Ω-GAN: Object Manifold Embedding GAN for Image Generation by Disentangling Parameters into Pose and Shape Manifolds

Yasutomo Kawanishi, Daisuke Deguchi, Ichiro Ide, Hiroshi Murase (Nagoya University)

Goal: Various shape/pose object image generation

Proposed 1: Parametric Manifold Embedding

Difficulty: The pose has circularity.

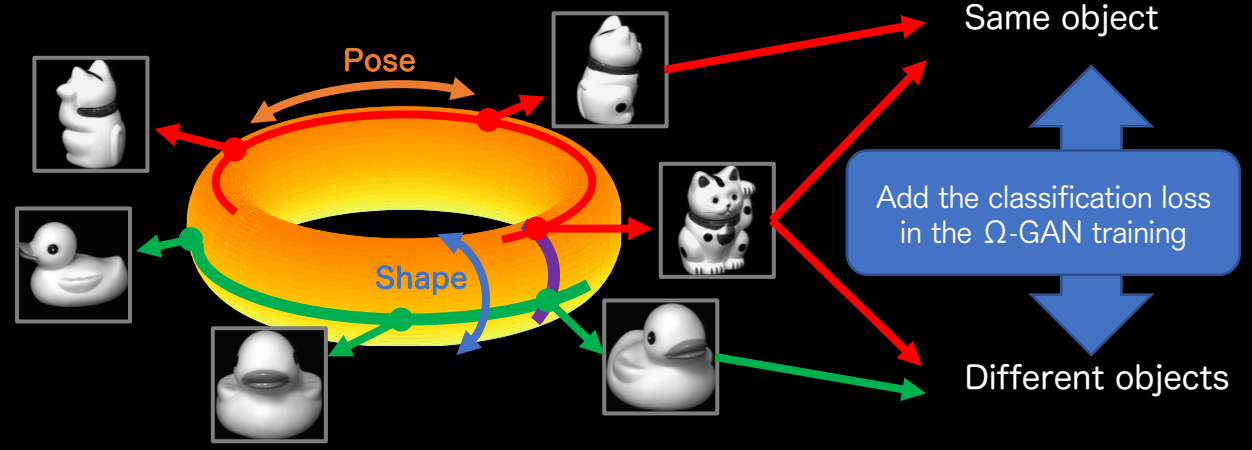
Sampling the noise variables from a distribution over the pose⊗shape manifold.

Proposed 2: Object Identity Loss

Difficulty: Object shape may change when changing the pose parameter.

Preserving the shape when changing the pose only.

An extension of the *Parametric Eigenspace* to a generative model



Structure of the Ω-GAN

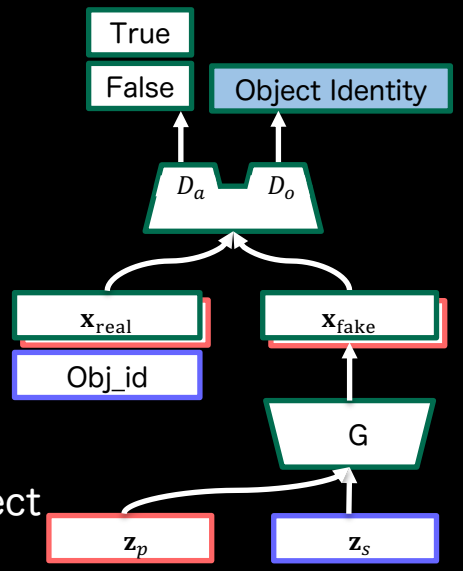
Generator

Generate an image from pose and shape parameters

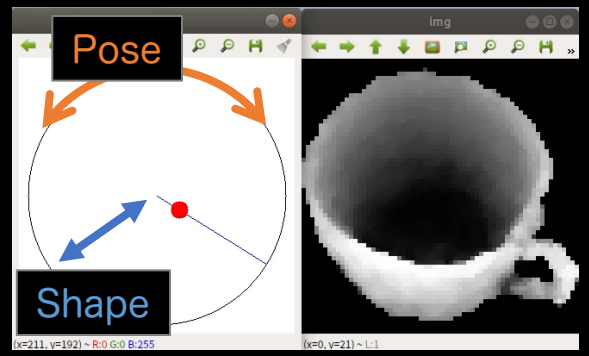
Discriminator (Based on cGAN)

