Inference of Grasping Pattern from Object Image Based on Interaction Descriptor

Tadashi Matsuo, Takuya Kawakami, Yoko Ogawa, Nobutaka Shimada

Ritsumeikan University

Introduction

- An object as a tool has its own function. The function is closely related to how a human grasp it [1].

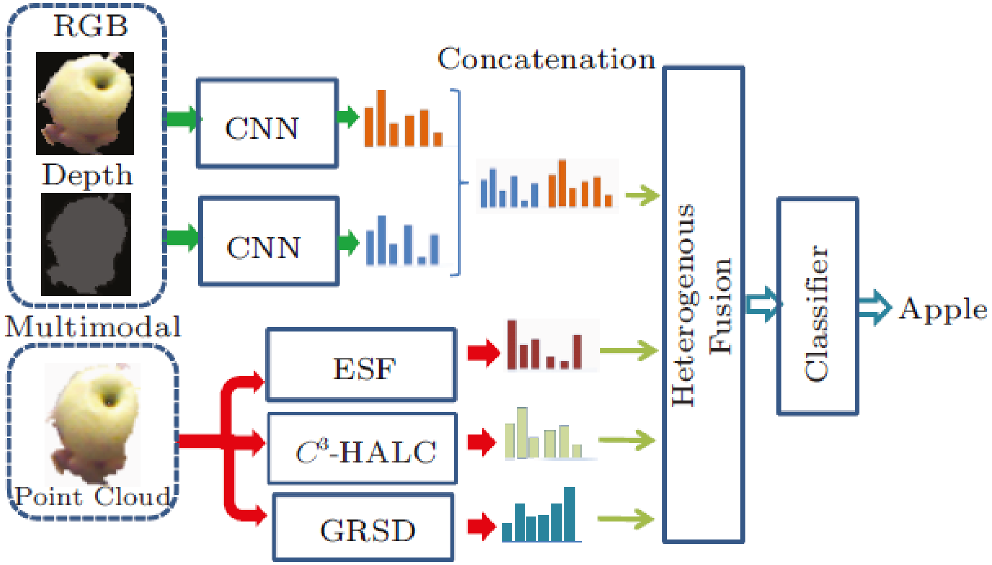
Can we estimate how to grasp an object from the object itself?

It will be useful for object recognition and robot manipulation.

[1] N. Kamakura, “Shape of hand and Hand motion”. Ishiyaku Publishers, 1989.

Related work

- Xiong Lv et al., "RGB-D Hand-Held Object Recognition Based on Heterogeneous Feature Fusion",
  Journal of Computer Science and Technology(2015)

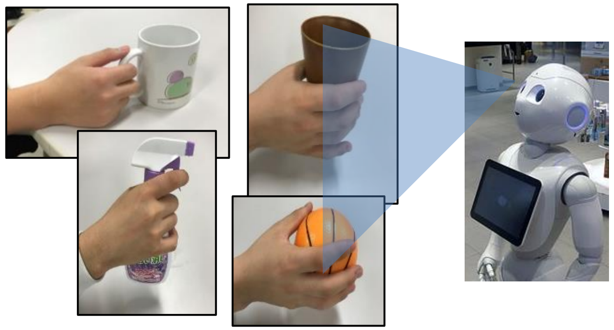


They achieved highly accurate classification by utilizing how to grasp an object, but…

- It estimates an object label only (not how to grasp it).
- All teacher labels must be given manually.

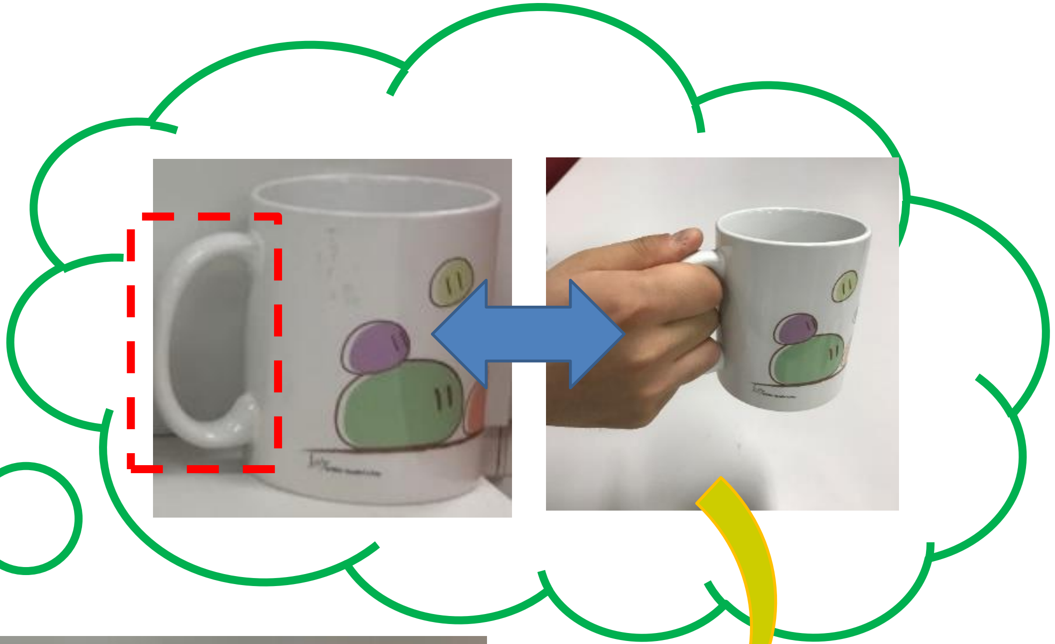
Our goal

Training



1.Learn human interactions without teacher labels.

2.Recall how a human grasp it from an object appearance.

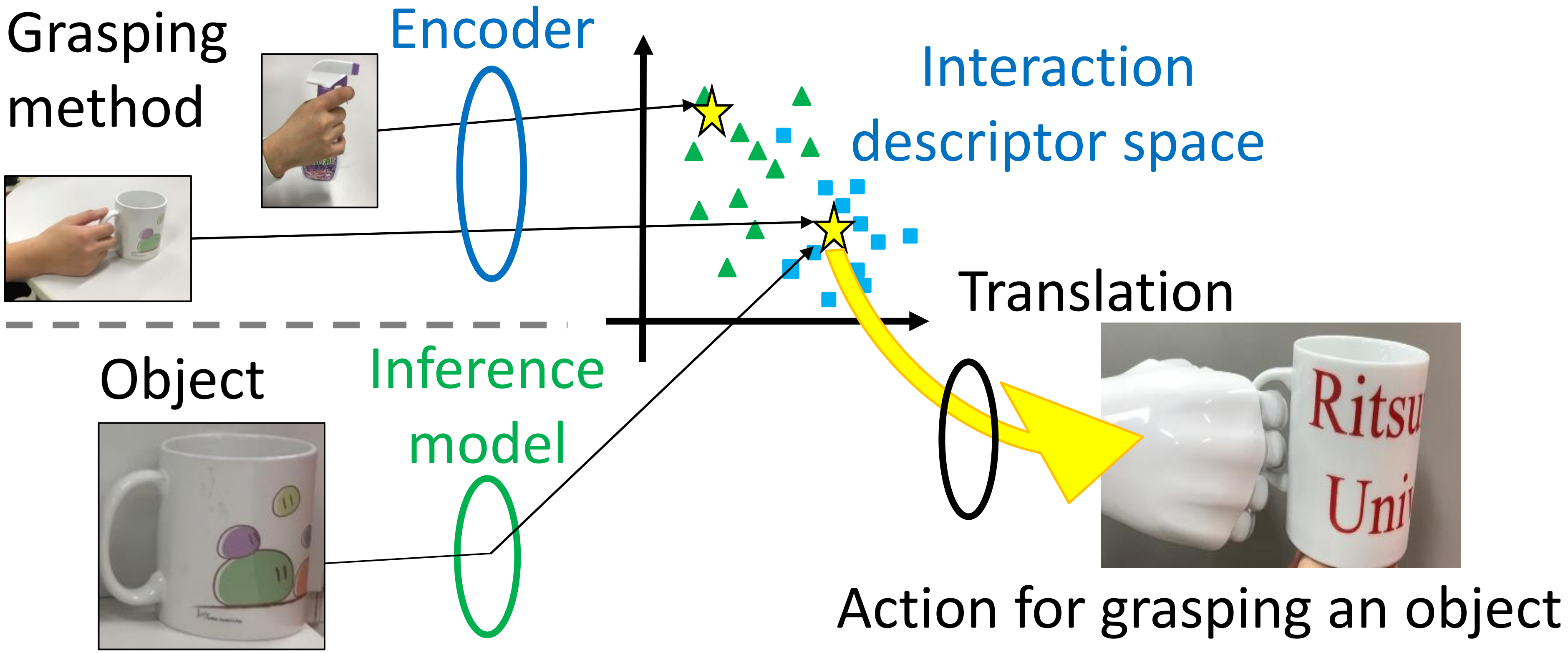


Object appearance

3.Make action to grasp it.

Proposed method

- We generate an interaction descriptor, a numeral representation of a human grasping method.
- And then we make an inference model to learn the relation between object and grasping method.



Flow of the presentation

1. Grasping image
2. Interaction descriptor
    1. Shift invariant auto-encoder
    2. Examples of shift invariant auto-encoder
    3. Results of interaction descriptor
3. Inference model
    1. Concept
    2. Recalled interactions from an object
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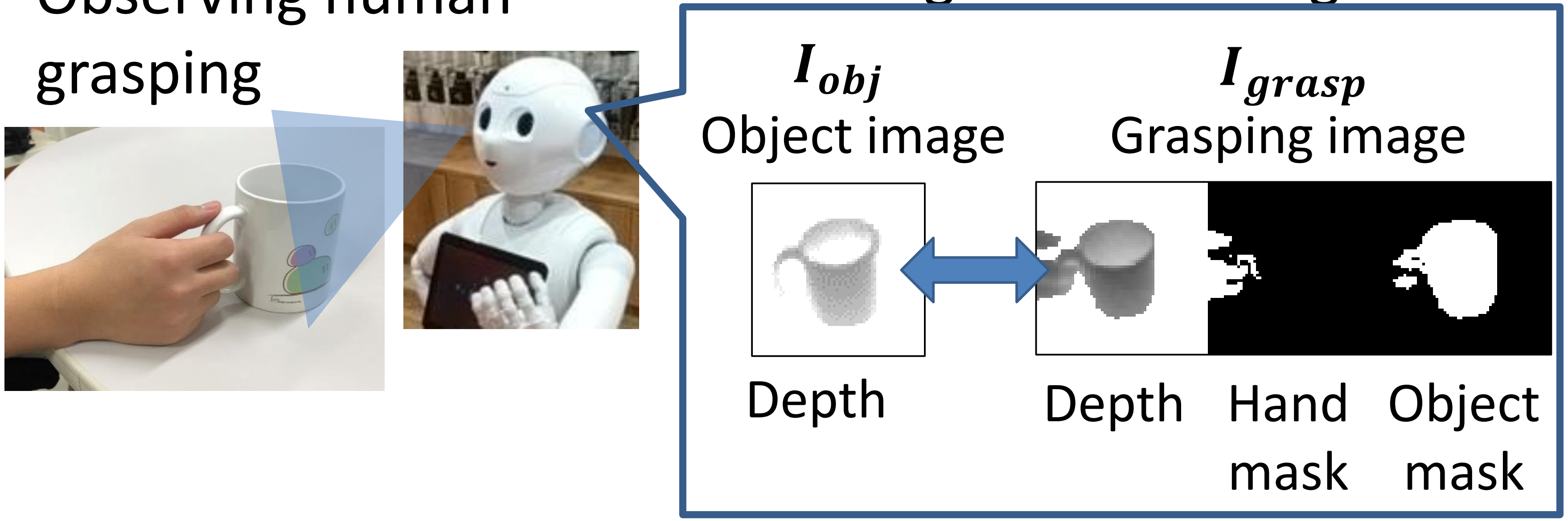
4. Conclusion

Grasping image

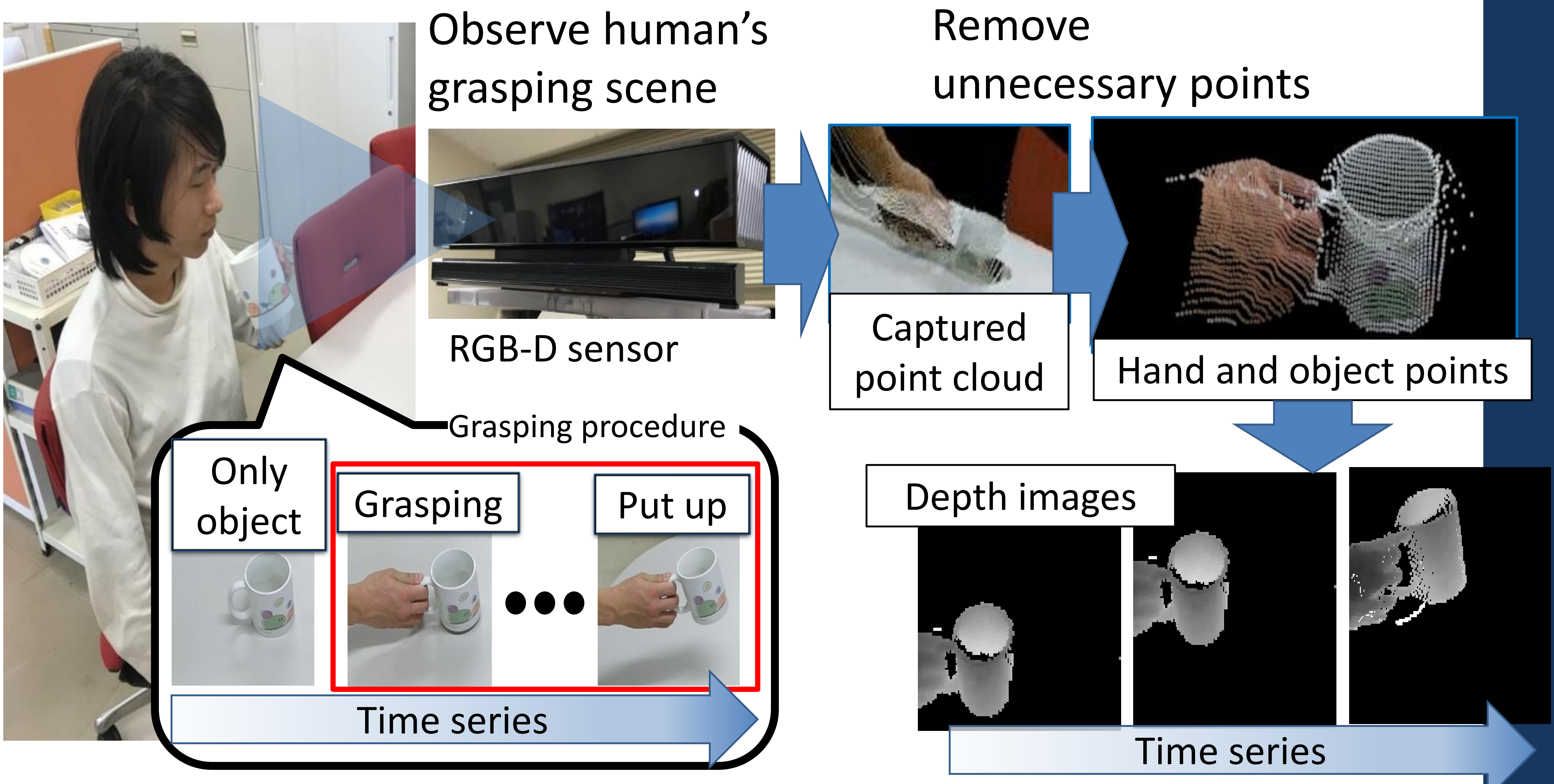
Automatically collect
Images for learning

