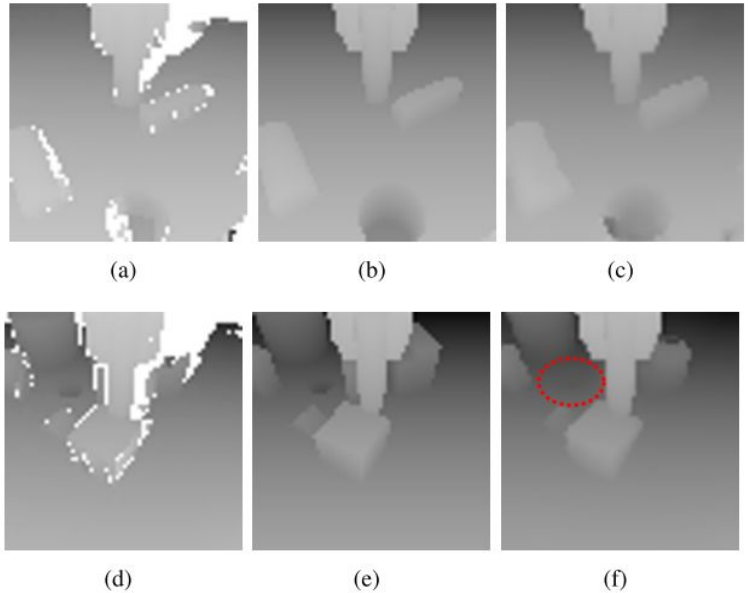
- A simple idea but works very effectively → gets a lot of citations (5K)
- The implementation is possible a hard part
- Nice website and github repo (~13K star)

RL Papers That Use Cycle GAN

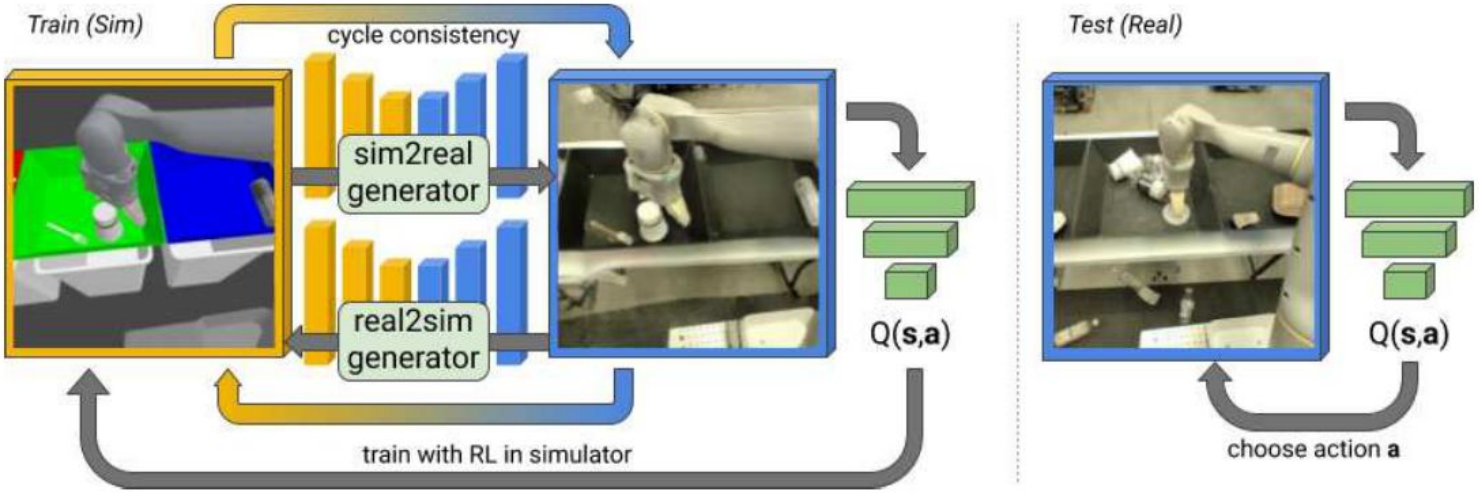
- Learning visual servo policies via planner cloning (use pix2pix instead) - Ulrich & Rob
- RL-CycleGAN: Reinforcement Learning Aware Simulation-To-Real - Rao et. al., CVPR 2020
- AVID: Learning Multi-Stage Tasks via Pixel-Level Translation of Human Videos - Laura et.al., RSS 2020

Planner Cloning

- Using pix2pix GAN to convert sim <-> real depth images
- Images a+d: real; b+e: simulated; c+f: prediction made by pix2pix
- A hole is missed in figure f
- Real depth images are pre-processed with pix2pix and the result is fed to the policy learned in simulation



RL-Cycle GAN



RL-CycleGAN: Reinforcement Learning Aware Simulation-To-Real - Rao et. al., CVPR 2020

Figure 1. RL-CycleGAN trains a CycleGAN which maps an image from the simulator (left) to a realistic image (middle), a jointly trained RL task ensures that these images are useful for that specific task. At test time, the RL model may be transferred to real robot (right).

