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Compositional GAN: Learning Image-Conditional Binary Composition

Samaneh Azadi, Deepak Pathak, Sayna Ebrahimi, Trevor Darrell

University of California, Berkeley

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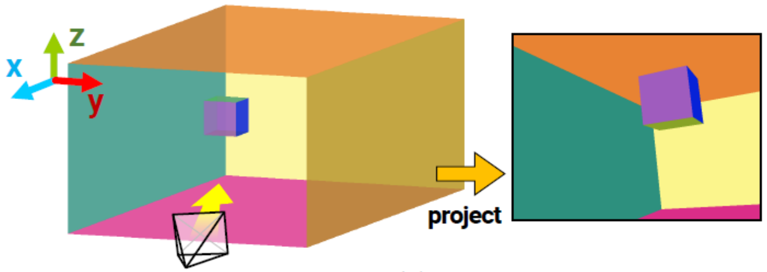
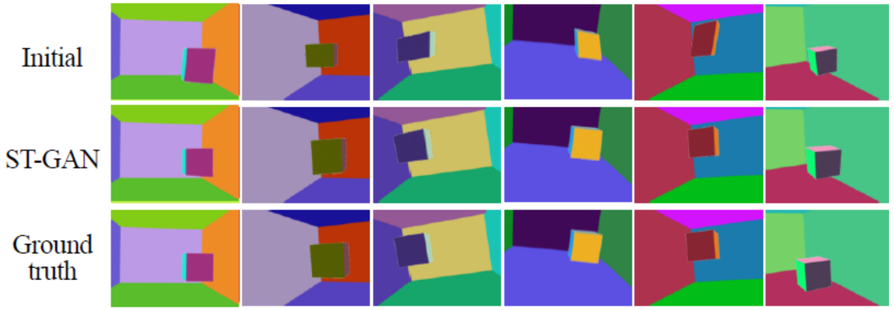
Slides compiled by Mengzhou Li

Introduction

- Modeling compositionality in natural images is a challenging problem due to complex interactions among different objects,
  - Relative scaling,
  - Spatial layout,
  - Occlusion,
  - Viewpoint transformation
- Recent work using spatial transformer networks (STN) within a GAN framework (ST-GAN) decomposes this problem by operating in a geometric warp parameter space to find a geometric modification for a foreground object.

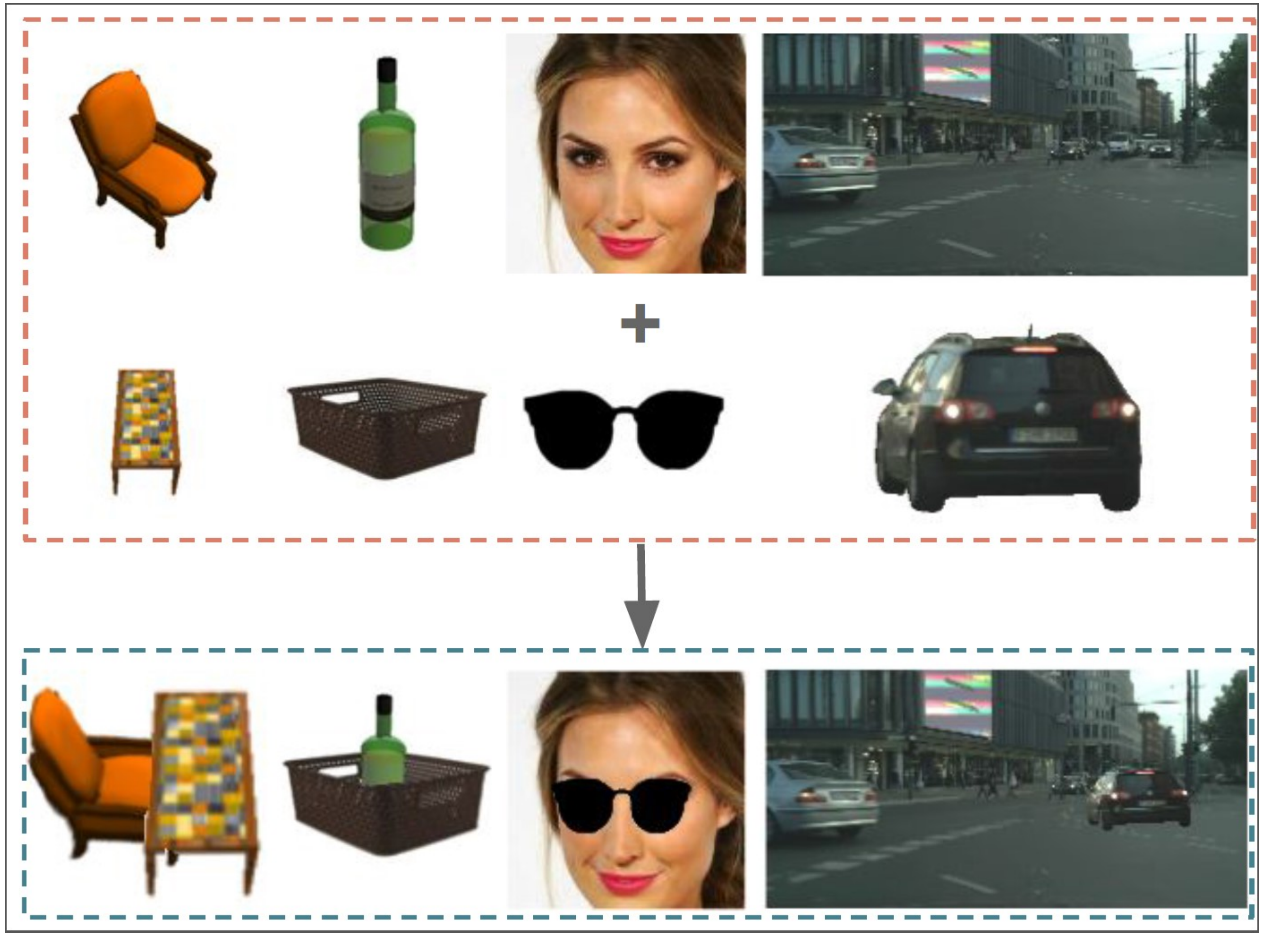


(a)



Motivation

• More general case and more complex interactions



• X + Y => C
• Assumption
The masks for X and Y in C are known

➢ Paired case
Training data contains X, Y and C

➢ Unpaired case
Training data contains only C

Approaches

For paired cases, *GAN not good at transforming objects spatially*

- Spatial Transformer Network (STN)
- Relative Appearance Flow Network (RAFN)

⇒Achieve scale and shift transformation of objects by STN, adjust viewpoint using RAFN