Observing human
grasping



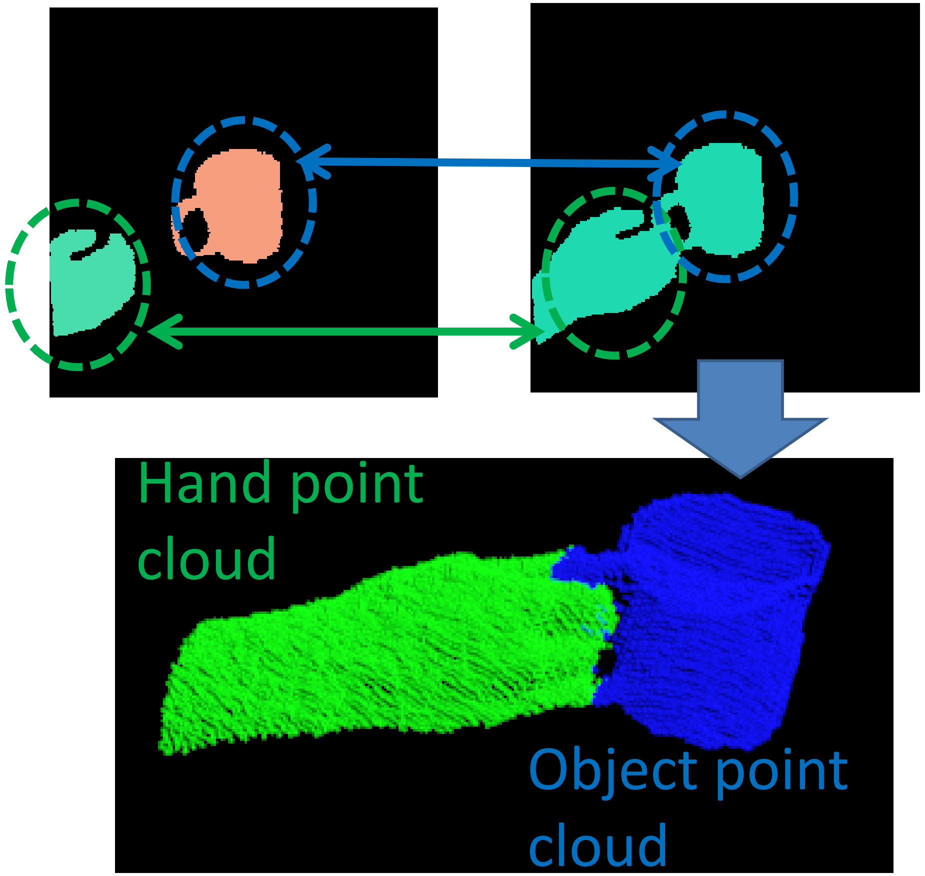
Grasping method is represented as a grasping image.
It consists of a depth image, hand mask and object mask.
It is paired with the corresponding object image.

Automatic collection of grasping images (1/2) - Capture

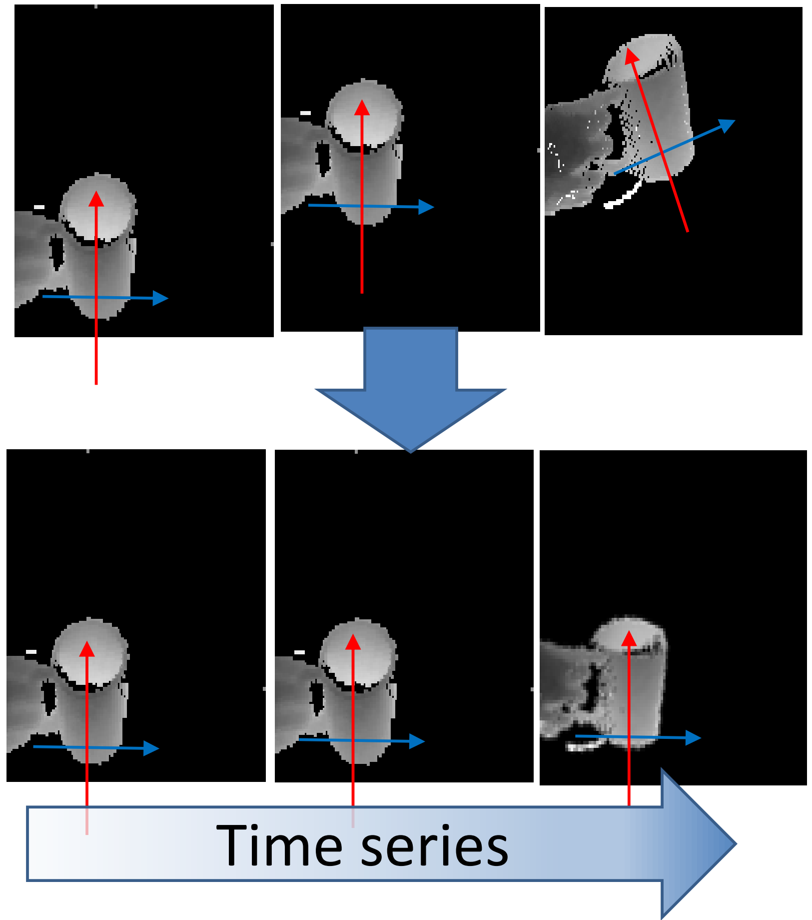


Automatic collection of grasping images (2/2) - Segmentation

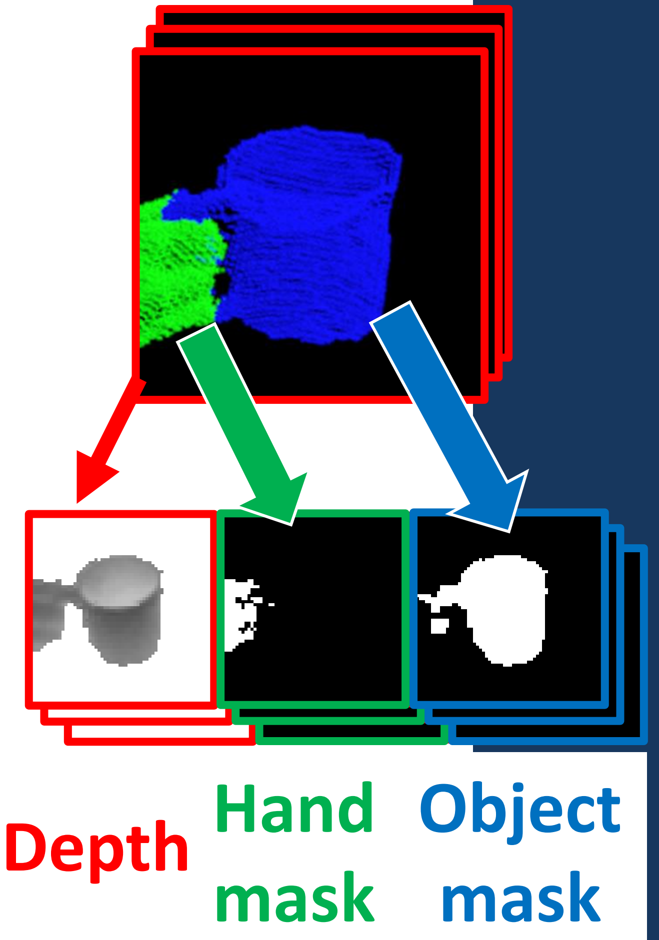
1. Segment **hand** and **object** points by using the image with isolated regions.



2. Align points based on the initial **object** points.



3. Generate grasping images



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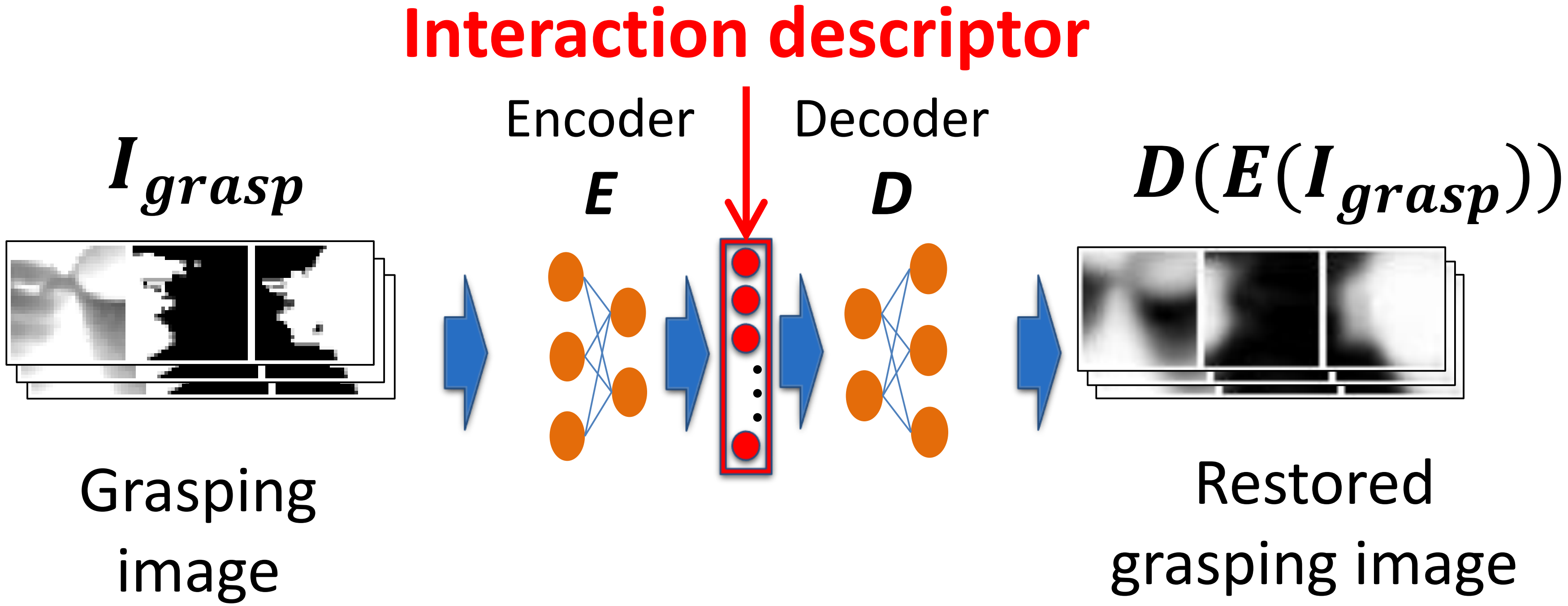
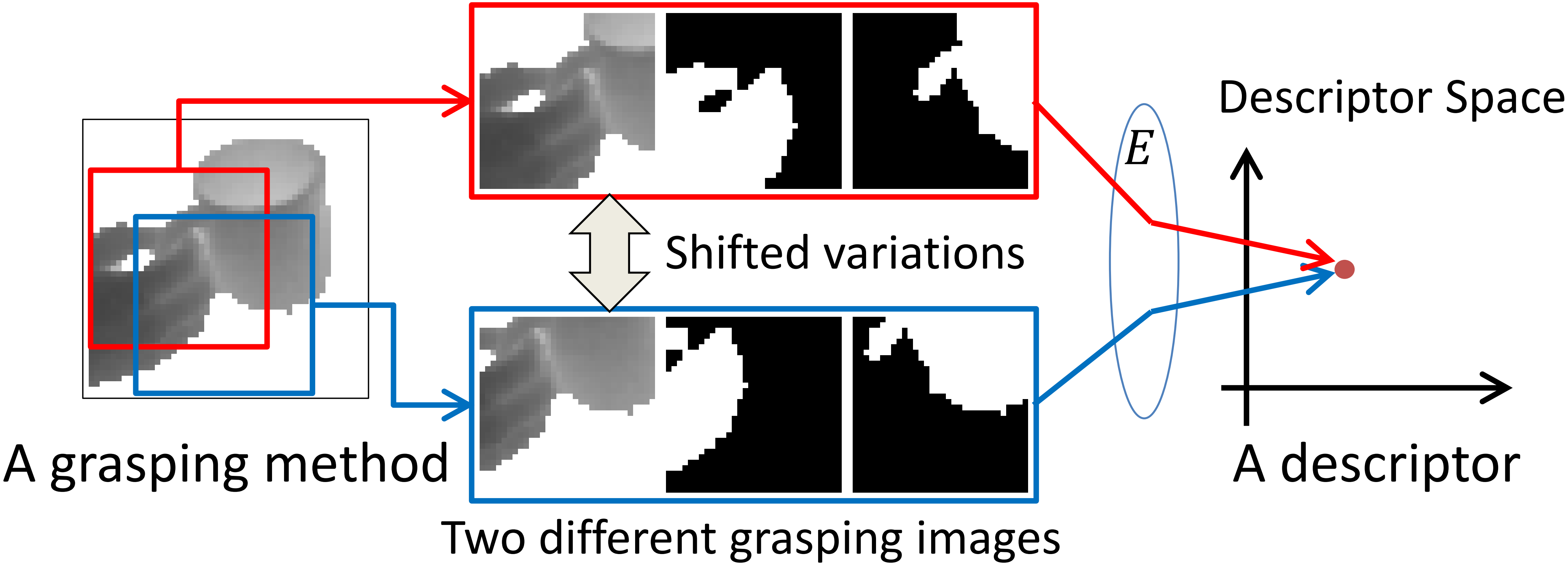
Interaction descriptor

We generate interaction descriptors by auto-encoder method;



- A low dimensional descriptor represents essence of an input.
- The auto-encoder (E and D) can be trained without teacher labels.