Add the contrastive loss

Real : Image of the same object
Fake : Generated from the similar parameters
||
Similar shapes (= Similar image features)



Example



Future work

- 3D-axes rotation
- Large variety of objects
- Representation of the shape parameter
- Investigate the relation to the Parametric Eigenspace

Ω-GAN: Object Manifold Embedding GAN for Image Generation by Disentangling Parameters into Pose and Shape Manifolds

Yasutomo Kawanishi, Daisuke Deguchi, Ichiro Ide, Hiroshi Murase (Nagoya University)

The loss function of the proposed GAN

$$
\begin{aligned}
&\min_G \max_D L(D,G) \\
&= \min_G \max_D \Big(\mathrm{E}_{\mathbf{x}\sim p_{\mathrm{data}}(\mathbf{x})}[\log D(\mathbf{x}|\mathbf{c})] \\
&\quad + \mathrm{E}_{\mathbf{z}\sim p_{\mathcal{M}_\mathbf{z}}(\mathbf{z})}[\log(1 - D(G(\mathbf{z}|\mathbf{z}_p)|\mathbf{z}_p))] \\
&\quad + \alpha \mathrm{E}_{\mathbf{x}_1,\mathbf{x}_2\sim p_{\mathrm{data}}(\mathbf{x})}[O_r(\mathbf{x}_1,\mathbf{x}_2)] \\
&\quad + \alpha \mathrm{E}_{\mathbf{z}_1,\mathbf{z}_2\sim p_{\mathcal{M}_\mathbf{z}}(\mathbf{z})}[O_f(G(\mathbf{z}_1|\mathbf{z}_{1p}), G(\mathbf{z}_2|\mathbf{z}_{2p}))]\Big), \qquad (1)
\end{aligned}
$$

Adversarial Loss

Object Identity Loss

Object identity loss for real images

$$
\begin{aligned}
O_r(\mathbf{a},\mathbf{b}) &= y_r(\mathbf{a},\mathbf{b}) d(\mathbf{a},\mathbf{b})^2 && (4)\\
&\quad + (1 - y_r(\mathbf{a},\mathbf{b})) \max(0, \tau - d(\mathbf{a},\mathbf{b}))^2, && (5)\\
d(\mathbf{a},\mathbf{b}) &= \|D_o(\mathbf{a}) - D_o(\mathbf{b})\|, && (6)\\
y_r(\mathbf{a},\mathbf{b}) &= \begin{cases} 1 & \text{if } l_r(\mathbf{a}) = l_r(\mathbf{b}) \\ 0 & \text{otherwise} \end{cases} && (7)
\end{aligned}
$$

The same object or not

Object identity loss for generated images

$$
\begin{aligned}
O_f(\mathbf{a},\mathbf{b}) &= y_f(\mathbf{a},\mathbf{b}) d(\mathbf{a},\mathbf{b})^2 && (8)\\
&\quad + (1 - y_f(\mathbf{a},\mathbf{b})) \max(0, \tau - d(\mathbf{a},\mathbf{b}))^2, && (9)\\
y_f(\mathbf{a},\mathbf{b}) &= \begin{cases} 1 & \text{if } l_f(\mathbf{a}) = l_f(\mathbf{b}) \\ 0 & \text{otherwise} \end{cases} && (10)
\end{aligned}
$$