For unpaired cases, cut out X and Y from C

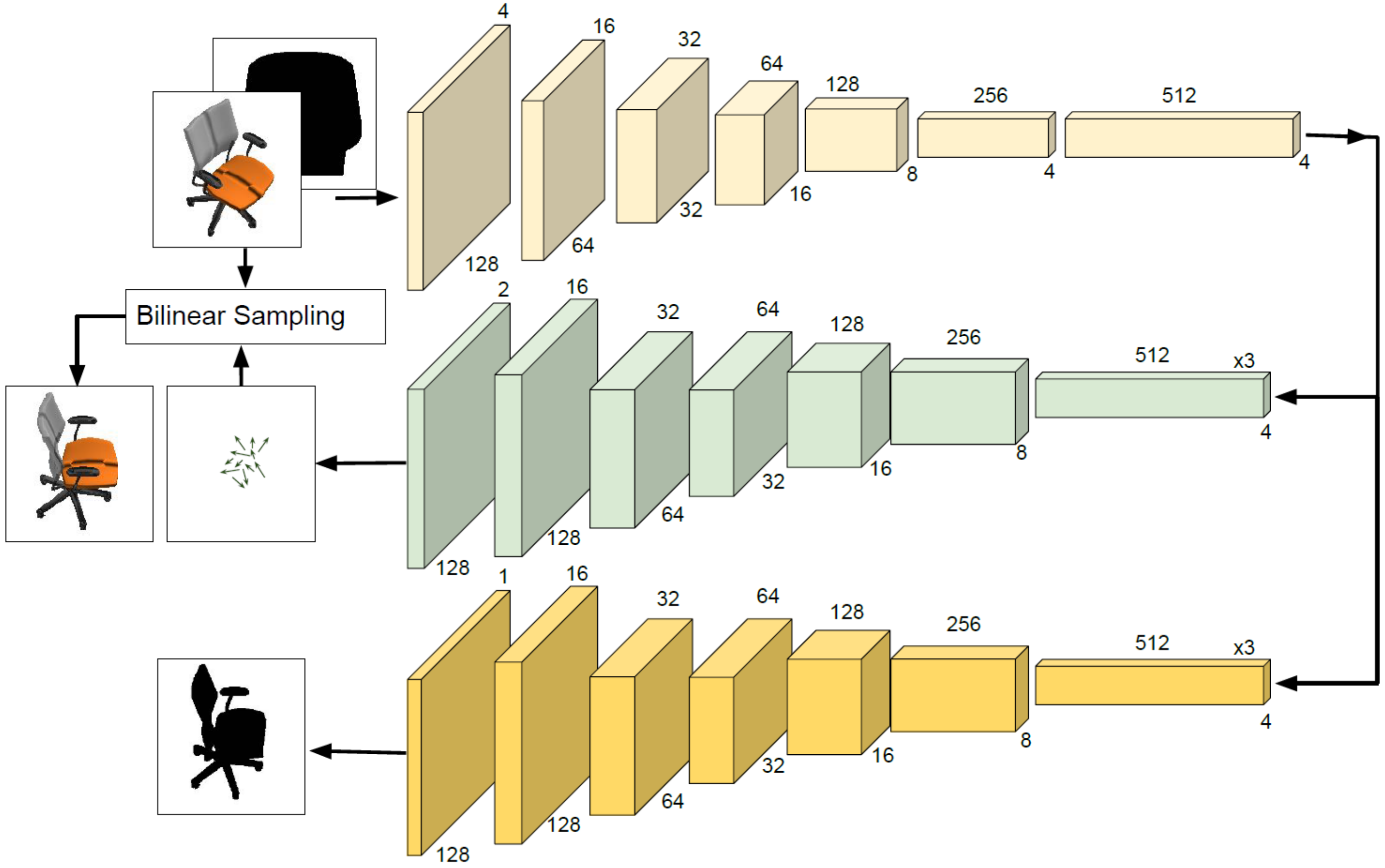
- Self-supervised inpainting network

⇒Obtained well aligned X and Y

Finally, use conditional GAN (CGAN) framework to achieve composition and refinement.

RAFN

- Relative Appearance Flow Network based on encoder-decoder



- Training data:

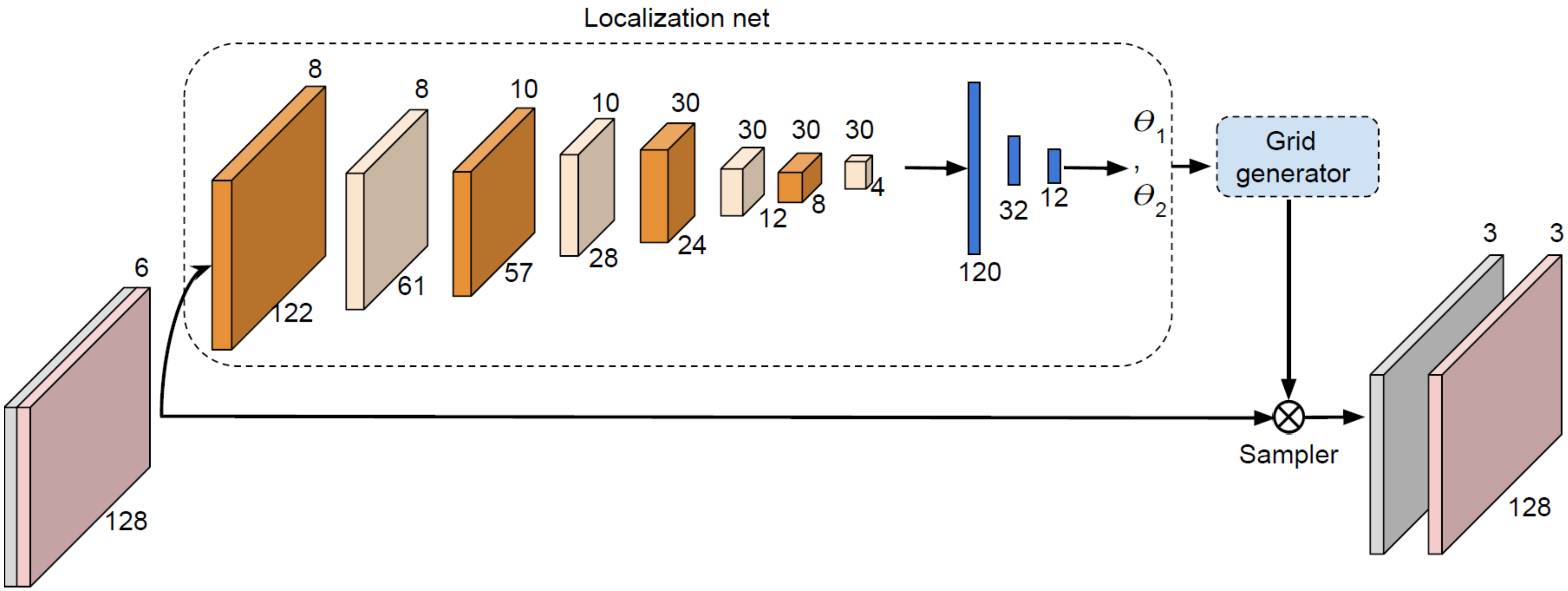
Xr, Y mask, X

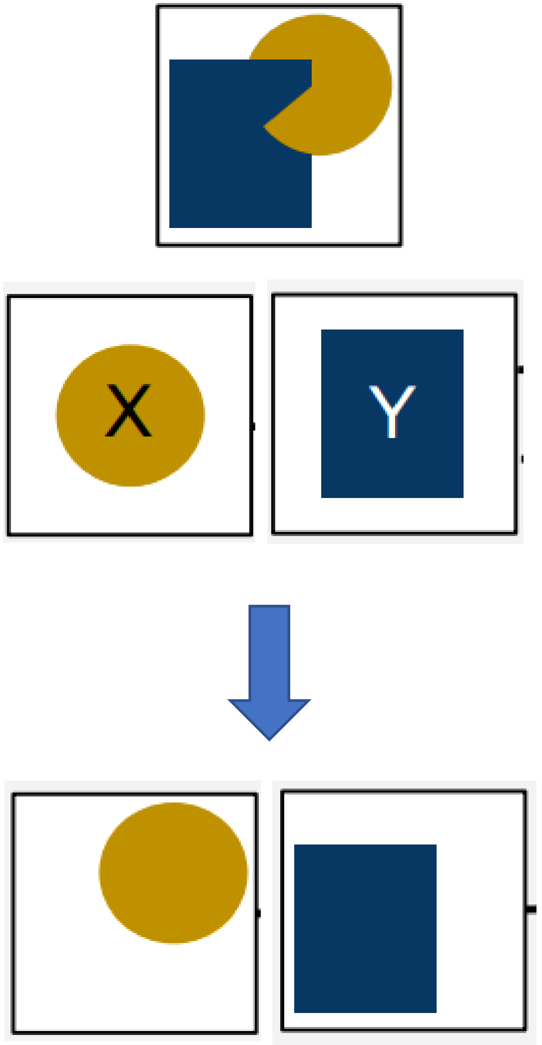
- Loss function

$$\begin{aligned}\mathcal{L}(G_{\text{RAFN}}) &= \mathcal{L}_{L_1}(G_{\text{RAFN}}) + \lambda \mathcal{L}_{\text{BCE}}(G^{M}_{\text{RAFN}}) \\ &= \mathbb{E}_{(x,y)}[\|x - G_{\text{RAFN}}(M^{\text{fg}}_{y}, x^{r})\|_1] \\ &+ \lambda \mathbb{E}_{x}[\hat{M}^{\text{fg}}_{x} \log M^{\text{fg}}_{x} + (1 - \hat{M}^{\text{fg}}_{x}) \log(1 - M^{\text{fg}}_{x})]\end{aligned}$$

STN

- Relative spatial transformer network





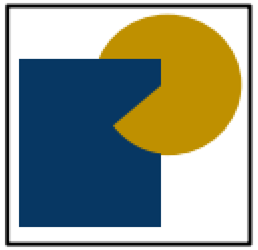
- Training data: X, Y, X^T, Y^T
- Loss function: $\mathcal{L}_{L_1}(\mathrm{STN}) = \mathbb{E}_{(x,y)}[||(x^c, y^c) - (x^T, y^T)||]$

Self-supervised inpainting network (CGAN)

- Training data:

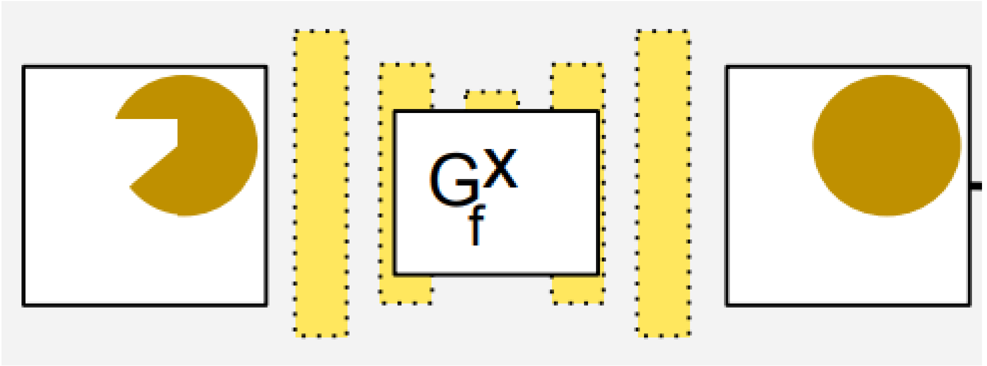
For X: cut out X from C with X mask, zero out pixel values in random area

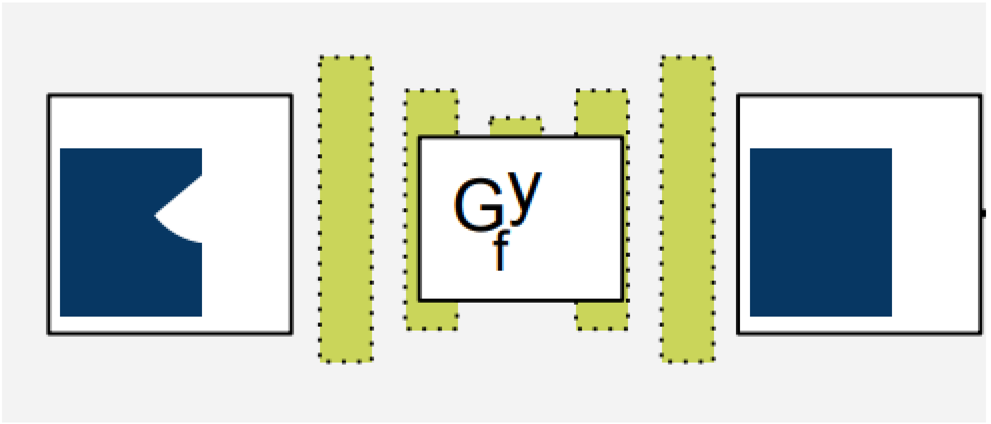
For Y: cut out Y from C with Y mask, zero out the X part