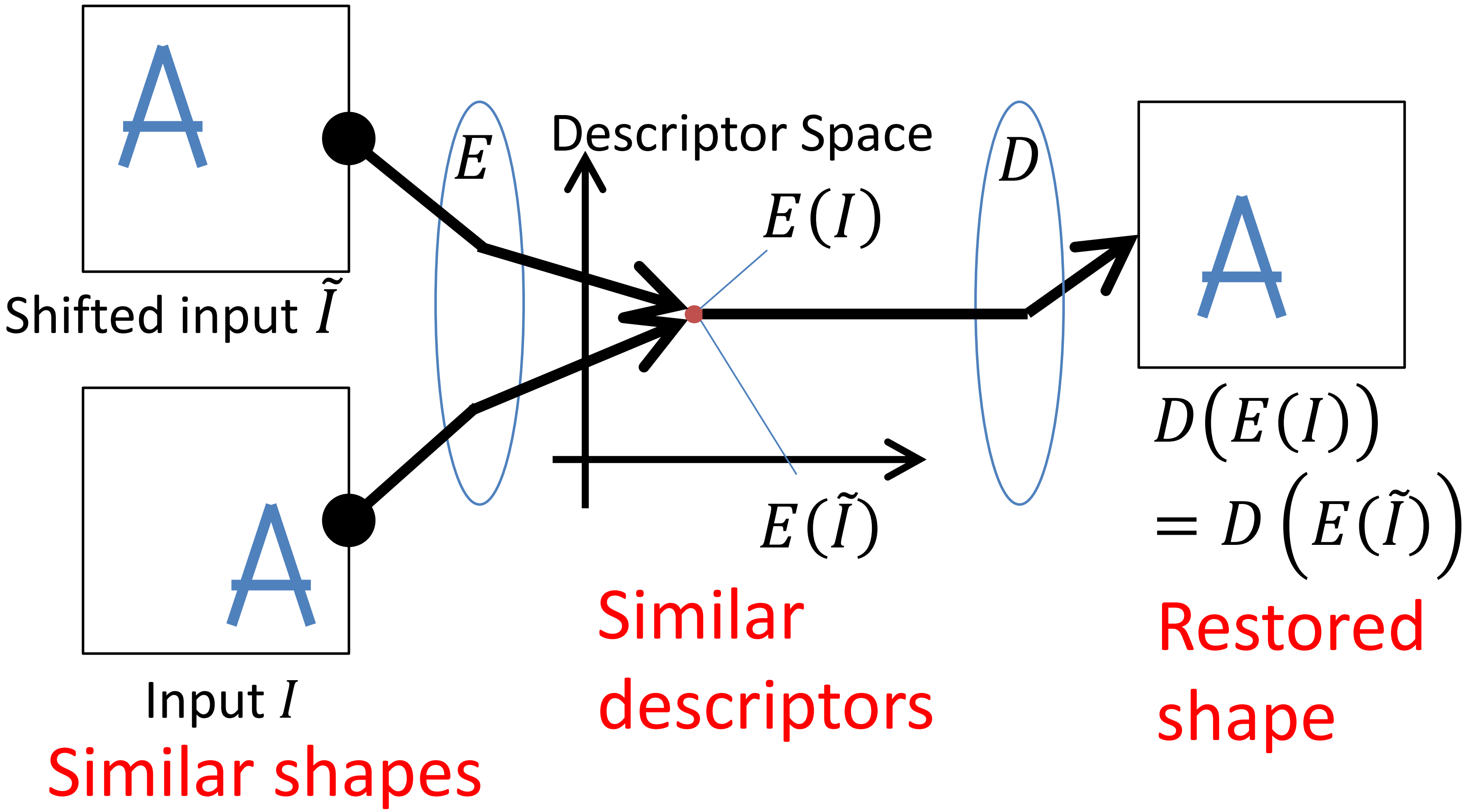
Desirable property of the encoder



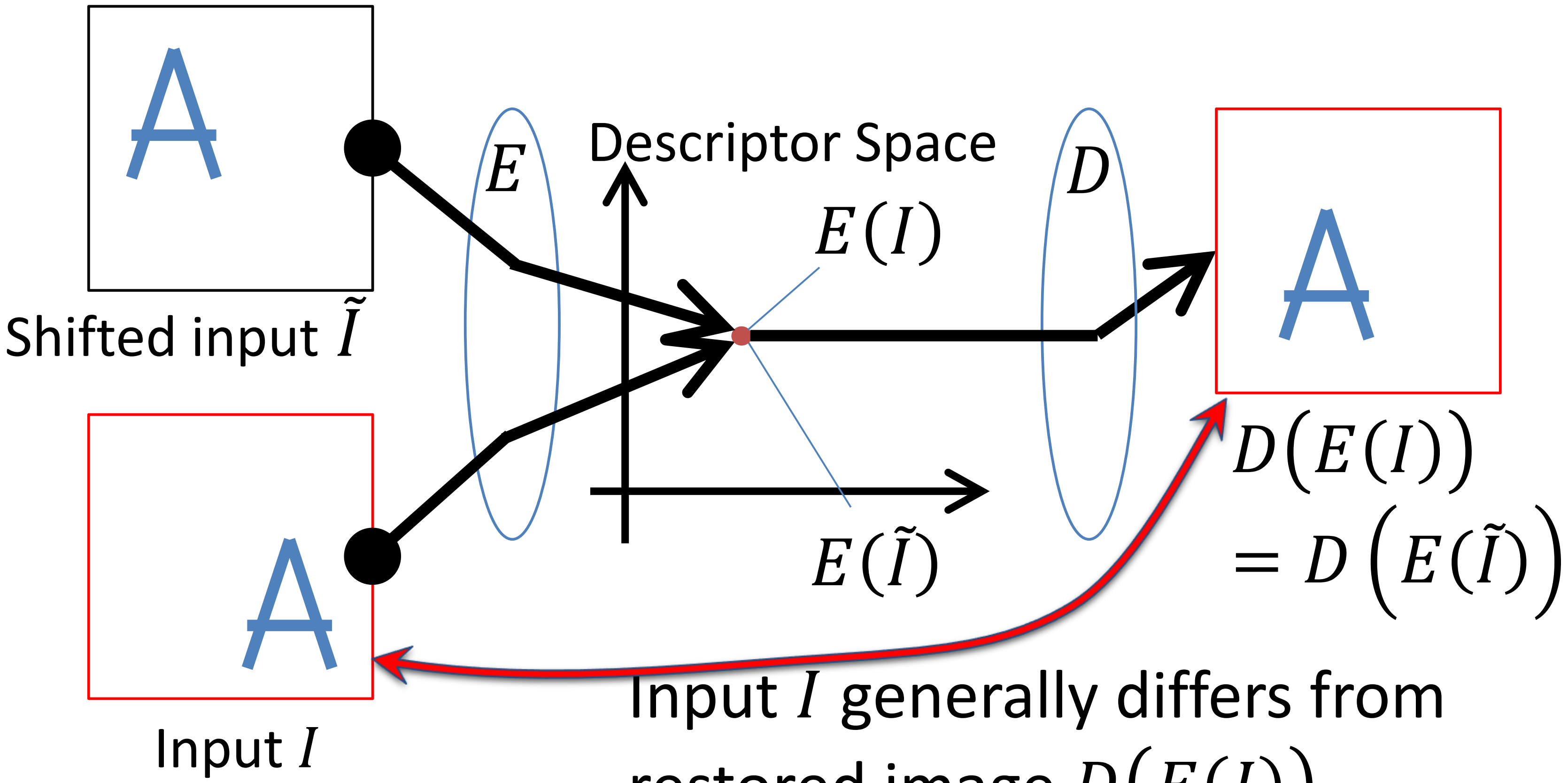
A grasping method should correspond to an interaction descriptor.

The encoder should ignore spatial shifts. **Shift invariant auto-encoder**

Shift invariant auto-encoder



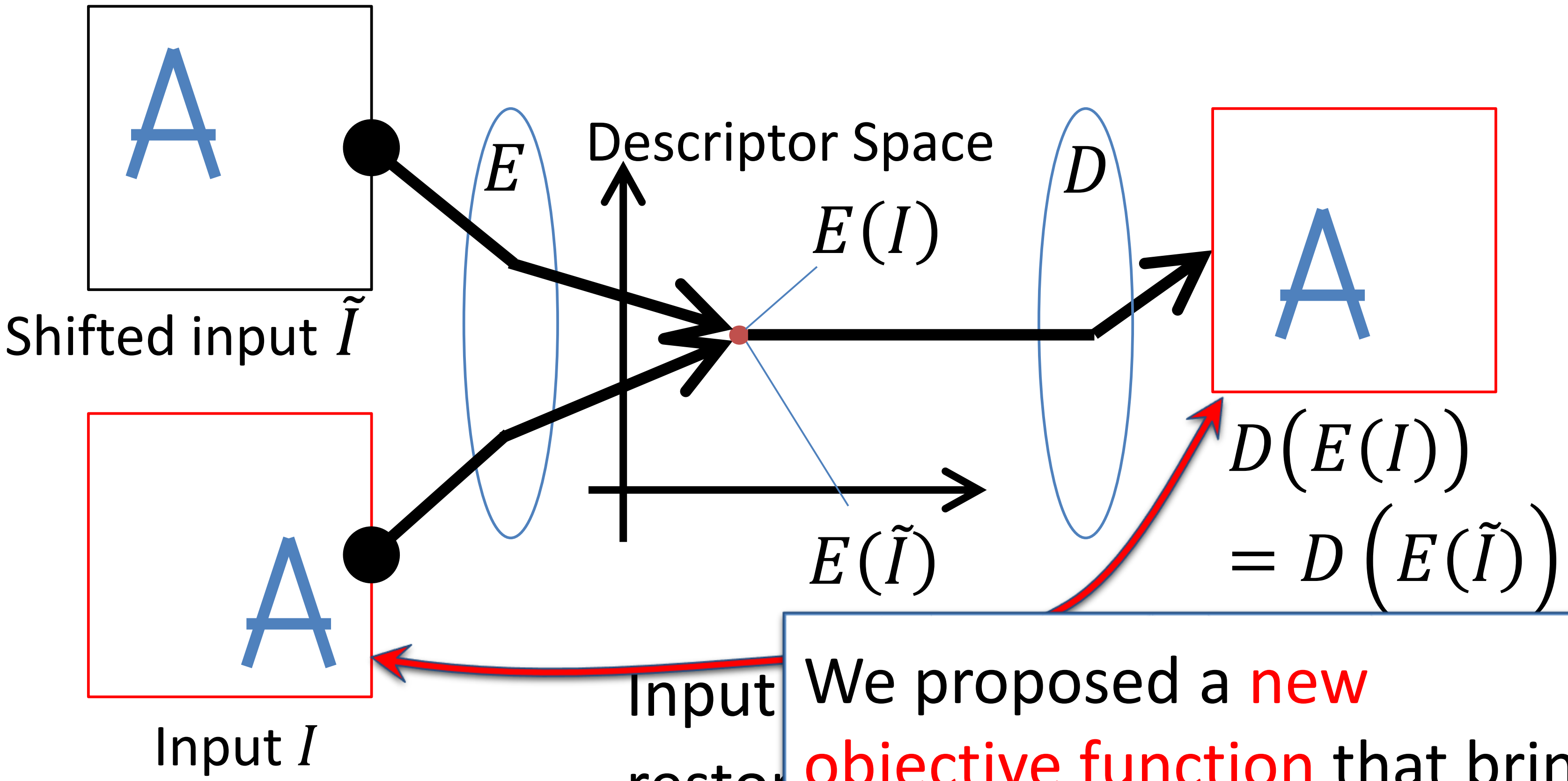
Shift invariant auto-encoder



Input I generally differs from restored image $D(E(I))$.

It cannot be trained with ordinary objective function $\sum_{I} \left\| D(E(I)) - I \right\|_{L2}^{2}$

Shift invariant auto-encoder



Input
restor

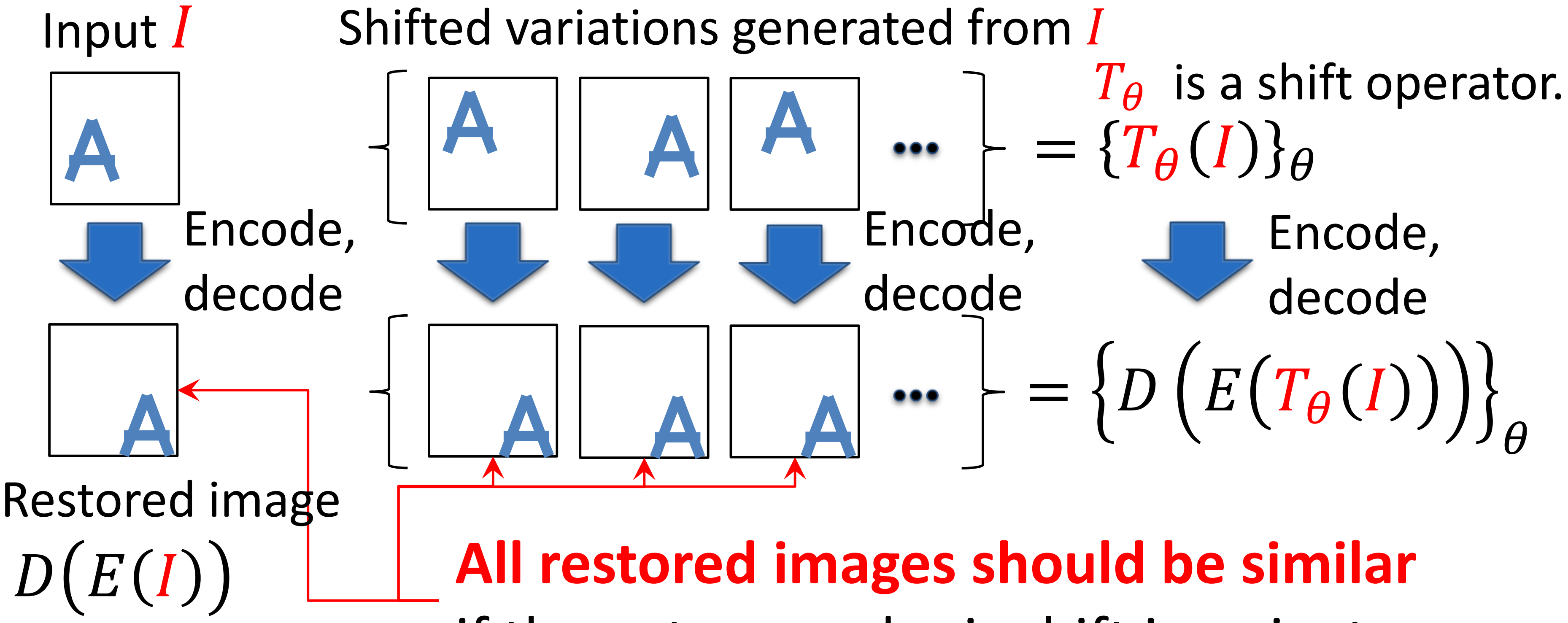
We proposed a new objective function that brings
- **shift invariance**,
- **shape restoration**.

It cannot be trained wi
ordinary objective functi

I

Cost function for shift invariant auto-encoder (1/3)

Evaluation of shift invariance

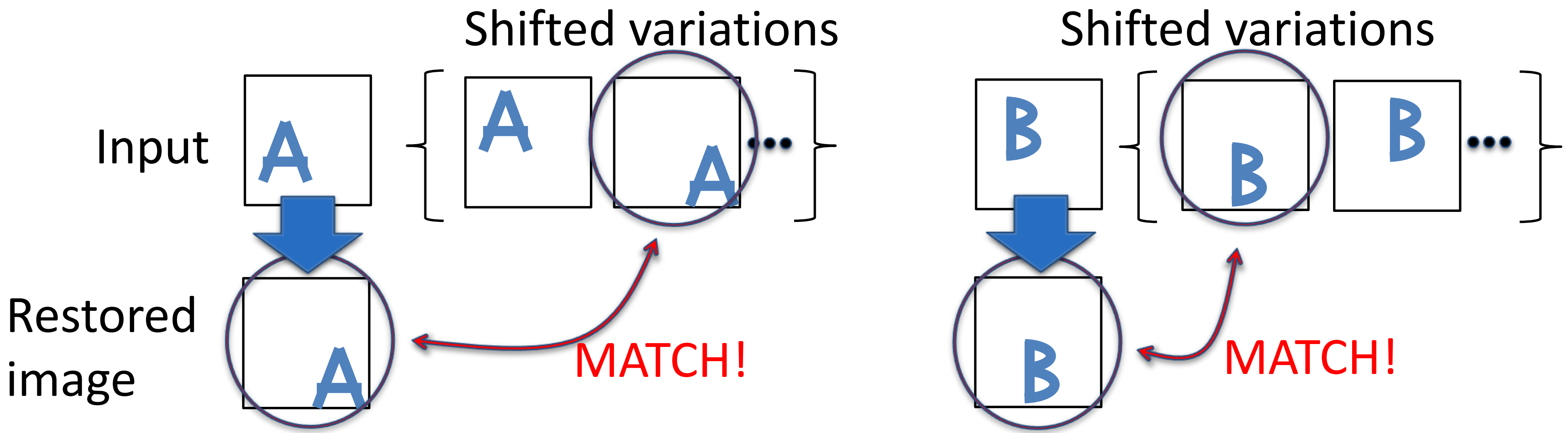


All restored images should be similar if the auto-encoder is shift invariant.

$$\sum_I \sum_\theta \left\| D\left(E(I)\right) - D\left(E\left(T_\theta(I)\right)\right) \right\|_{L2}^2$$

Train E, D so that they minimize this term.