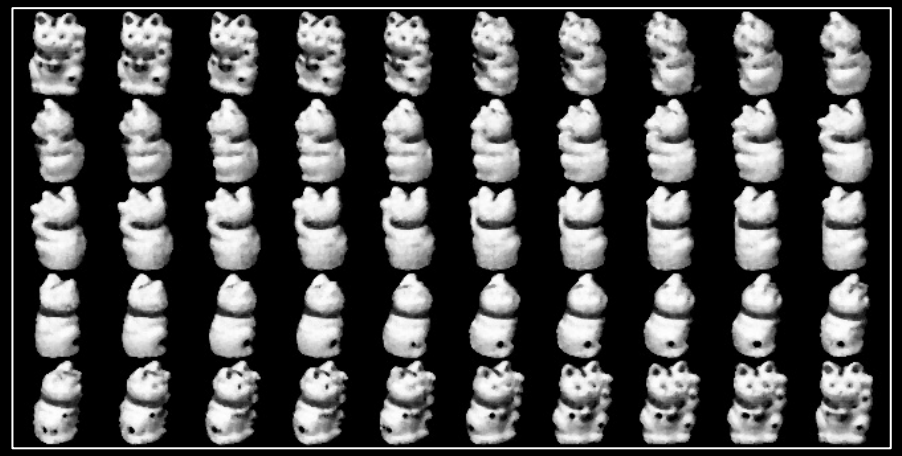
The same parameter or not

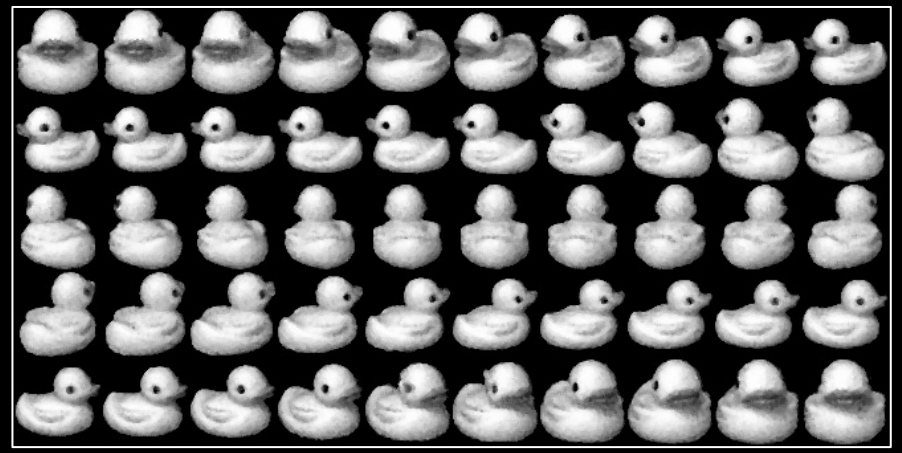
Ω-GAN: Object Manifold Embedding GAN for Image Generation by Disentangling Parameters into Pose and Shape Manifolds

Yasutomo Kawanishi, Daisuke Deguchi, Ichiro Ide, Hiroshi Murase (Nagoya University)

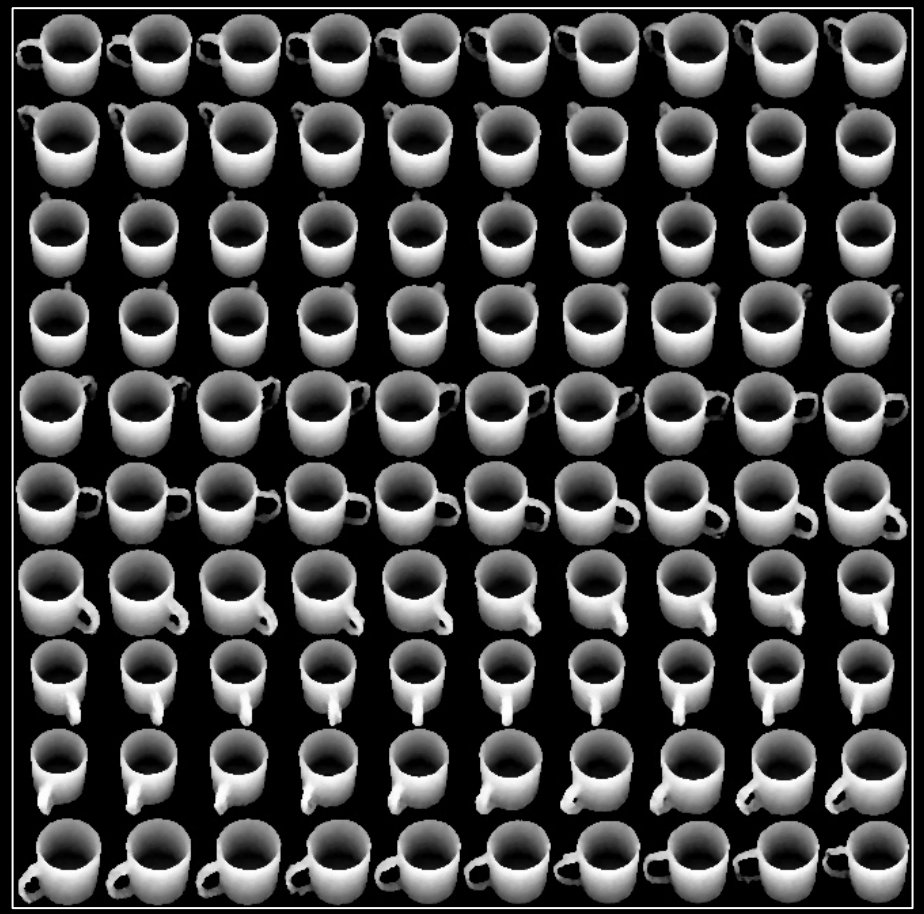
Generated image examples

Trained on the COIL-20





Trained on the ShapeNet (mug class)