- Loss function

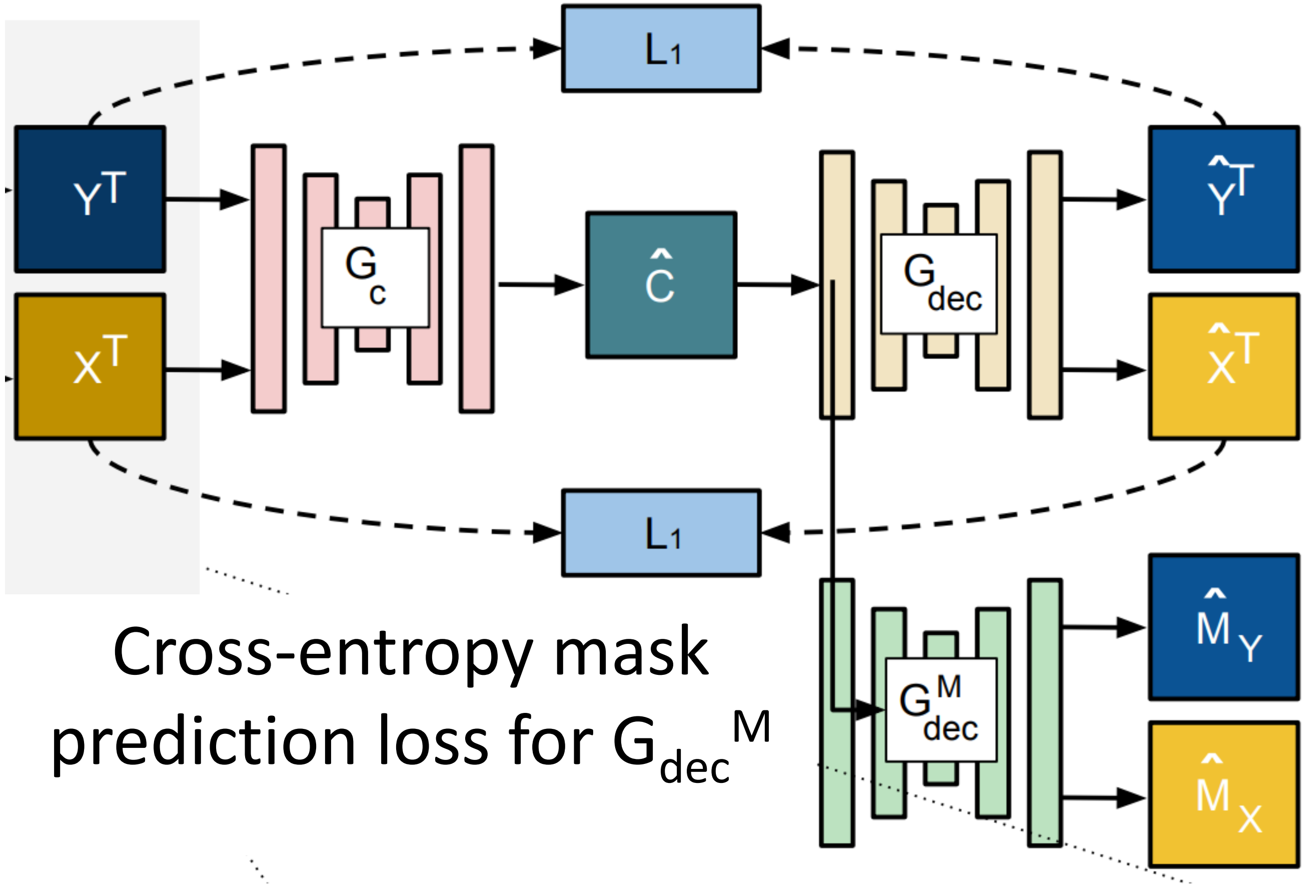
$$\mathcal{L}(G_f) = \mathcal{L}_{L_1}(G_f) + \lambda \mathcal{L}_{cGAN}(G_f, D_f)$$





Supervising composition by decomposition

- Self-consistent Composition-by-Decomposition (CoDe) based on CGAN



Cross-entropy mask prediction loss for G_{dec}^M

- Training data:

X^T, Y^T, Masks, C

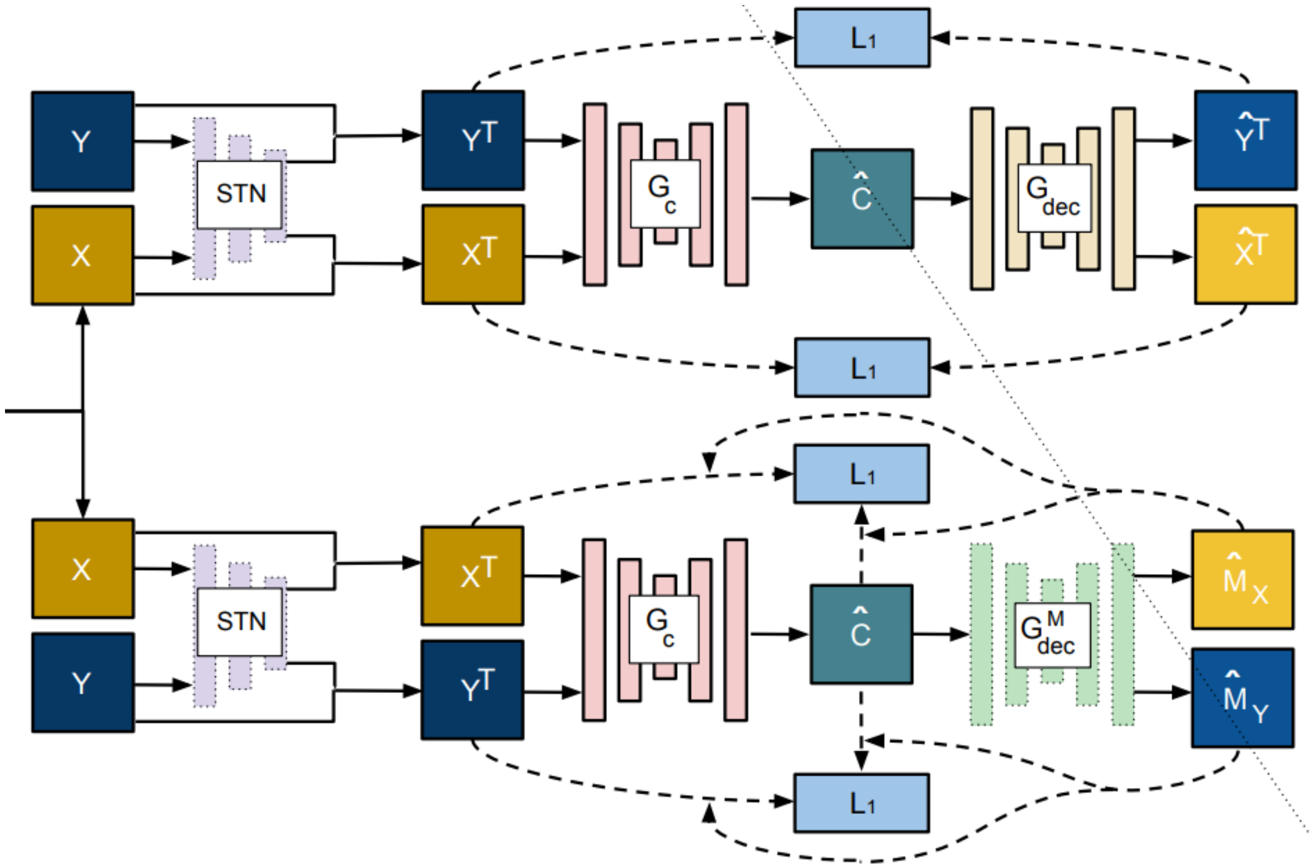
- Loss function

$$
\begin{aligned}
\mathcal{L}_{L_1}(G_c) &= \mathbb{E}_{(x,y,c)}\left[\|c-\hat{c}\|_1\right], \\
\mathcal{L}_{L_1}(G_{dec}) &= \mathbb{E}_{(x,y)}\left[\|(x^T, y^T) - G_{dec}(\hat{c})\|_1\right], \\
\mathcal{L}_{cGAN}(G_c, D_c) &= \mathbb{E}_{(x,y,c)}\left[\log D_c(x^T, y^T, c)\right] \\
&+ \mathbb{E}_{(x,y)}\left[1 - \log D_c(x^T, y^T, \hat{c})\right],
\end{aligned}
$$