Cost function for shift invariant auto-encoder (2/3)
Evaluation of shape restoration



A restored image should match with one of shifted images
if the auto-encoder can restore a shape.

$$\sum_I \left\| D\big(E(I)\big) - T_{\hat{\theta}(I)}(I) \right\|_{L2}^2$$

Train E, D so that they minimize this term.

where $\hat{\theta}(I)$ means the "best" transform parameter:

$$\hat{\theta}(I) = \arg\min_{\theta} \left\| D\big(E(I)\big) - T_{\theta}(I) \right\|_{L2}^2$$

Cost function for shift invariant auto-encoder (3/3) Total form

$$C(E,D) = \lambda_{inv} C_{inv}(E,D) + \lambda_{res} C_{res}(E,D) + \lambda_{spa} C_{spa}(E)$$

Invariance term $C_{inv}(E,D)$

$$\sum_{I}\sum_{\theta} \left\| D(E(I)) - D\left(E(T_{\theta}(I))\right) \right\|_{L2}^{2}$$

Restored image should be unchanged even if inputs are transformed with any parameter.

Restoration term $C_{res}(E,D)$

$$\sum_{I} \left\| D(E(I)) - T_{\hat{\theta}(I)}(I) \right\|_{L2}^{2}$$

Restored image should match with one of transformed images.

Sparseness term

$C_{spa}(E)$

$$\sum_{I \in S} \frac{\|E(I)\|_{L1}^{2}}{\|E(I)\|_{L2}^{2}}$$

Descriptor $E(I)$ should be a sparse vector.

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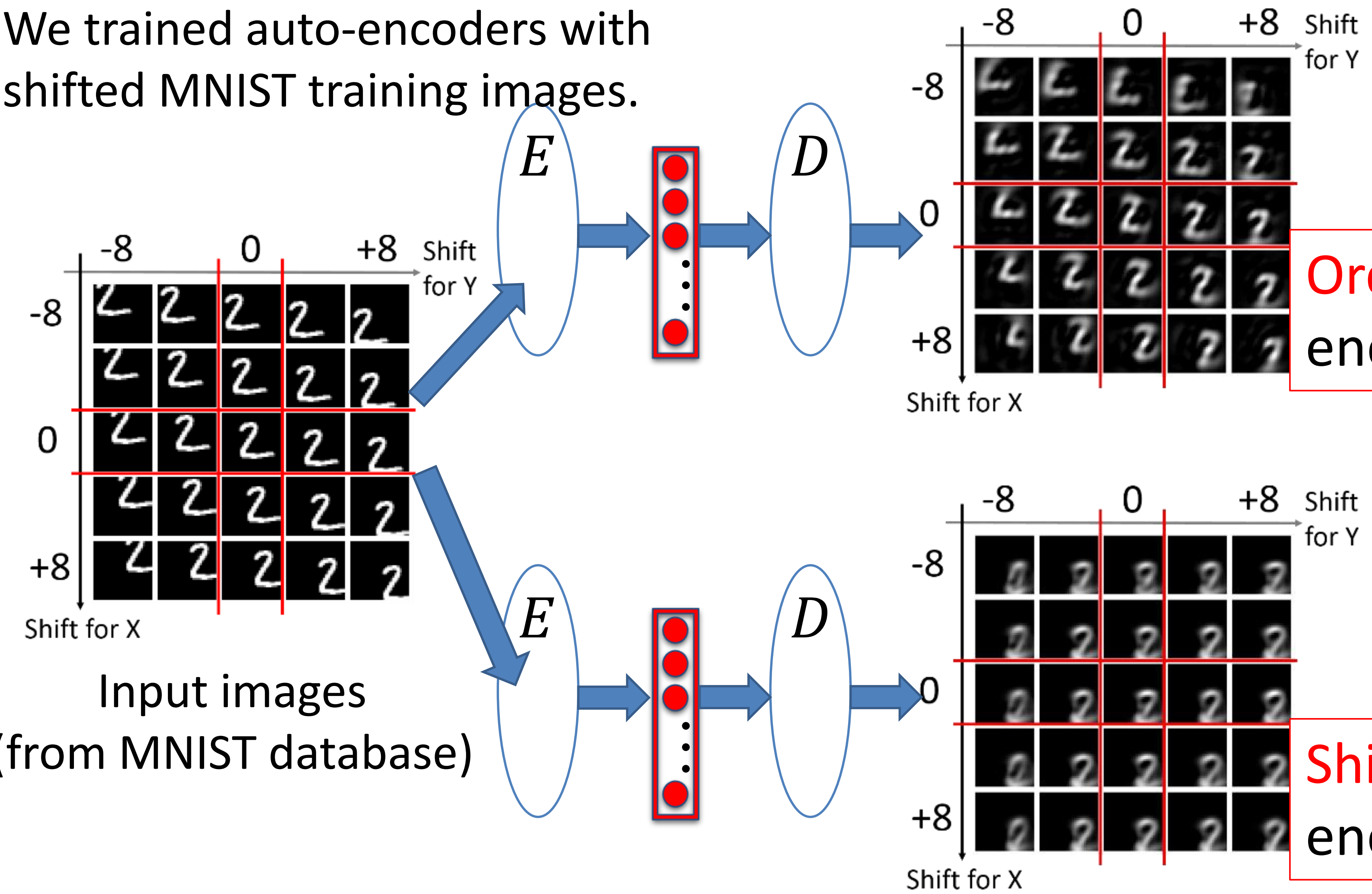
Example of shift invariant auto-encoder (1/2)

We trained auto-encoders with shifted MNIST training images.



Input images (from MNIST database)

Restored by ordinary auto-encoder

Ordinary auto-encoder encodes shape and position.

Restored by shift invariant auto-encoder

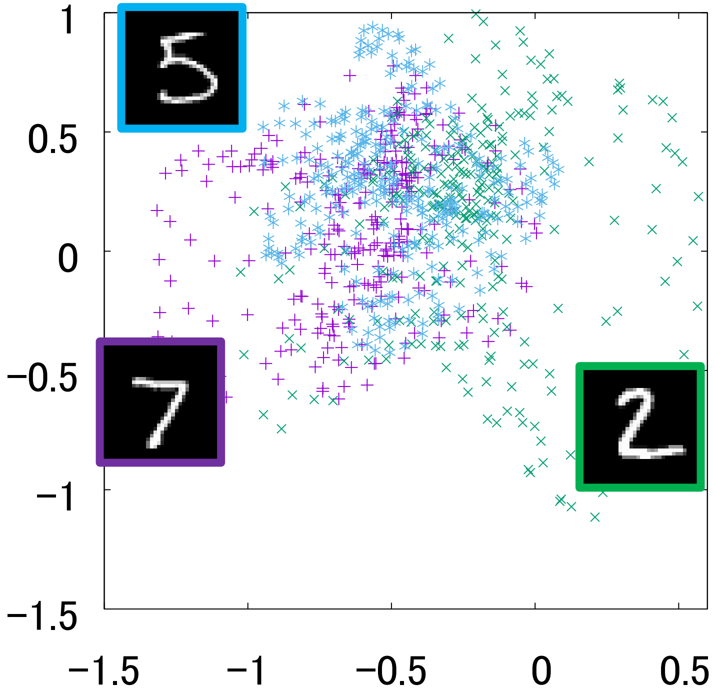
Shift invariant auto-encoder encodes shape itself.

T. Matsuo, et al., "Transform invariant auto-encoder," IROS 2017, https://doi.org/10.1109/IROS.2017.8206047

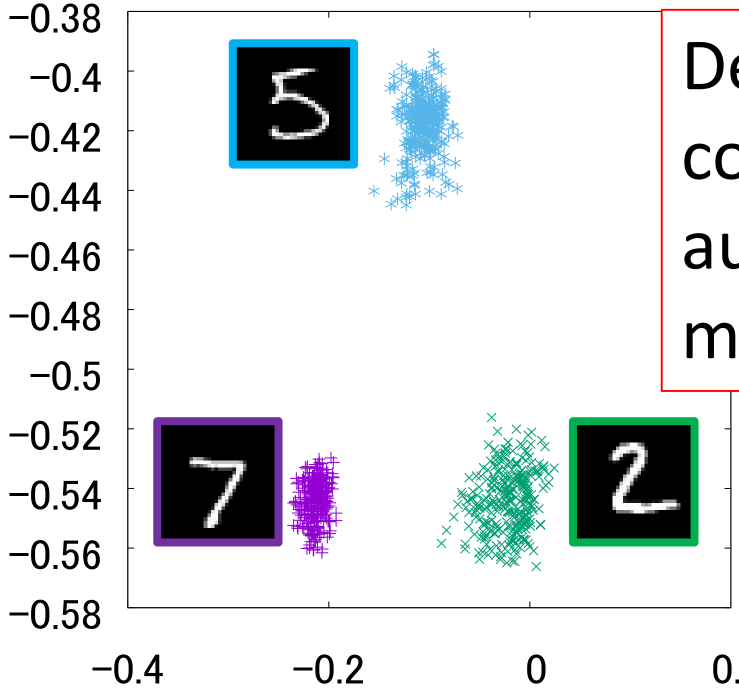
Example of shift invariant auto-encoder (2/2)
Distribution of descriptors

Input:32×32
Descriptor dim: 30
Max shift width: 8

Distributions of descriptors from shifted test images such as  .



Ordinary auto-encoder



Shift invariant auto-encoder

Descriptors from common shapes automatically make a cluster.

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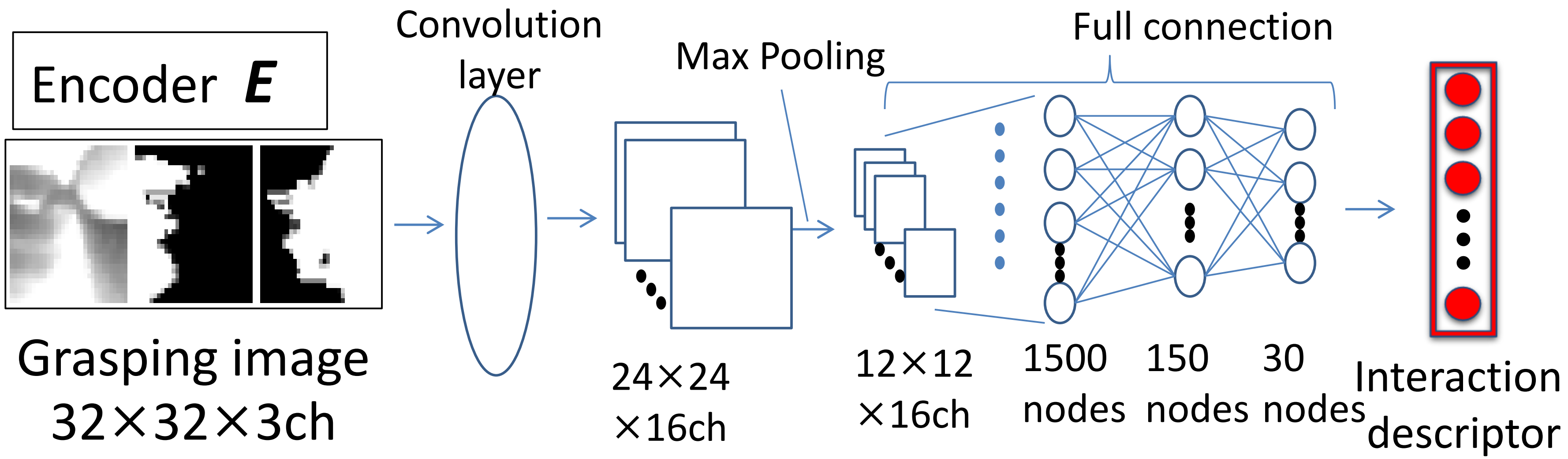
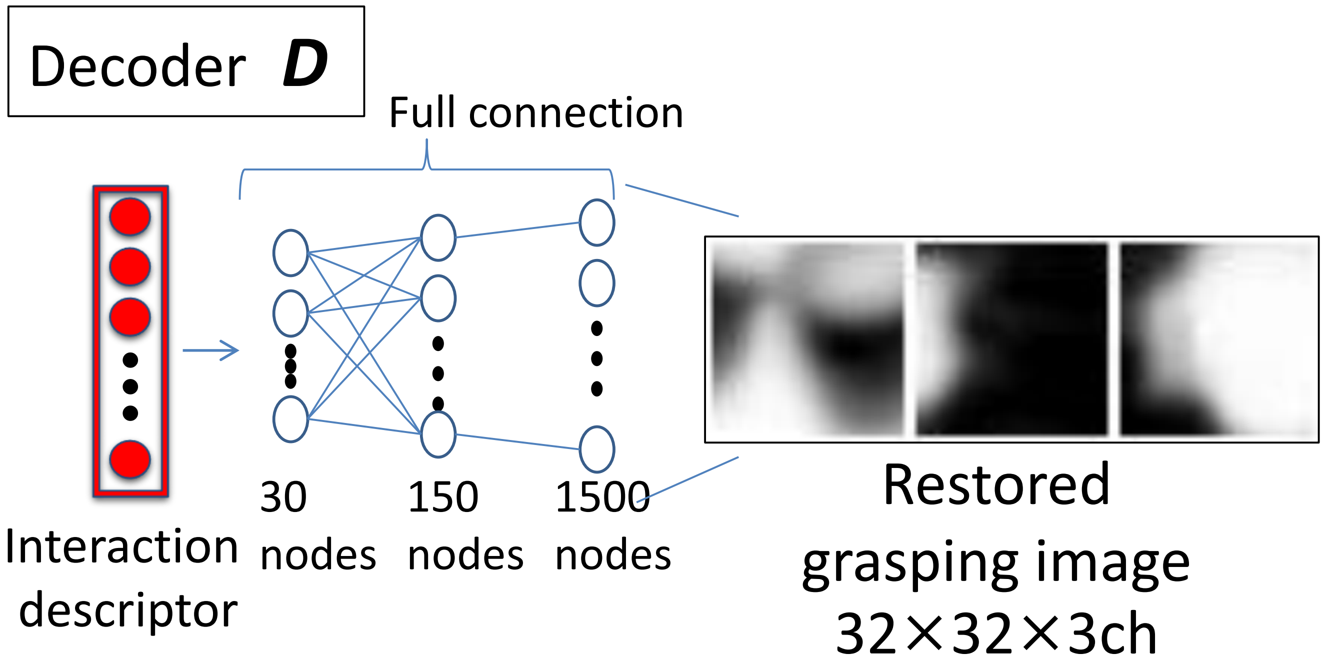
Structure of auto-encoder