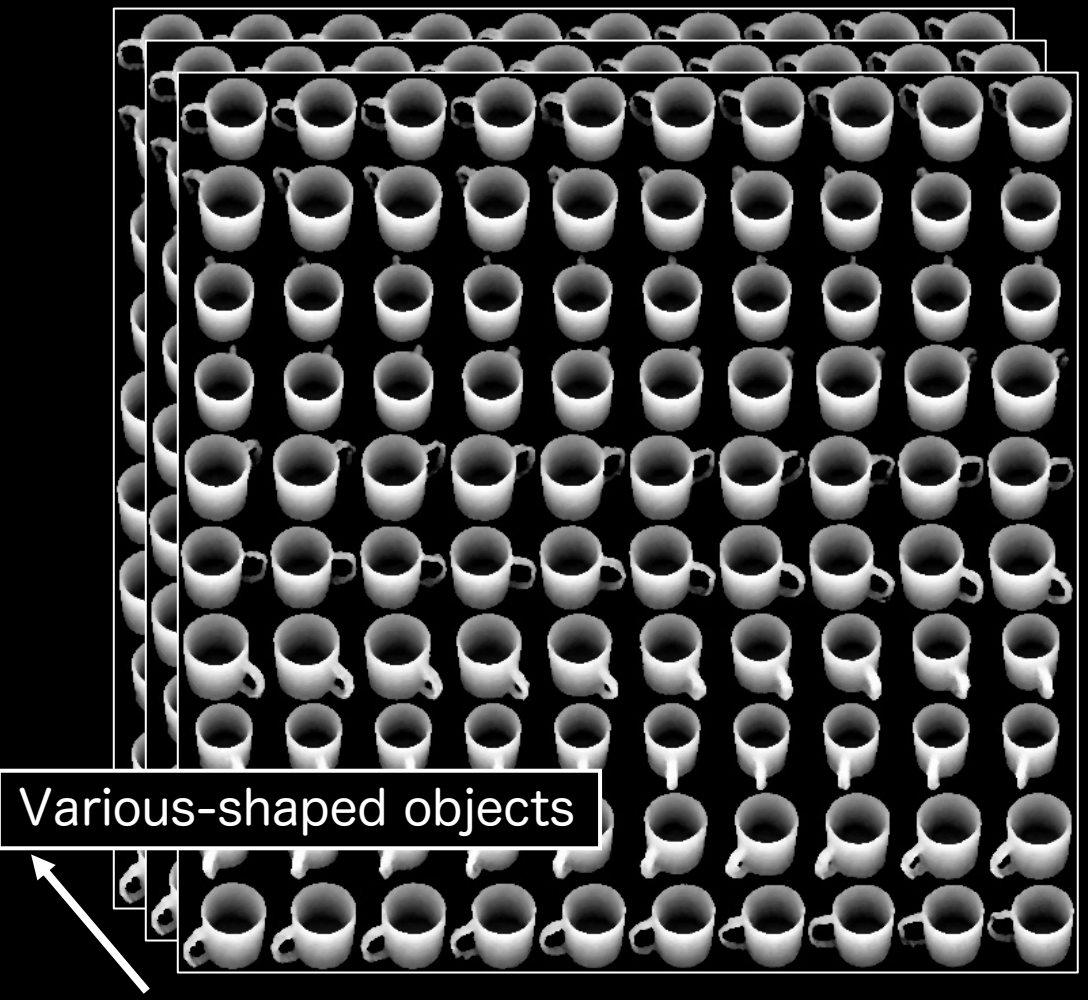


Ω-GAN: Object Manifold Embedding GAN for Image Generation by Disentangling Parameters into Pose and Shape Manifolds