- Naive image-2-image generative model is task-agnostic (Ulrich's case) - the model might filter out useful features for the task
- Jointy trained with RL loss to fix to make it task-aware
- Make sure Q-value for an image is unchanged over the sim2real image translation

RL-Cycle GAN

Sim2Real: G: X → Y, Real2Sim: F: Y → X

$$\mathcal{L}_{RL-CycleGAN}(G, F, D_X, D_Y, Q) = \lambda_{GAN}\mathcal{L}_{GAN}(G, D_Y) + \lambda_{GAN}\mathcal{L}_{GAN}(F, D_X) + \lambda_{cycle}\mathcal{L}_{cyc}(G, F) + \lambda_{RL-scence}\mathcal{L}_{RL-scene}(G, F) + \lambda_{RL}\mathcal{L}_{RL}(Q)$$

$$\mathcal{L}_{RL}(Q) = \mathbb{E}_{(x,a,r,x')} d(Q(x, a), r + \gamma V(x'))$$

$$\mathcal{L}_{RL-scene}(G, F) = d(q_x, q'_x) + d(q_x, q''_x) + d(q'_x, q''_x) + d(q_y, q'_y) + d(q_y, q''_y) + d(q'_y, q''_y)$$

$$(x, a) \sim \mathcal{D}_{sim}, (y, a) \sim \mathcal{D}_{real}$$

$$q_x = Q_{sim}(x, a)$$

$$q'_x = Q_{real}(G(x), a)$$

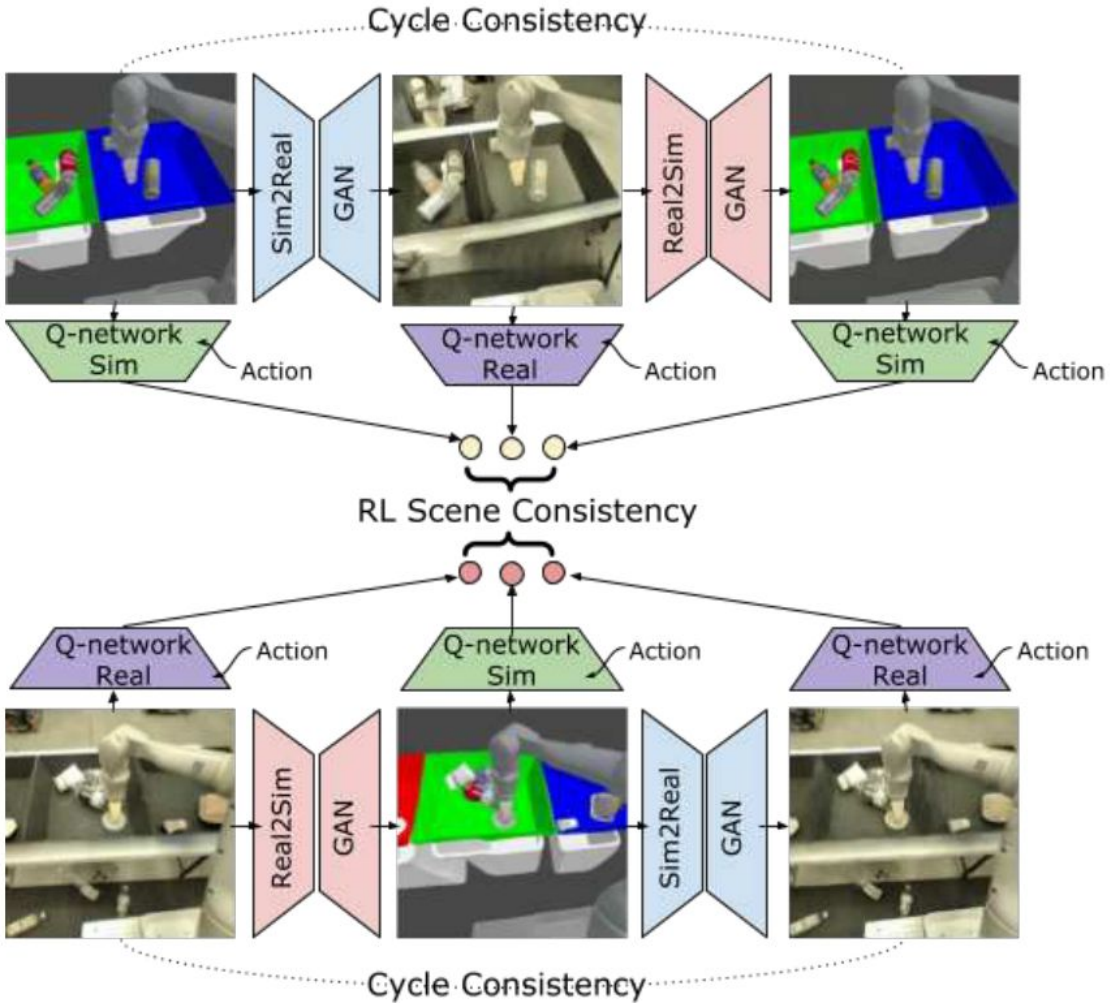
$$q''_x = Q_{sim}(F(G(x)), a)$$

$$q_y = Q_{real}(y, a)$$

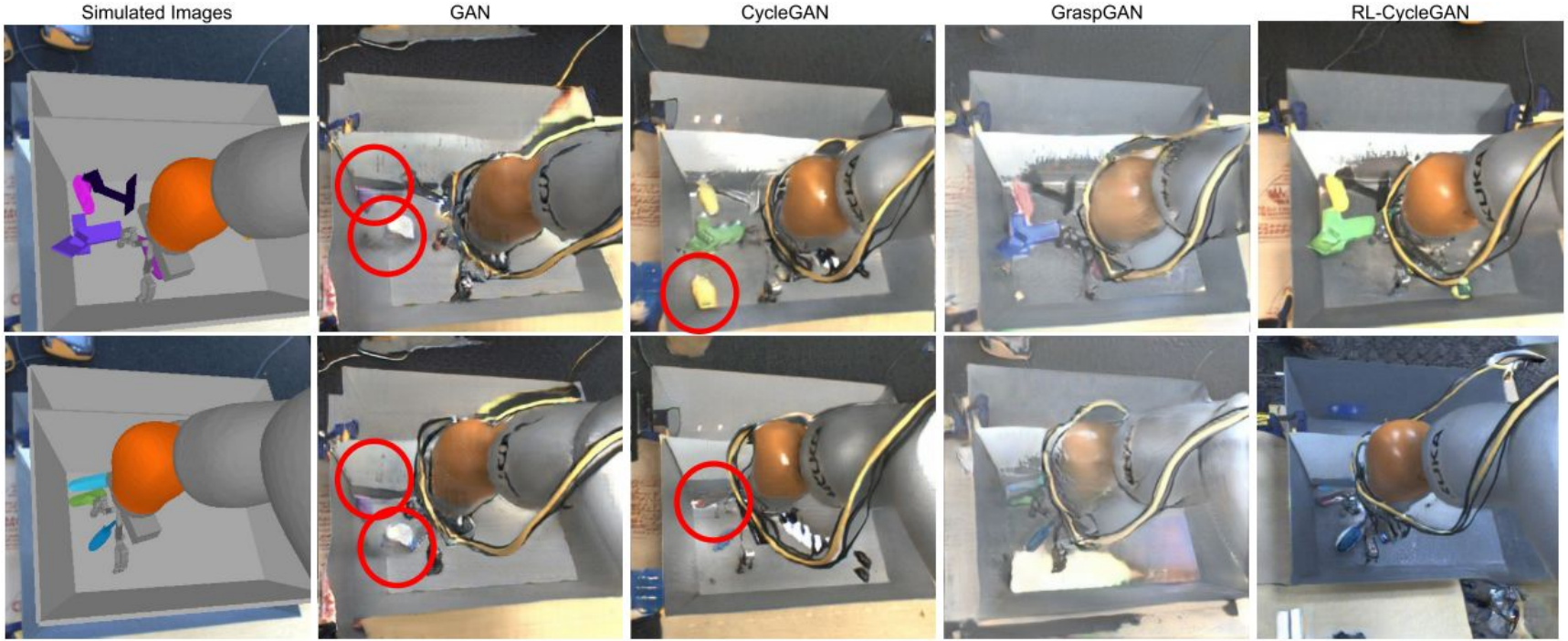
$$q'_y = Q_{sim}(F(y), a)$$

$$q''_y = Q_{real}(G(F(y)), a)$$

RL-Cycle GAN


Cycle Consistency
Sim2Real
GAN
Real2Sim
GAN
Q-network Sim
Action
Q-network Real
Action
Q-network Sim
Action
RL Scene Consistency
Q-network Real
Action
Q-network Sim
Action
Q-network Real
Action
Real2Sim
GAN
Sim2Real
GAN
Cycle Consistency

RL-Cycle GAN



AVID

- Use CycleGAN to convert images of human demonstration to images of a robot performing the task
- Then use a model-based learning approach (MPC + CEM) to learn in a stage-wise fashion with human inputs to mark a stage is successful or not