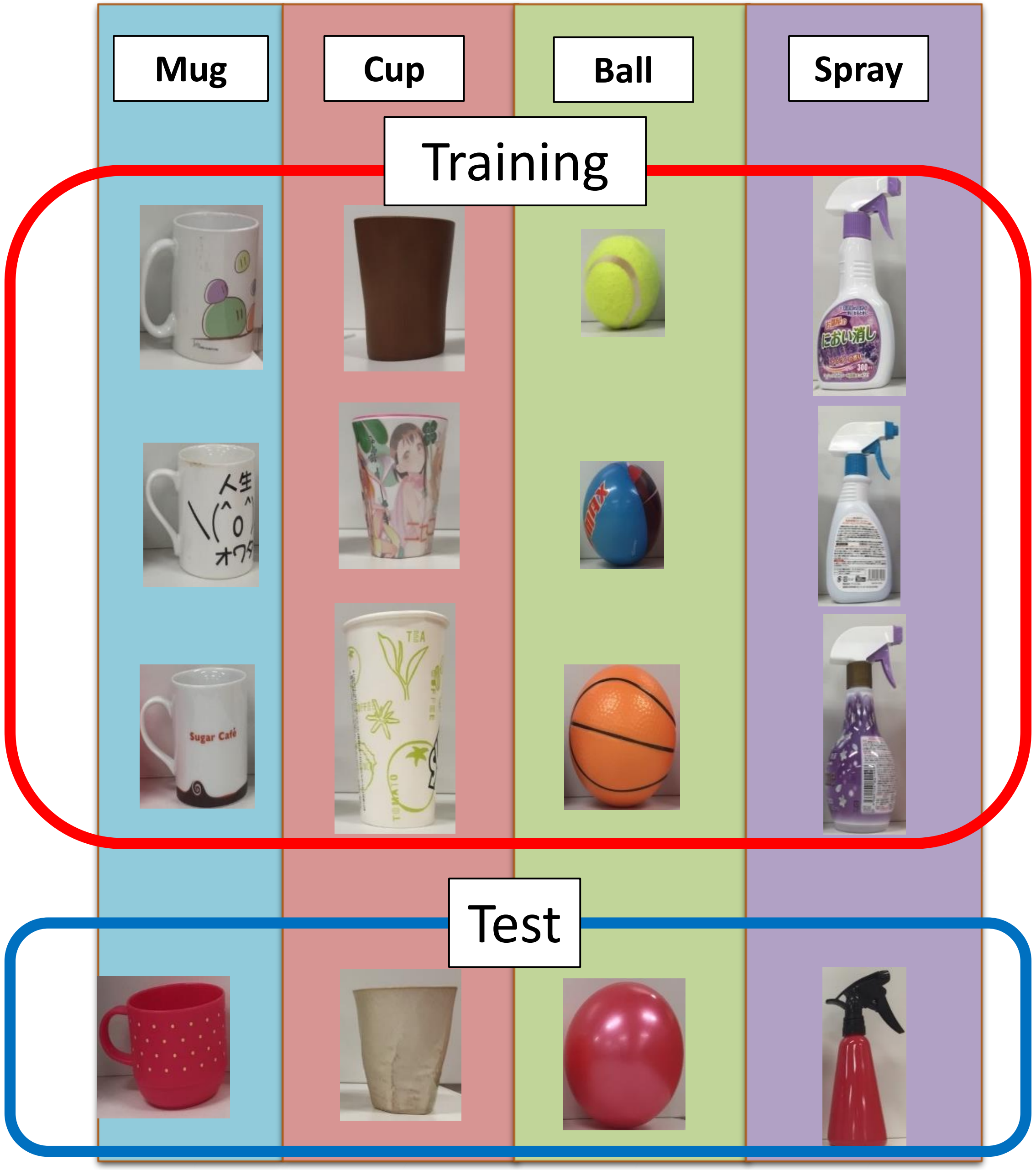




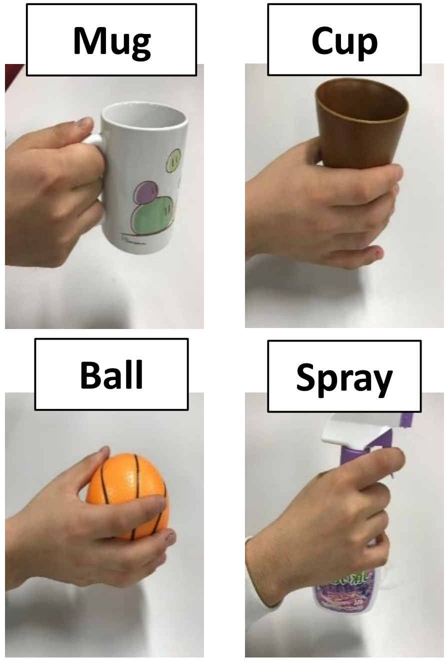
Parameters

Input size: 32×32×3
Descriptor dimension: 30
Kernel size: 9×9

Objects and grasping methods

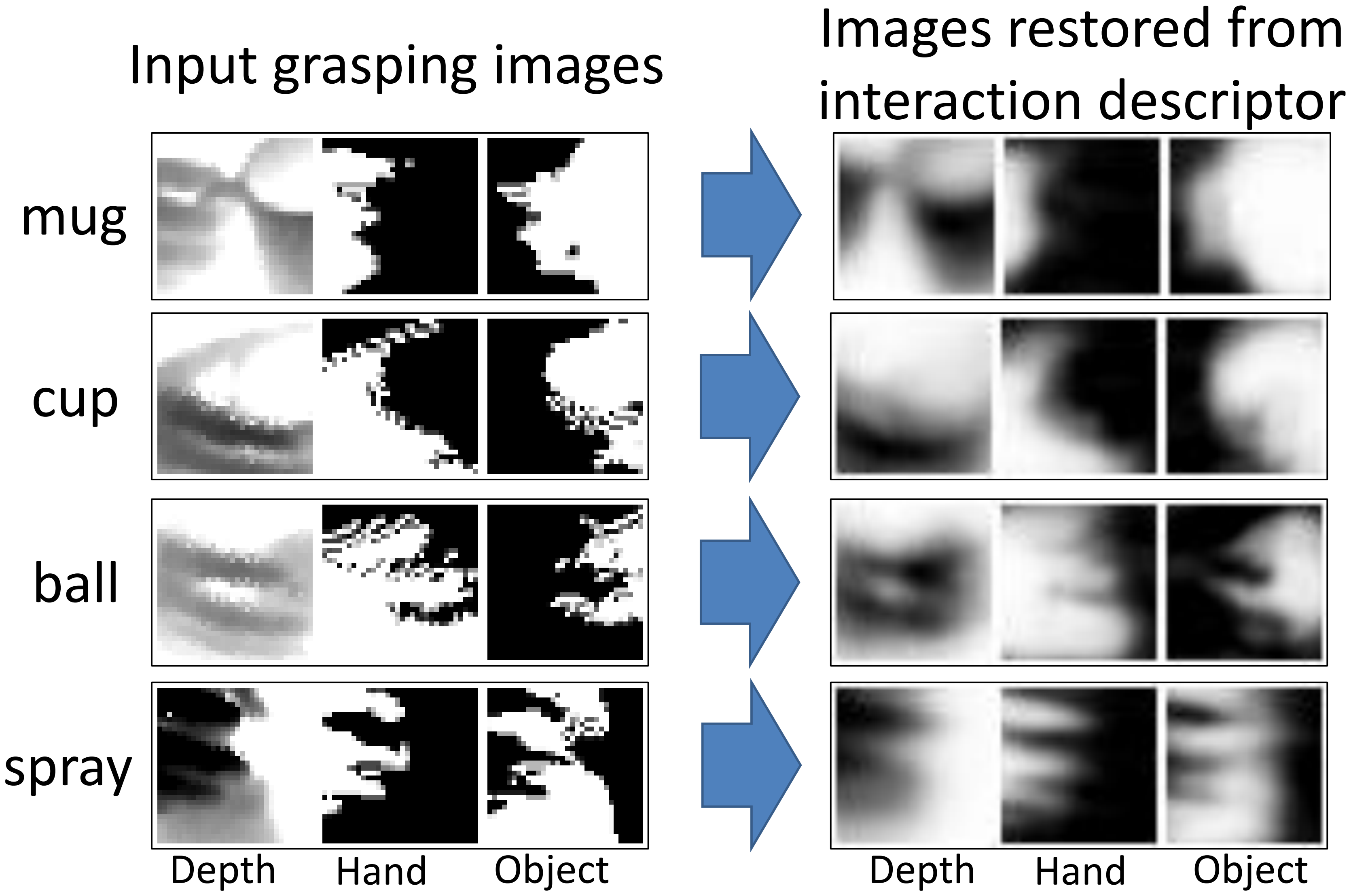


Grasping methods



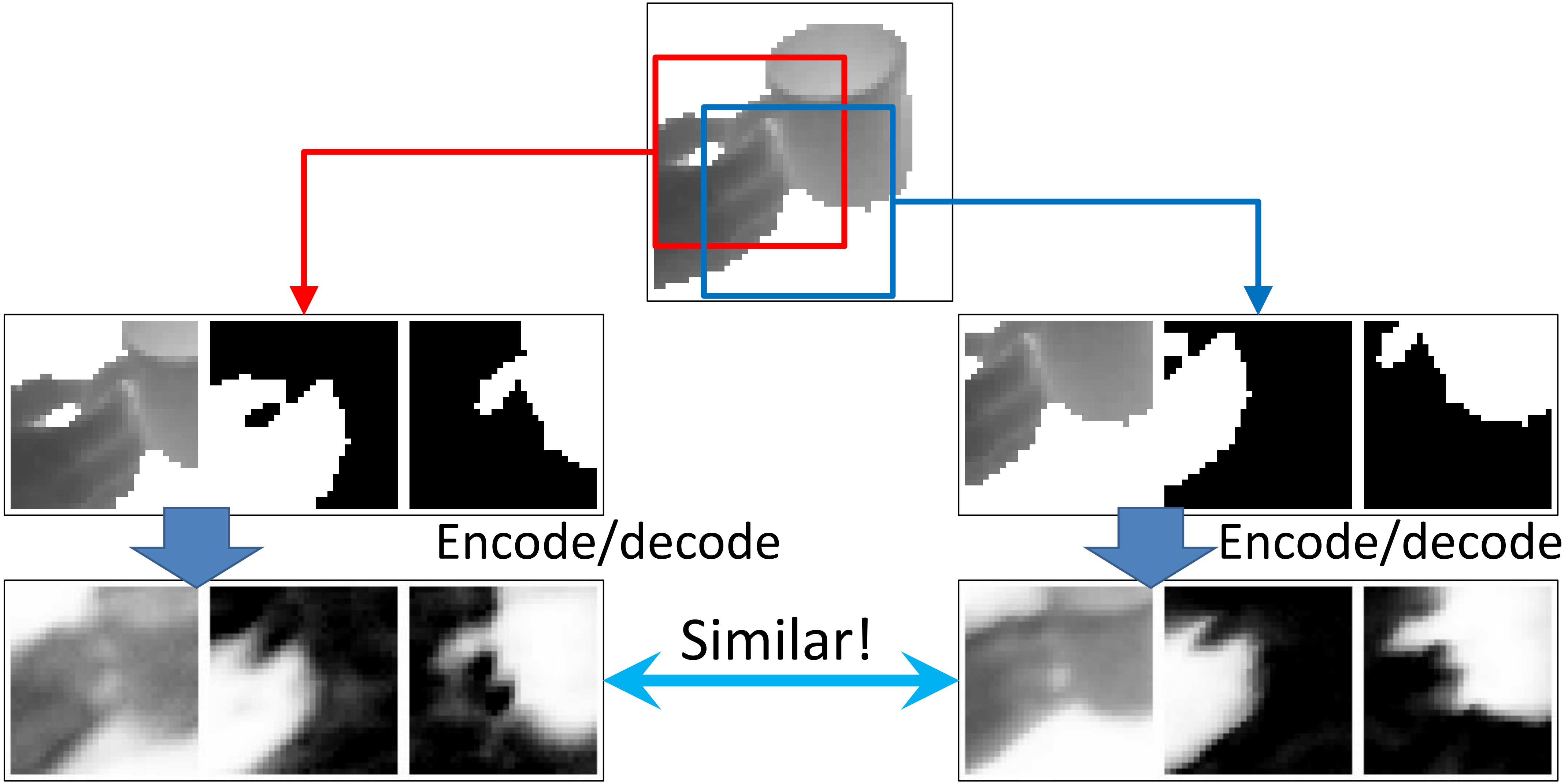
Training images:
80scenes×12kinds
= 960
Test images:
80scenes×4kinds
= 320

Restored grasping images



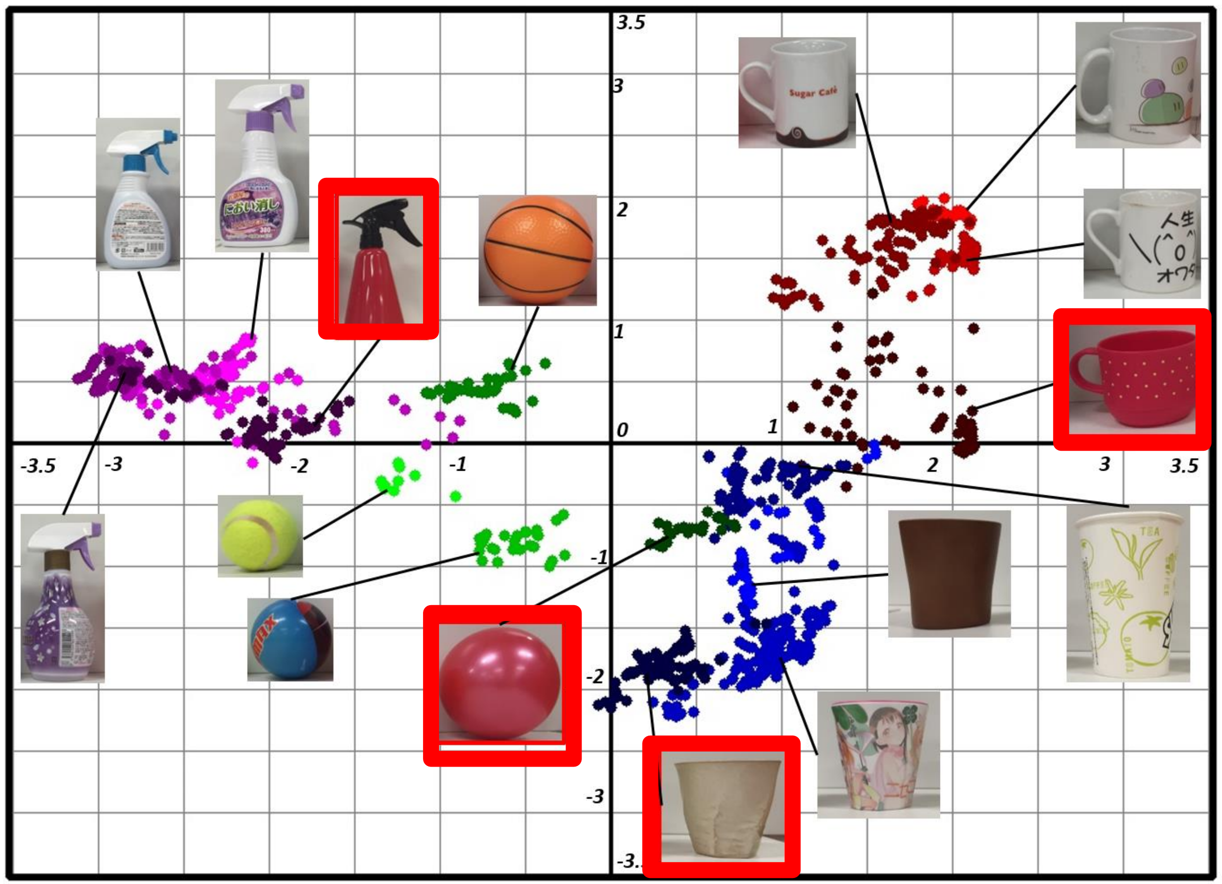
Interaction descriptor has approximate shape information.