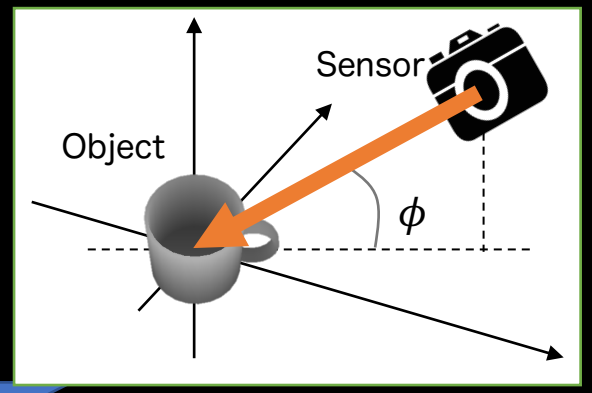
Yasutomo Kawanishi, Daisuke Deguchi, Ichiro Ide, Hiroshi Murase (Nagoya University)

Application of the generated images: Data augmentation for Object Pose Estimation

Generated from the GAN trained on the ShapeNet (Mug)



Train a pose estimation CNN combined with the real data



Pose estimation error (mean degree error) ↓

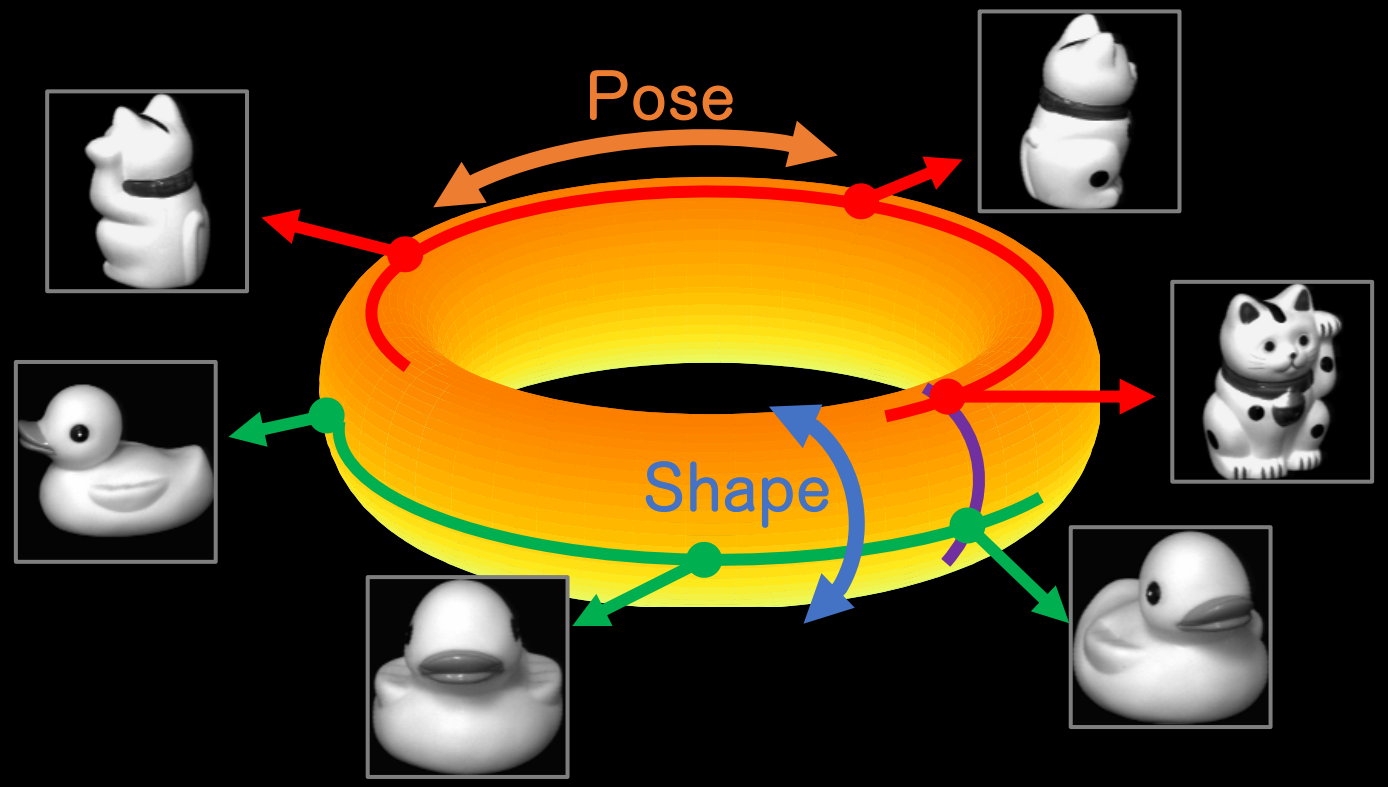
Trained with	View angles			
	60°	45°	30°	0°
Original data only	11.43	17.63	18.03	21.88
Scale / Translation	10.37	18.02	17.83	21.99
Generated images by using the GAN	**6.68**	**12.35**	**16.94**	**19.64**