$$
\begin{aligned}
\mathcal{L}_{cGAN}(G_{dec}, D_{dec}) = \mathbb{E}_{(x,y)}\big[\log D_{dec}(\hat{c}, x^c) \\
+ \log D_{dec}(\hat{c}, y^c)\big] + \mathbb{E}_{(x,y)}\big[(1 - \log D_{dec}(\hat{c}, \hat{x}^T)) \\
+ (1 - \log D_{dec}(\hat{c}, \hat{y}^T))\big].
\end{aligned}
$$

Example-Specific Meta-Refinement (ESMR)

- Self-consistent Composition-by-Decomposition (CoDe) based on CGAN

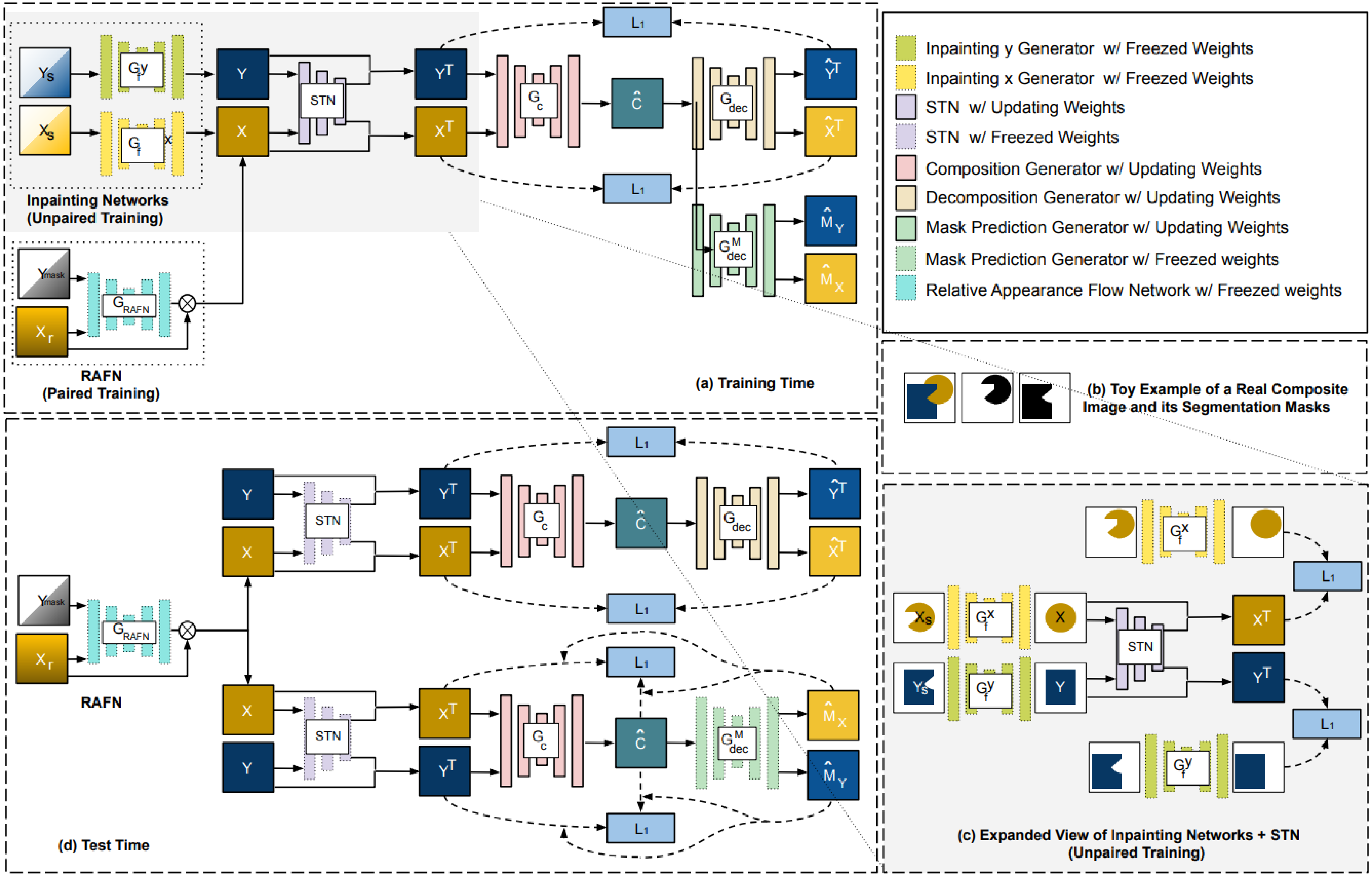


- Loss function

$$
\begin{aligned}
\mathcal{L}(G) \quad = \quad & \lambda(\|\hat{x}^T - x^T\|_1 + \|\hat{M}_x \odot \hat{c} - \hat{M}_x \odot x^T\|_1 \\
+ \quad & \|\hat{y}^T - y^T\|_1 + \|\hat{M}_y \odot \hat{c} - \hat{M}_y \odot y^T\|_1) \\
+ \quad & [\mathcal{L}_{\text{cGAN}}(G_c, D_c) + \mathcal{L}_{\text{cGAN}}(G_{\text{dec}}, D_{\text{dec}})],
\end{aligned}
$$