Effect of shift invariant auto-encoder



Interaction descriptors represent a typical shape without position.

Distribution of interaction descriptors



2nd principal component

1st principal component

Non-frame:
Object for
training

Red frame:
Object for test

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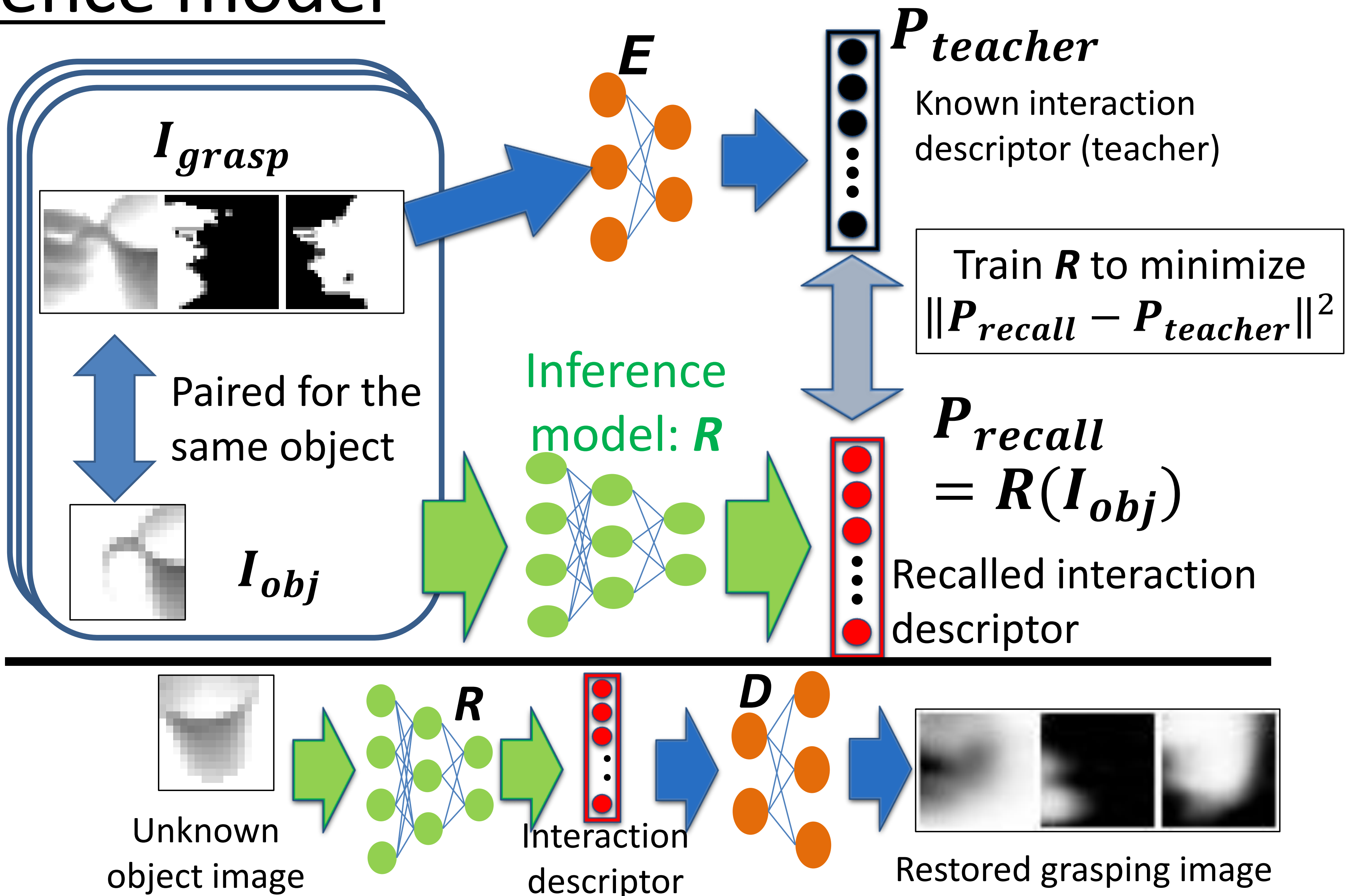
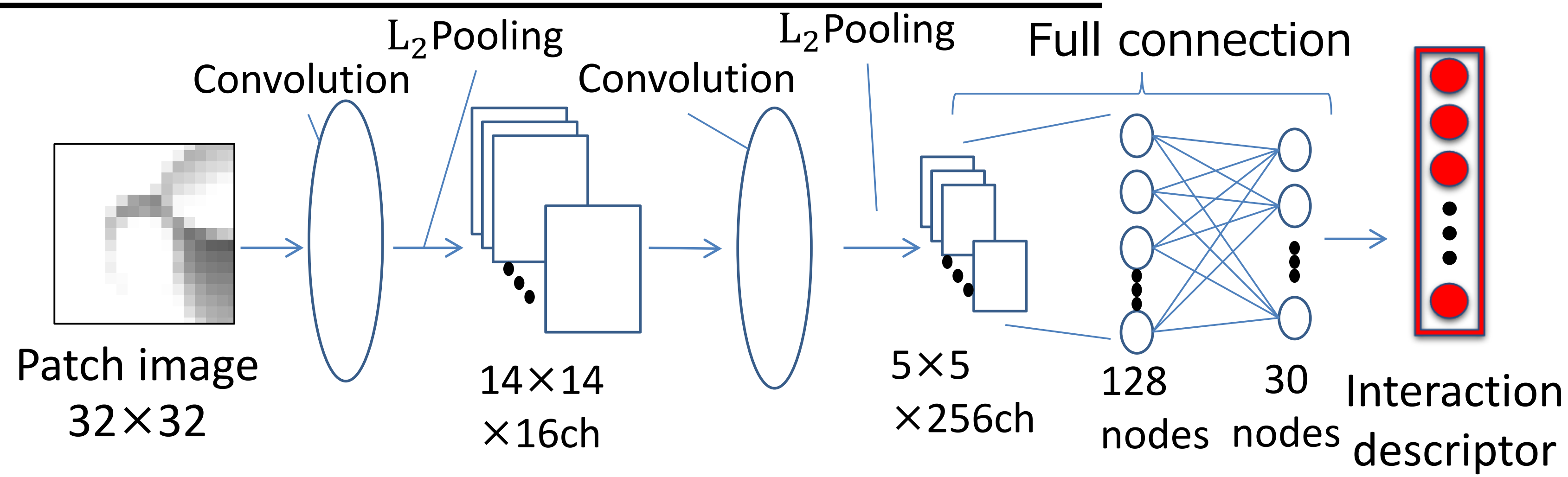
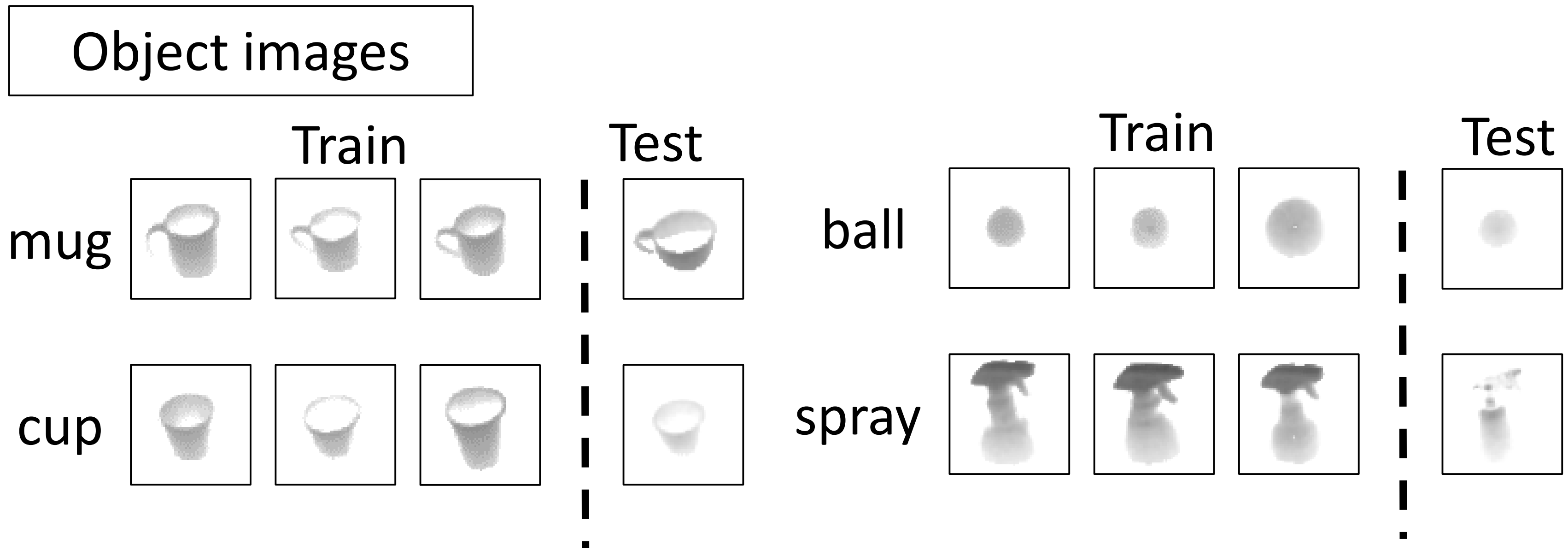
Inference model