Ω-GAN: Object Manifold Embedding GAN for Image Generation via Disentangling Parameters into Pose and Shape Manifolds

ICPR2020

Yasutomo Kawanishi, Daisuke Deguchi, Ichiro Ide, Hiroshi Murase
Nagoya University

Goal: Image Generation by controlling the pose and shape parameters



Ω-GAN: Object Manifold Embedding GAN

- Contribution 1: Parametric Manifold Embedding
  - Difficulty: The pose has circularity.

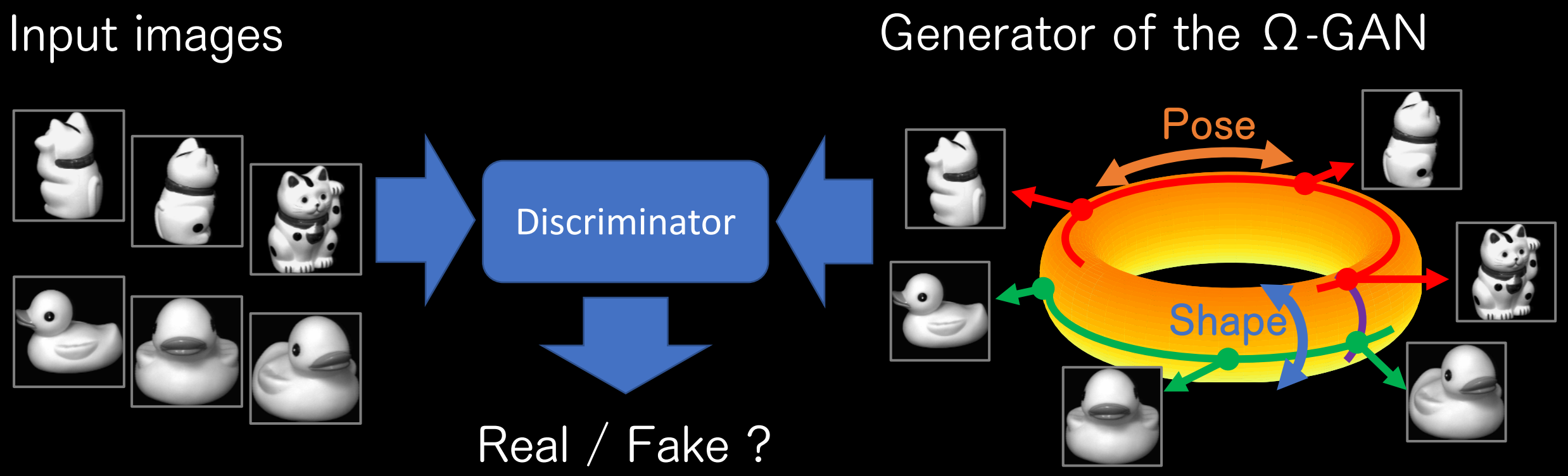
Sampling the noise variables from a distribution over the pose⊗shape manifold.

- Contribution 2: Object Identity Loss
  - Difficulty: Object shape may change when changing the pose parameter.

Preserving the shape while changing the pose only.

Contribution Ⅰ: Parametric Manifold Sampling

Sampling the noise variables from a distribution over the pose⊗shape manifold.



Contribution 2: Object Identity Loss

Preserving the shape while changing the pose only.