- Freeze STN, RAFN, and G_{dec}^{M}

- Only refine the weights of CoDe

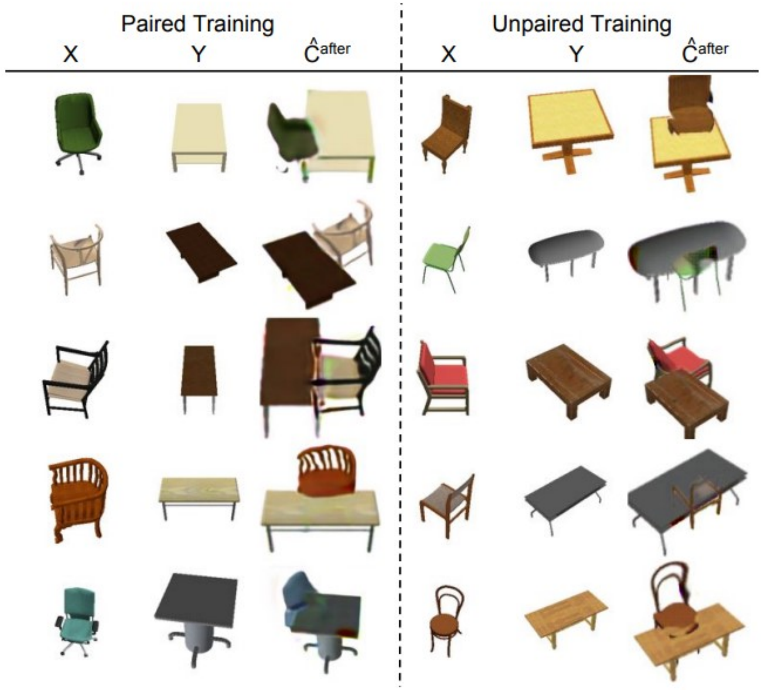


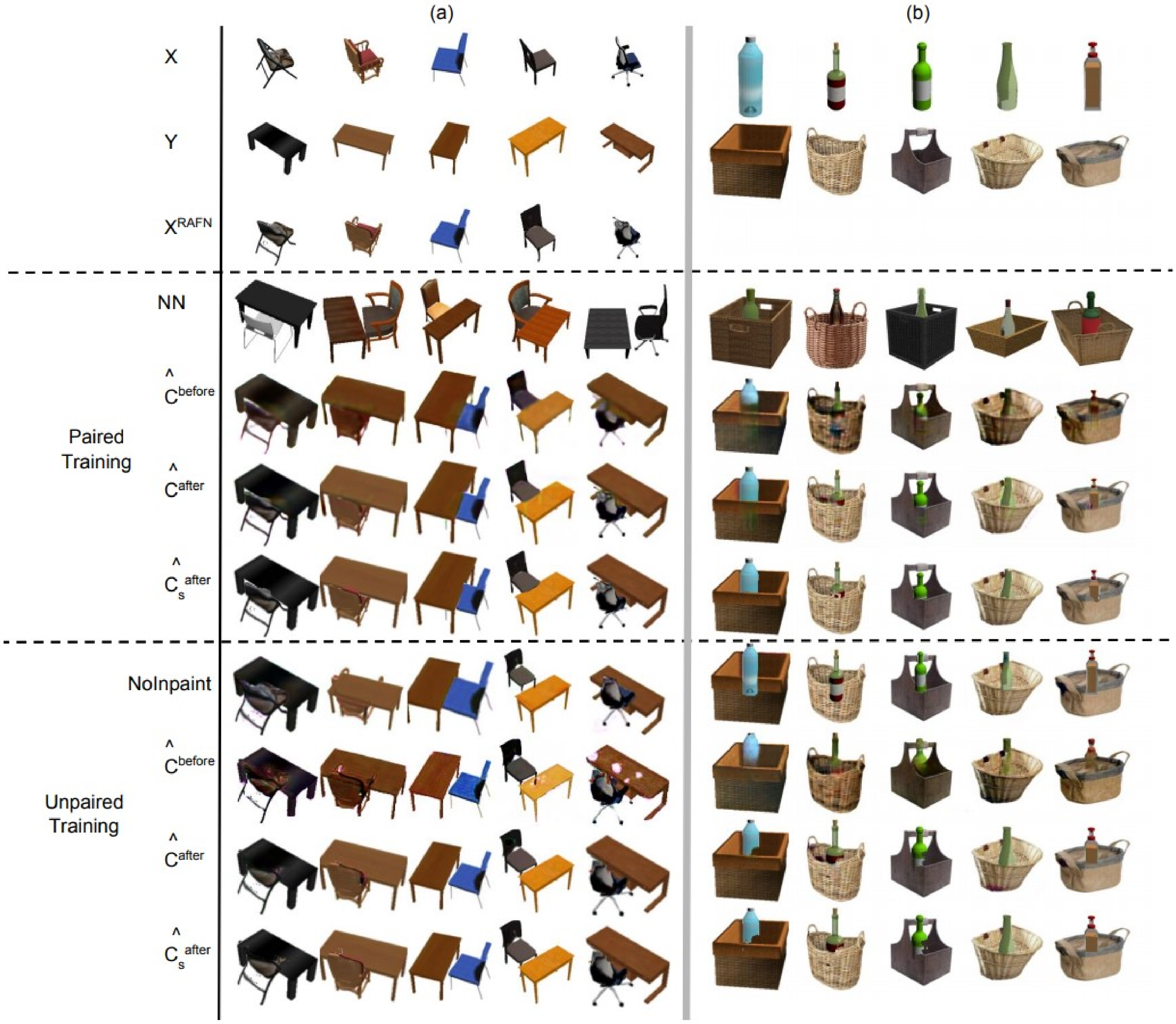
Inpainting y Generator w/ Freezed Weights
Inpainting x Generator w/ Freezed Weights
STN w/ Updating Weights
STN w/ Freezed Weights
Composition Generator w/ Updating Weights
Decomposition Generator w/ Updating Weights
Mask Prediction Generator w/ Updating Weights
Mask Prediction Generator w/ Freezed weights
Relative Appearance Flow Network w/ Freezed weights
Inpainting Networks (Unpaired Training)
RAFN (Paired Training)
(a) Training Time
(b) Toy Example of a Real Composite Image and its Segmentation Masks
(c) Expanded View of Inpainting Networks + STN (Unpaired Training)
(d) Test Time
RAFN
STN
L1

Results:

Table 1. AMT user evaluation comparing components of our model on the synthetic datasets. 2nd column: number of test images, 3rd column: % preferences to after vs. before refinement, 4th column: % preferences to paired training vs. unpaired.

Inputs	# test images	after-vs-before refinement	paired-vs-unpaired
Chair-Table	90	71.3%	57%
Basket-Bottle	45	64.2%	57%





Results:

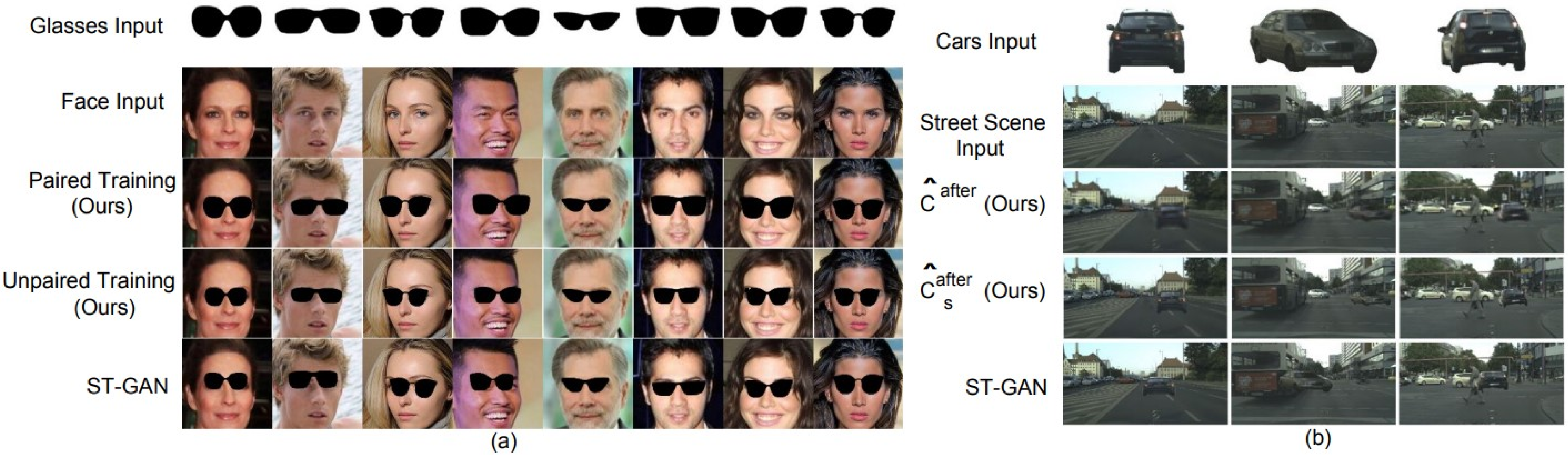
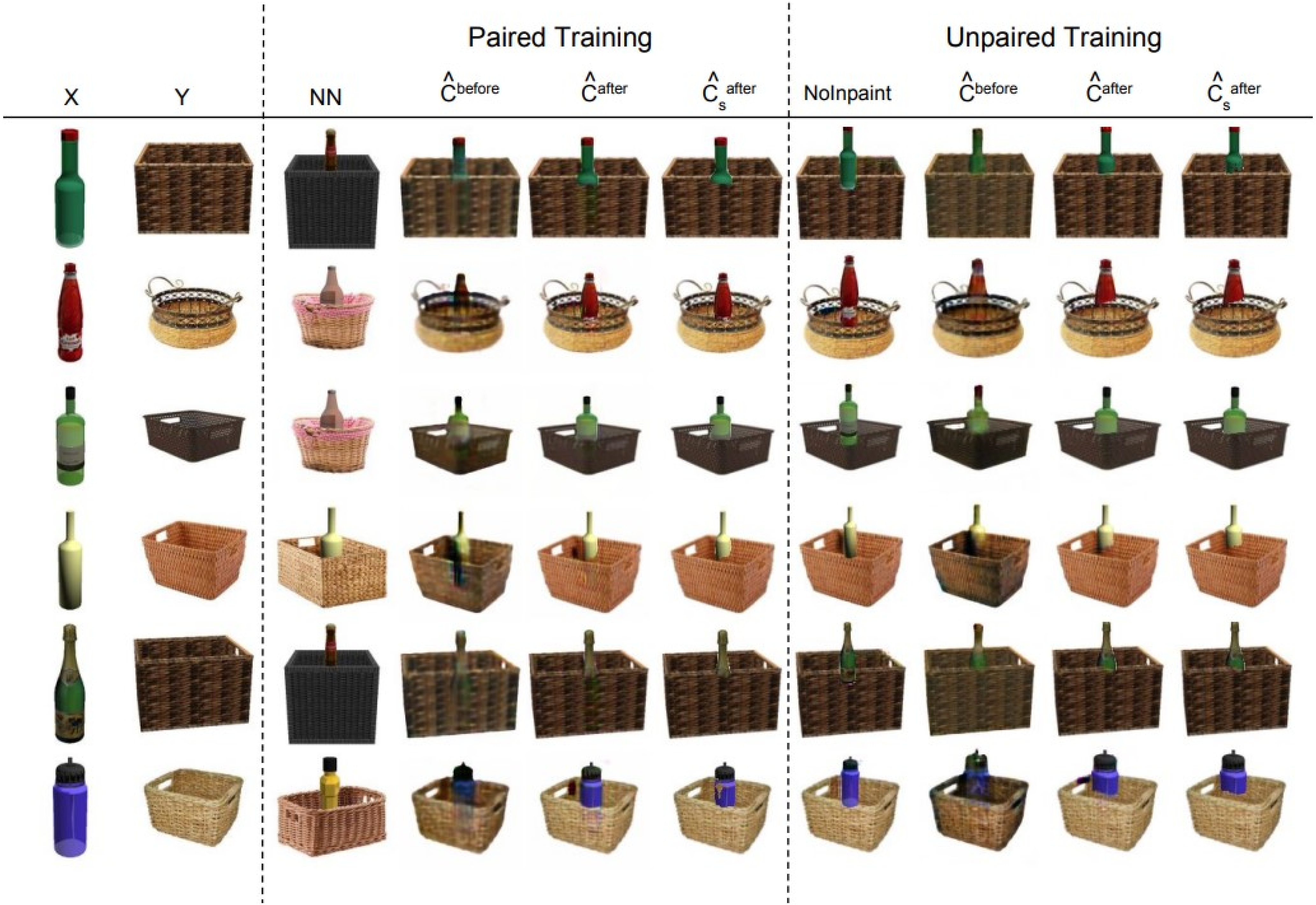
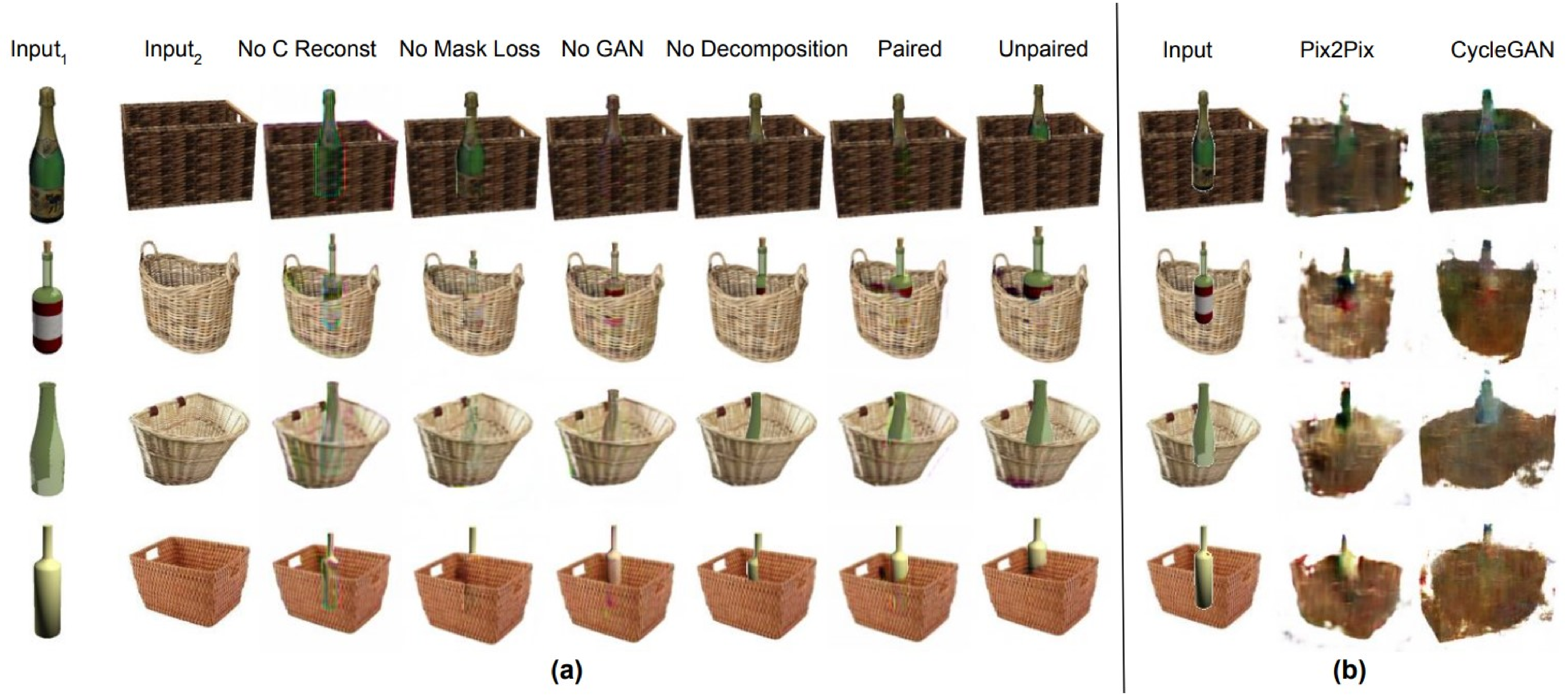