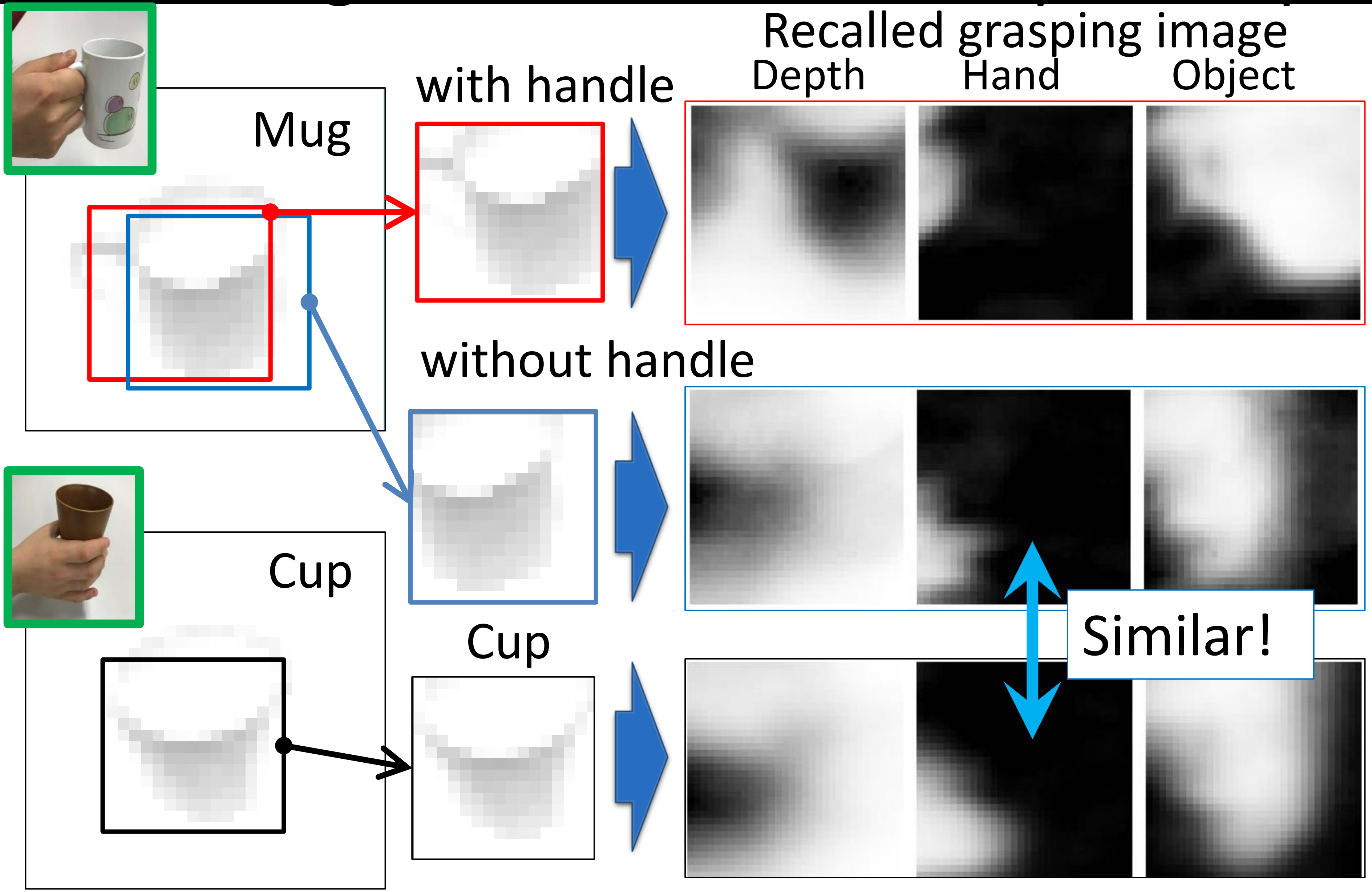


Structure of the inference model

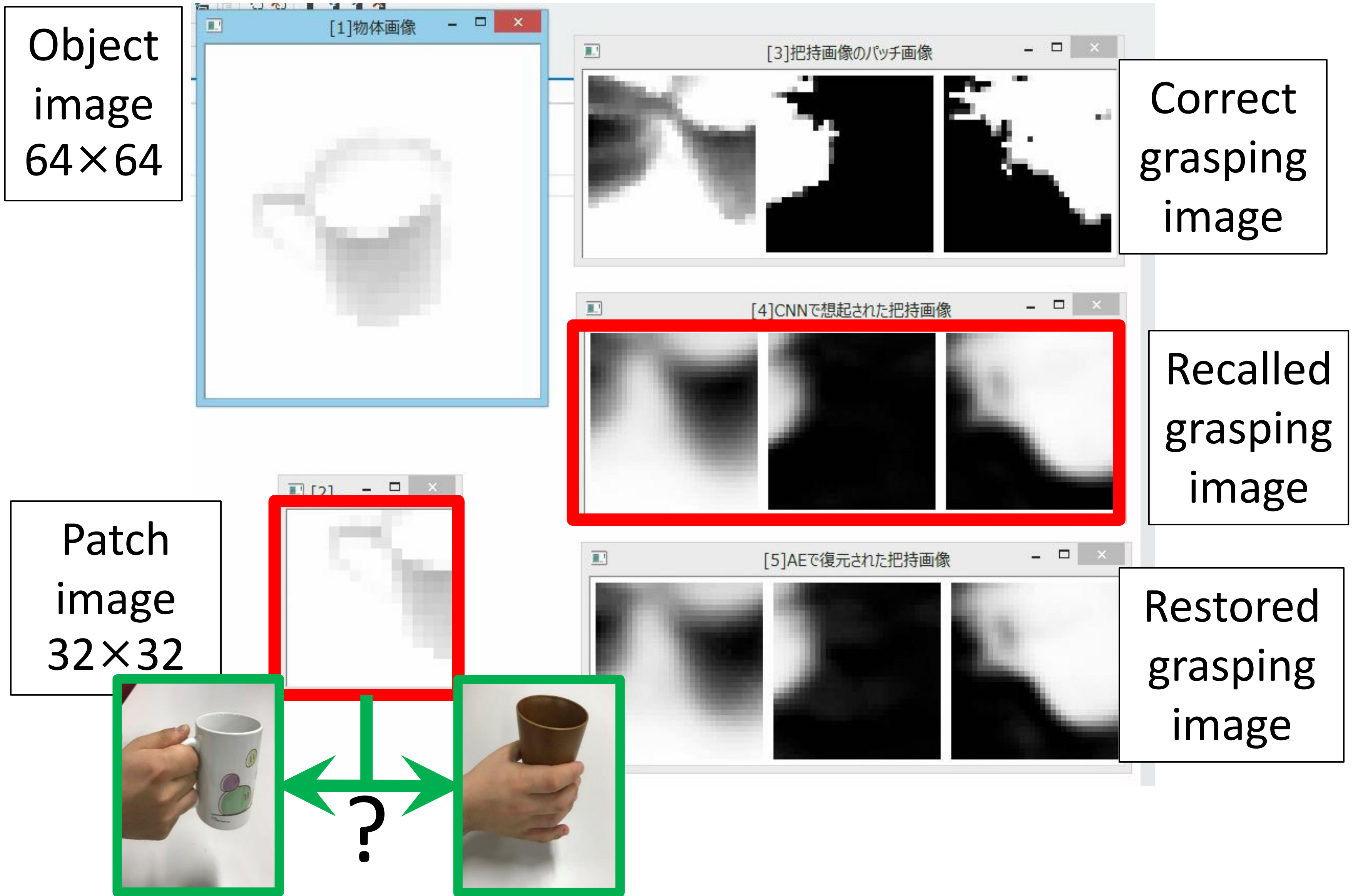




Recall from images with/without an important part



Recall from images with/without an important part



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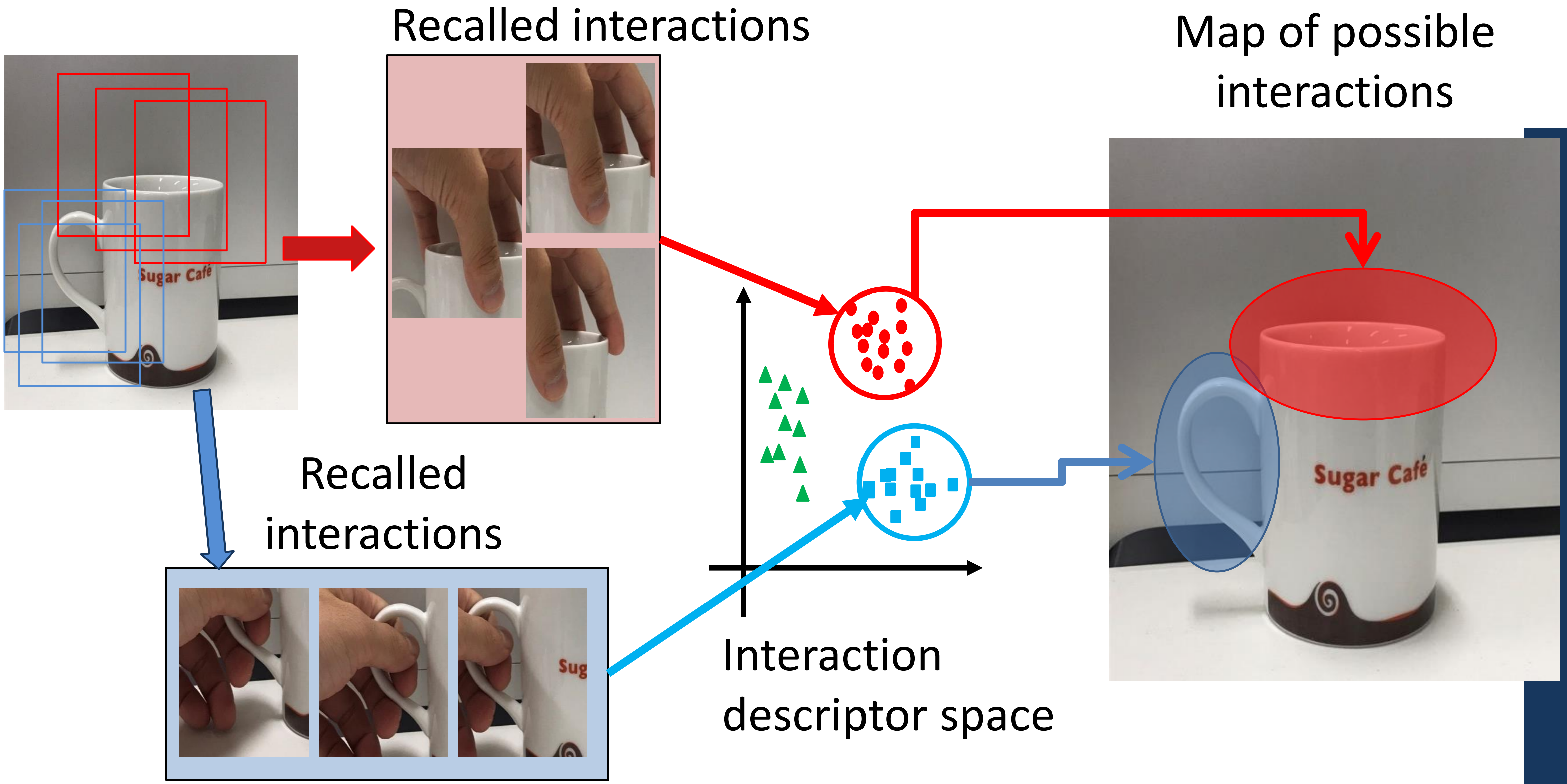
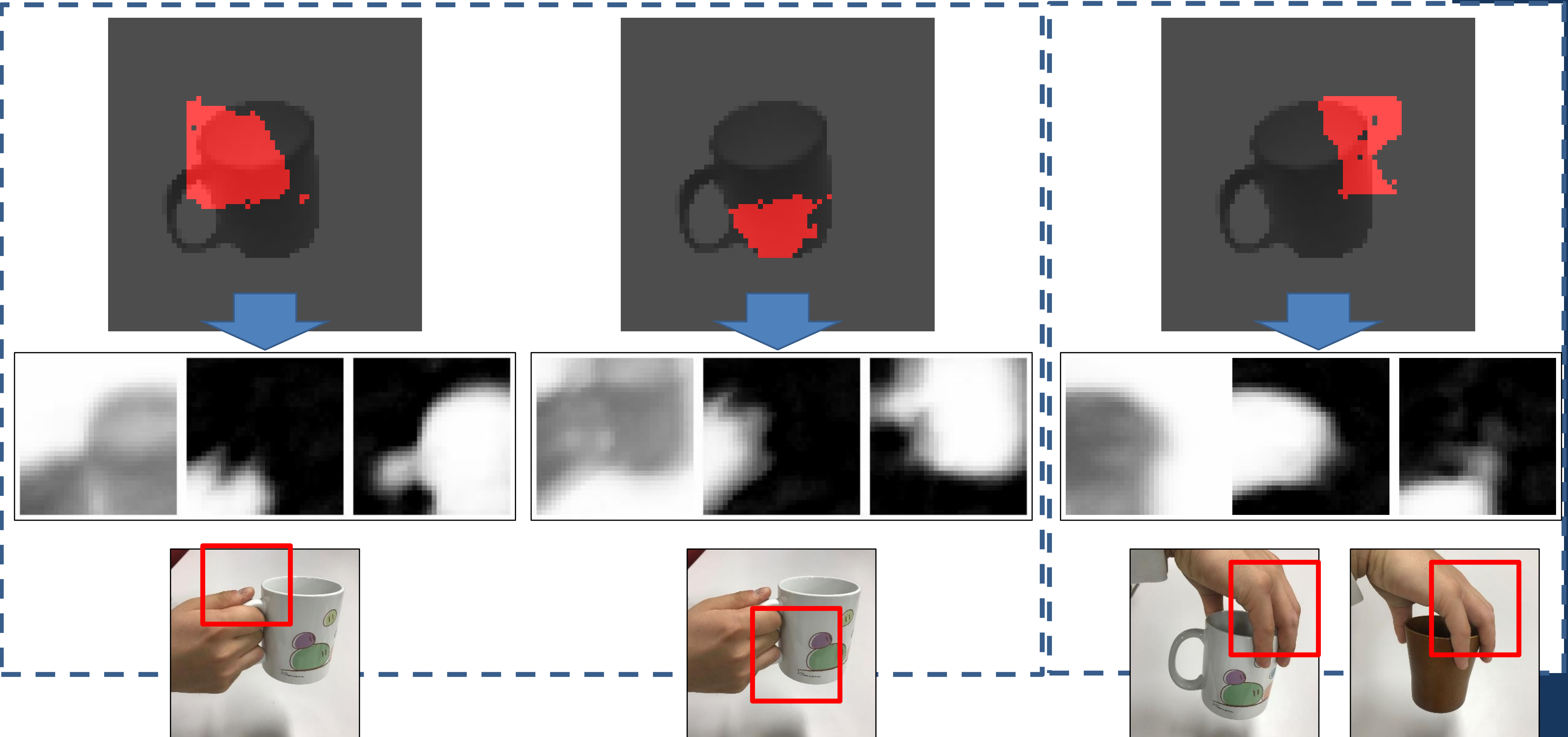
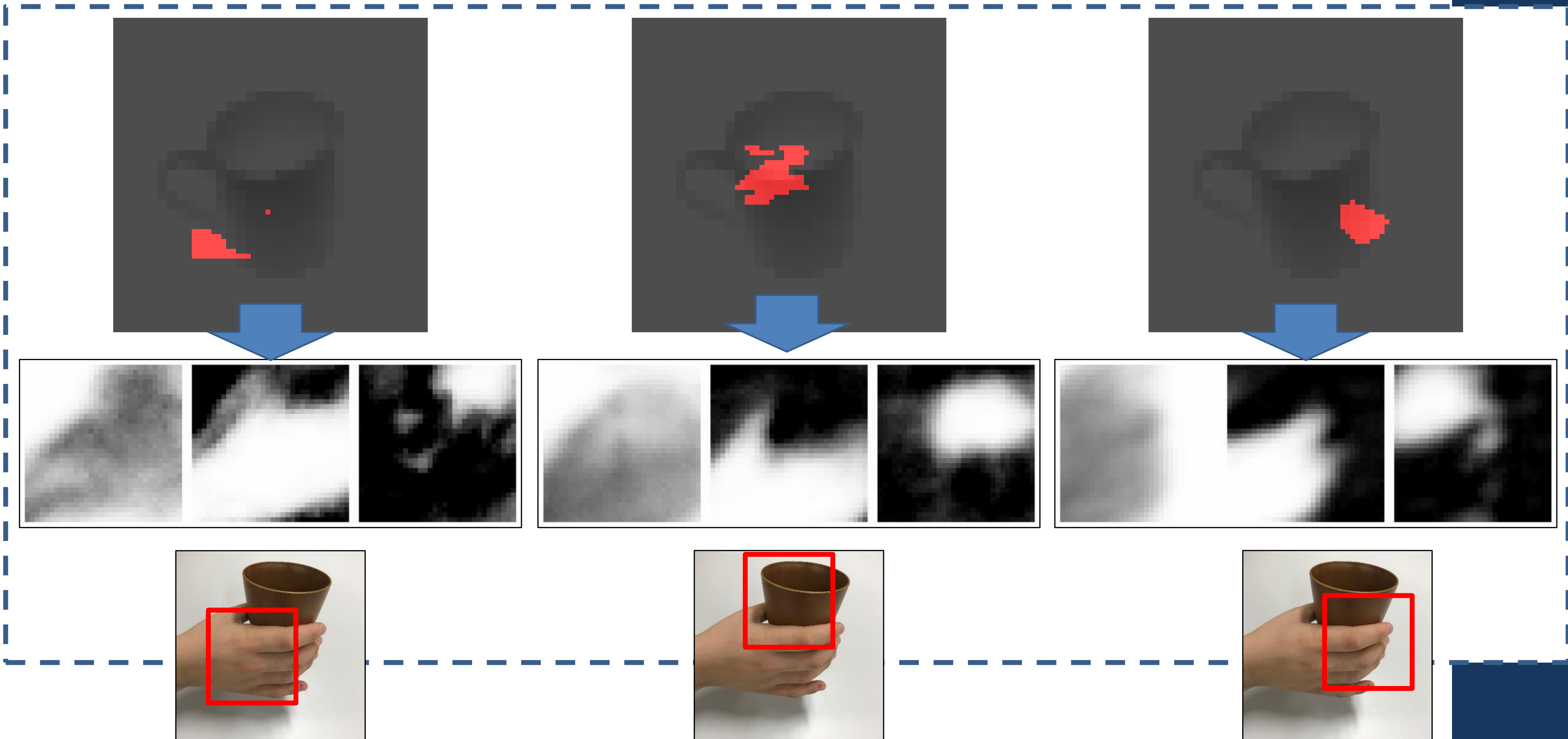
Interaction map on an object



Clusters of recalled descriptors (train)



Clusters of recalled descriptors(test)



Conclusion

- We proposed a method to recall grasping method from an object. It is based on:
  - Interaction descriptor by shift invariant auto-encoder
    We can generate numeral representation of grasping method without teacher labels.
  - Inference model by CNN
    The relation between object shape and grasping method can be modeled by utilizing interaction descriptor.
- The proposed method can estimate hand region for grasping an object from the object itself.
- The proposed method will be useful for robot manipulator.

Multiple grasping types for object

To see part-specific inference, we train auto-encoder and inference model with below grasping types.