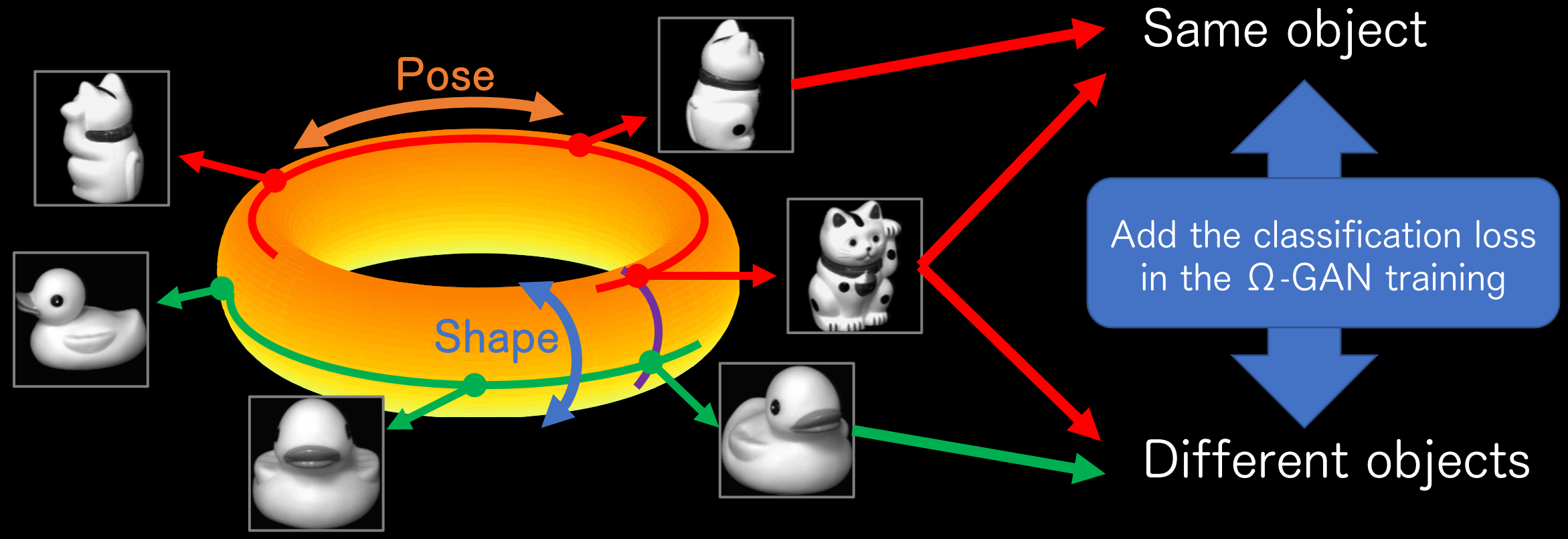


Image Generation Result: COIL-20

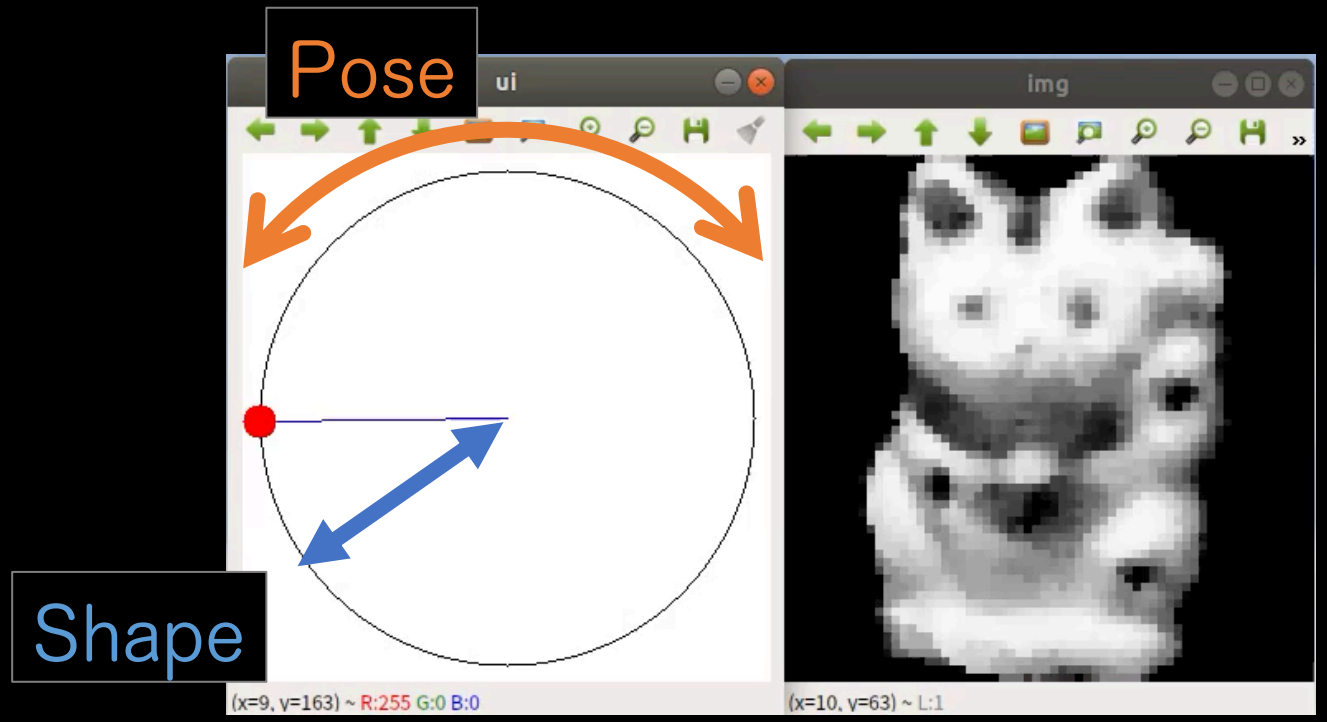
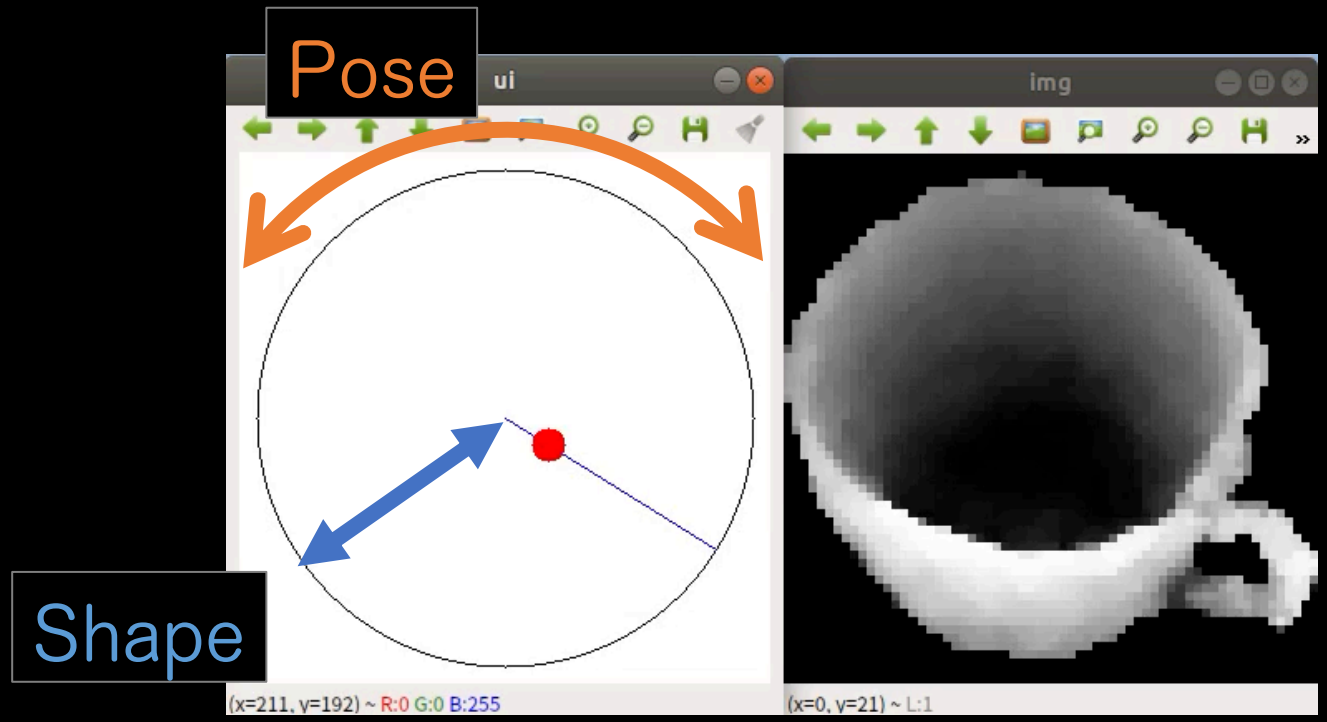


Image Generation Result: Mug dataset



Conclusion

- Ω-GAN (Object Manifold Embedding GAN) is proposed.

  Contribution 1: Parametric Manifold Embedding
  Contribution 2: Object Identity Loss

- Future work: Extend the method to

  Object 3D rotation
  Other applications