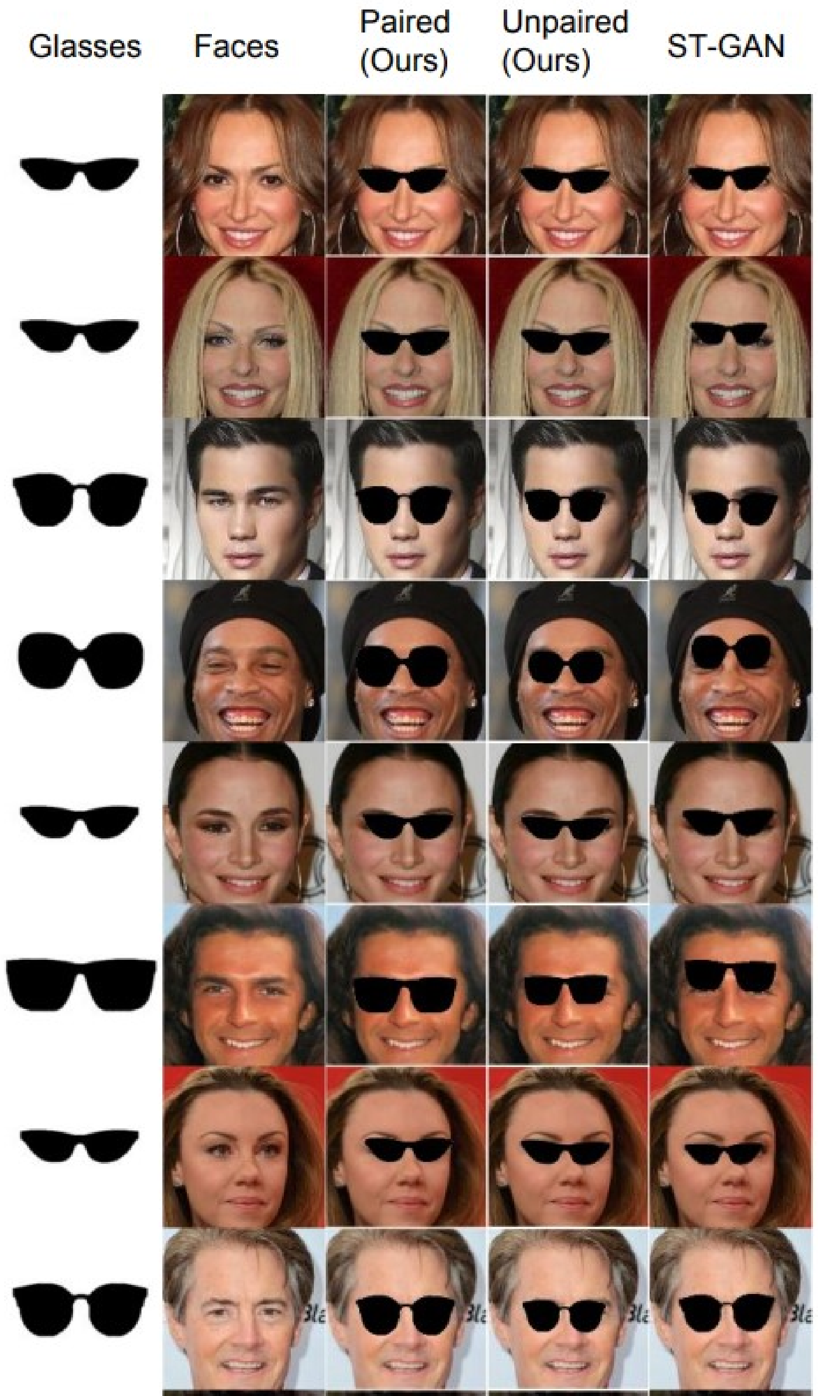
Figure 5. (a) Test examples for the face-sunglasses composition task. *Top two rows*: input sunglasses and face images, *3rd and 4th rows*: the output of our compositional GAN for the paired and unpaired models, respectively, *Last row*: images generated by the ST-GAN [16] model, (b) Test examples for the street scene-car composition task. *Top two rows*: input cars and street scenes, *3rd and 4th rows*: the output of our compositional GAN after the meta-refinement approach. Here, $\hat{c}^{\text{after}}$ shows the output of the composition generator and $\hat{c}_{\text{s}}^{\text{after}}$ represents the summation of the masked transposed inputs, *Last row*: images generated by ST-GAN.



Paired Training
Unpaired Training
X
Y
NN
$\hat{C}^{before}$
$\hat{C}^{after}$
$\hat{C}_s^{after}$
NoInpaint
$\hat{C}^{before}$
$\hat{C}^{after}$
$\hat{C}_s^{after}$


Input1
Input2
No C Reconst
No Mask Loss
No GAN
No Decomposition
Paired
Unpaired
Input
Pix2Pix
CycleGAN
(a)
(b)


Cars
Street Scenes
$\hat{C}^{before}$
$\hat{C}^{after}$
$\hat{C}_s^{after}$
ST-GAN
NN


Glasses
Faces
Paired (Ours)
Unpaired (Ours)
ST-GAN

Thanks for your attention