Grasping type 1 | Grasping type 2

mug

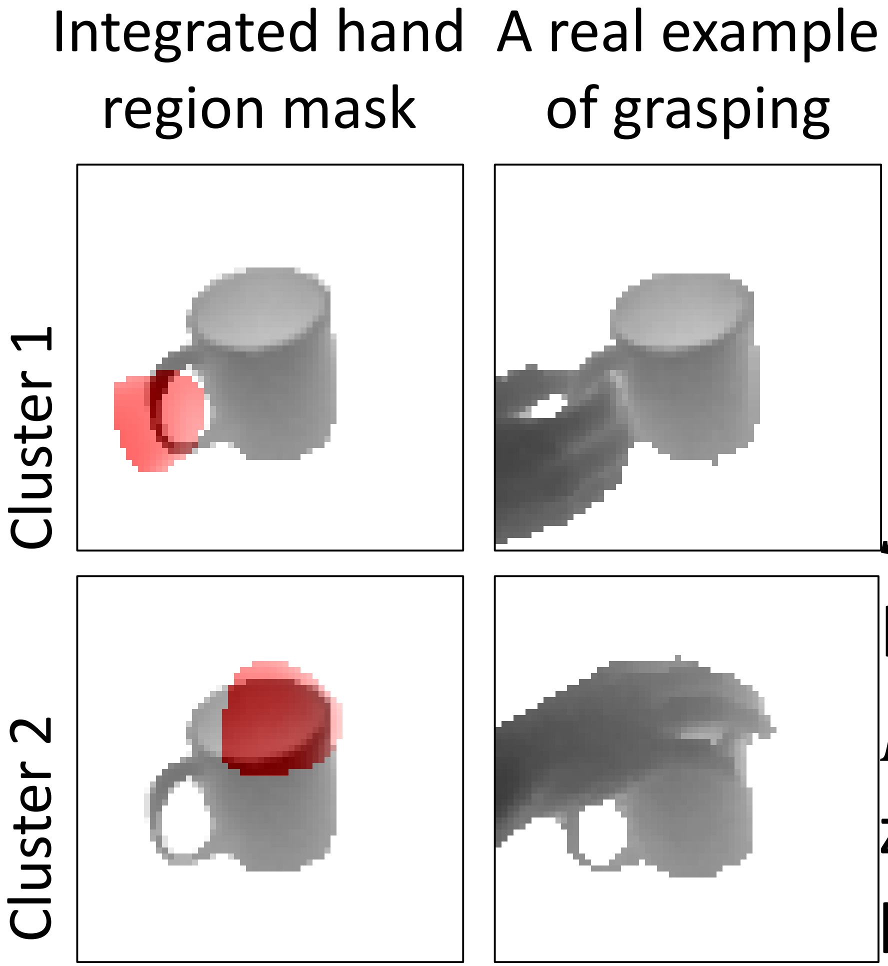
cup

Grasping type 1 | Grasping type 2

ball

spray

Integrated hand region mask



The integrated hand mask for cluster i is defined as:

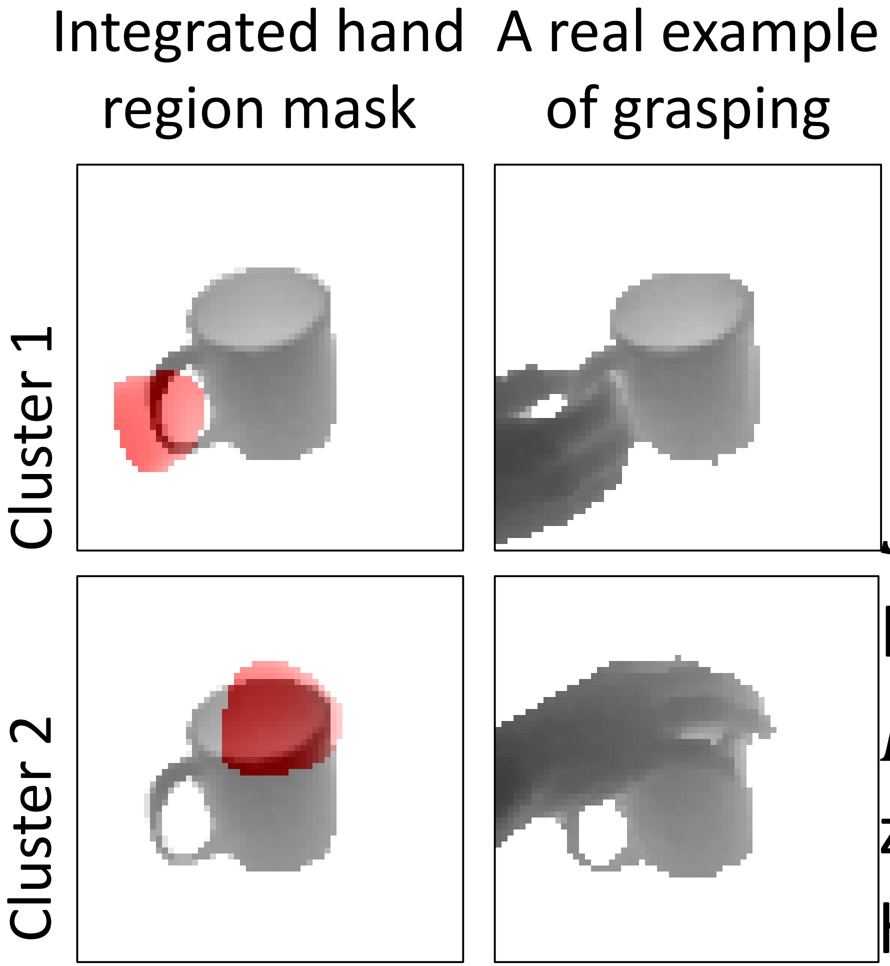
$$P_i(x,y) = \frac{S_i(x,y)}{N_i(x,y)}$$

$S_i(x,y)$: Sum of recalled hand mask in the i-th cluster

$N_i(x,y)$: Number of non-zero at (x,y) of recalled hand mask in the i-th cluster

Integrated hand region mask indicates hand region when human grasps the object.

Integrated hand region mask



The integrated hand mask for cluster i is ... as:

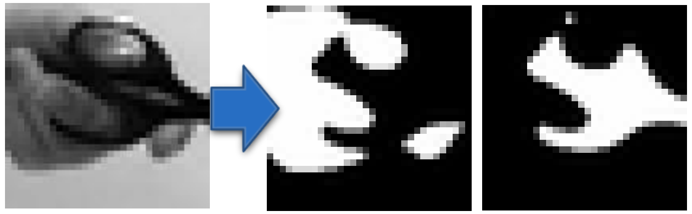
$$\ldots) = \frac{S_i(x,y)}{N_i(x,y)}$$

$S_i(x,y)$: Sum of recalled ha... in the i-th cluster

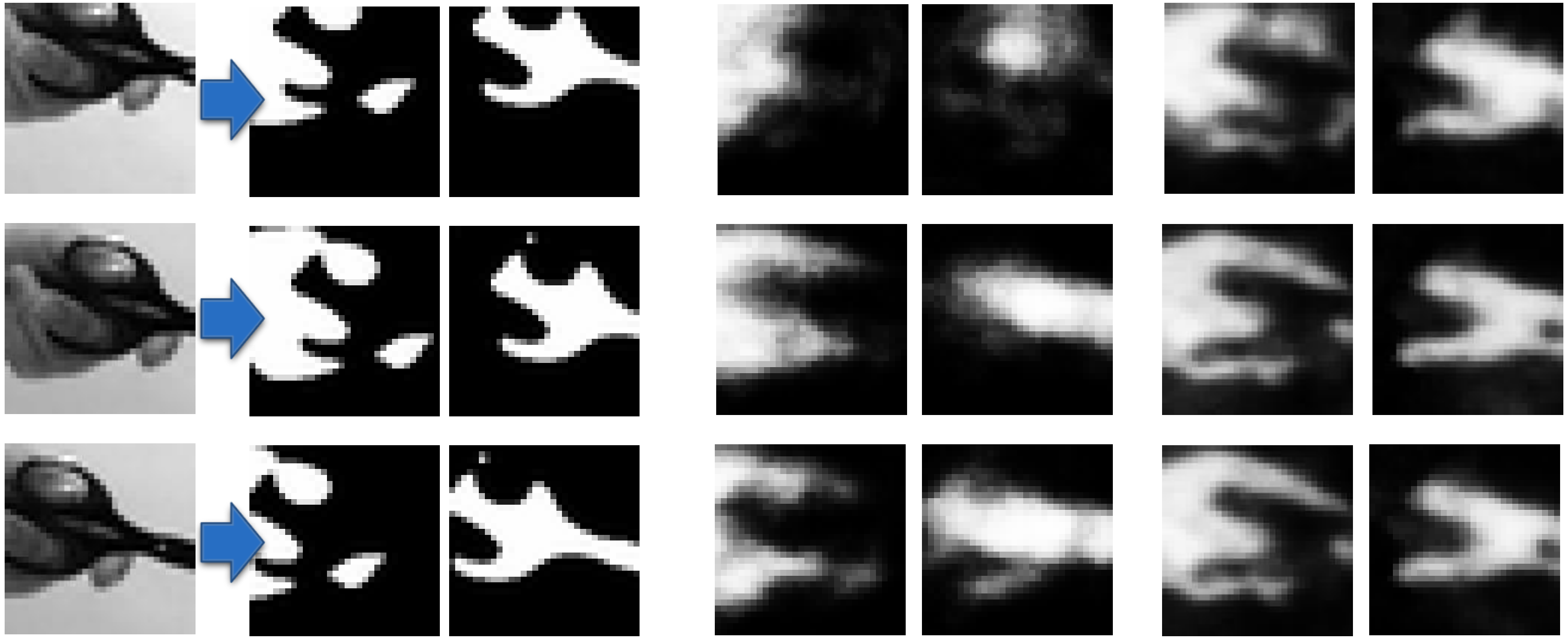
N... Number of non-ze...) of recalled hand mask in the i-th cluster

Integrated hand region mask indicate hand region when a human grasps the object.

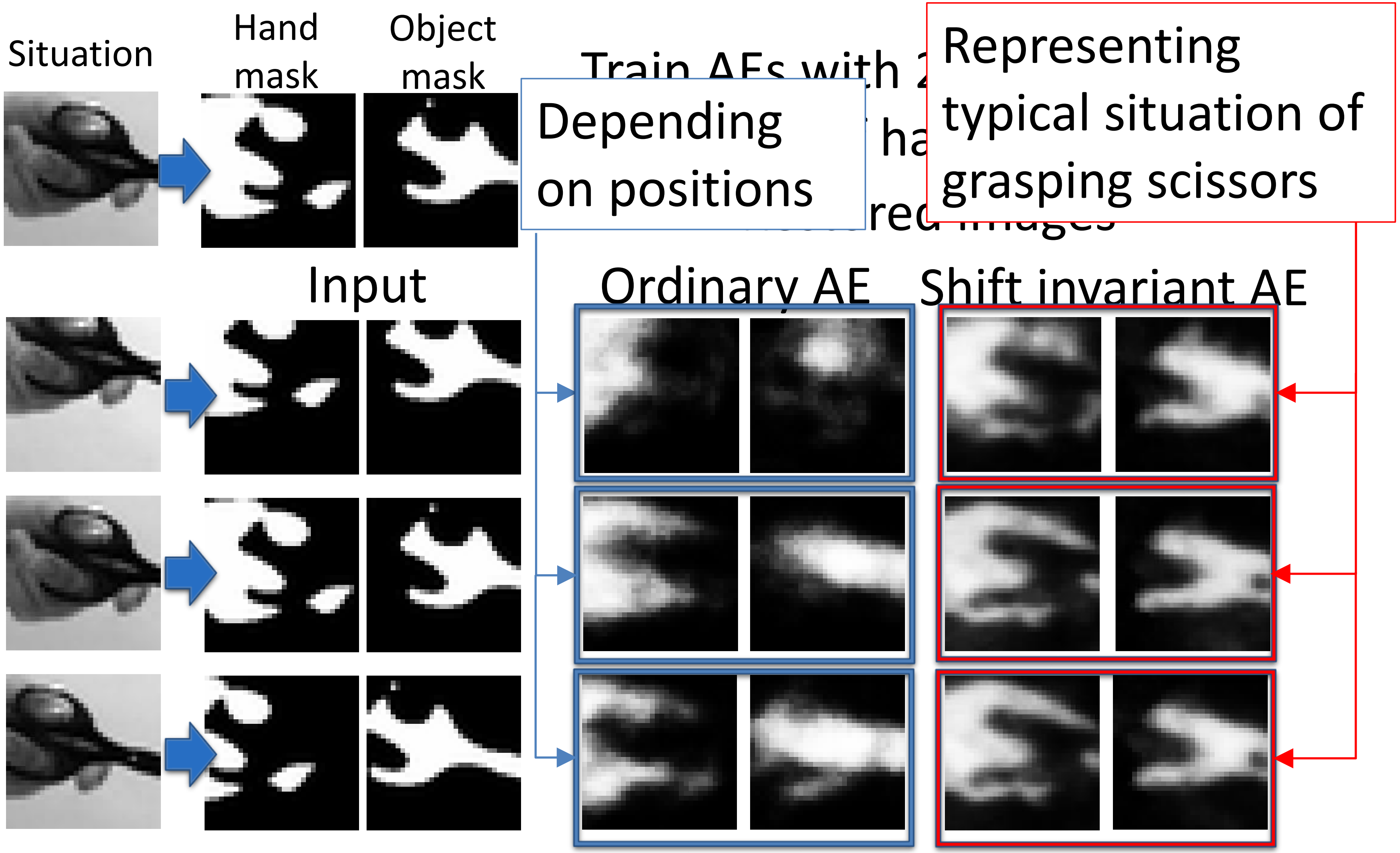
Example for hand-object interaction

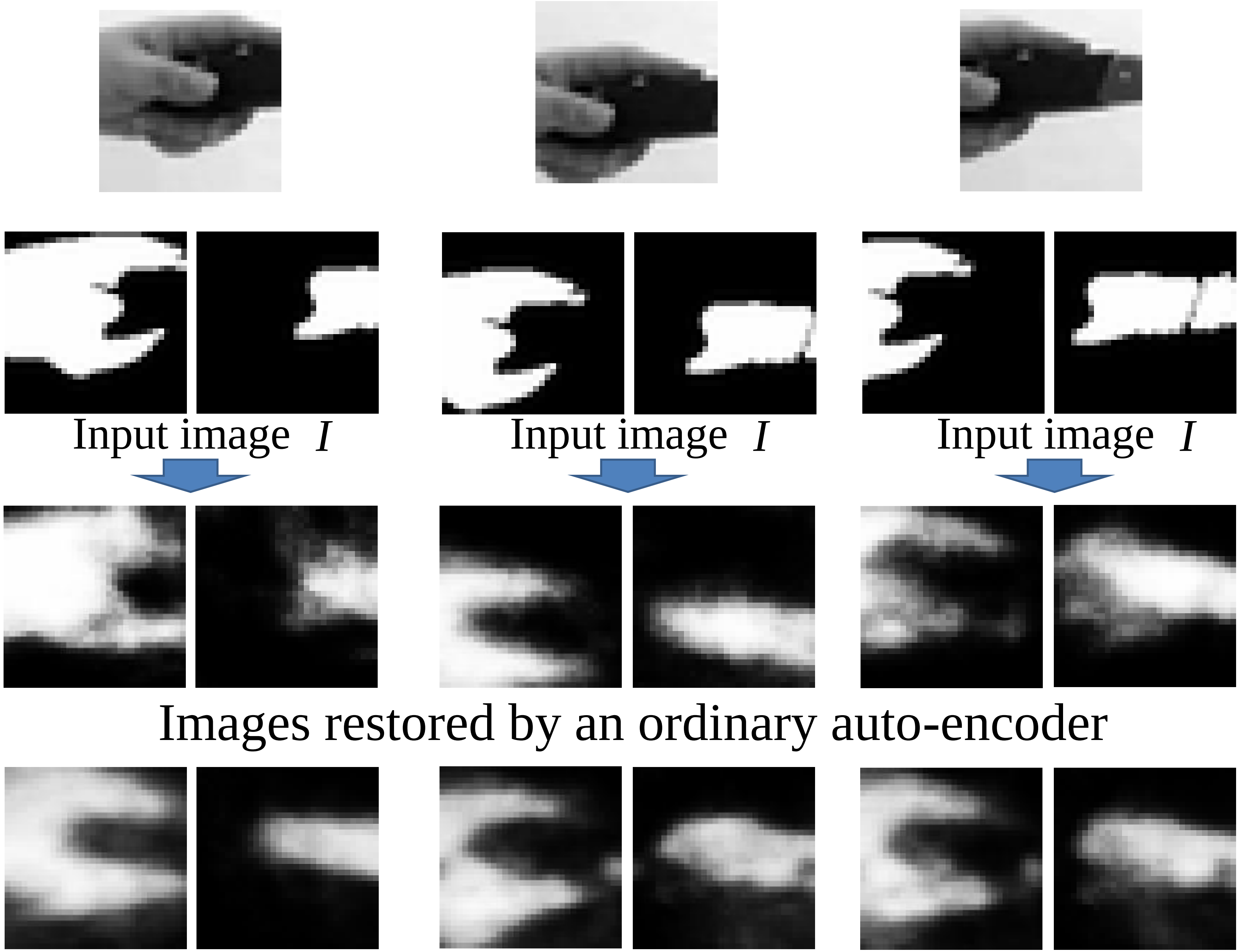


Train AEs with 2-channel images consisting of hand/object masks.



Example for hand-object interaction





Images restored by a shift invariant auto-encoder