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STOW: Discrete-Frame Segmentation and Tracking of Unseen Objects for Warehouse Picking Robots

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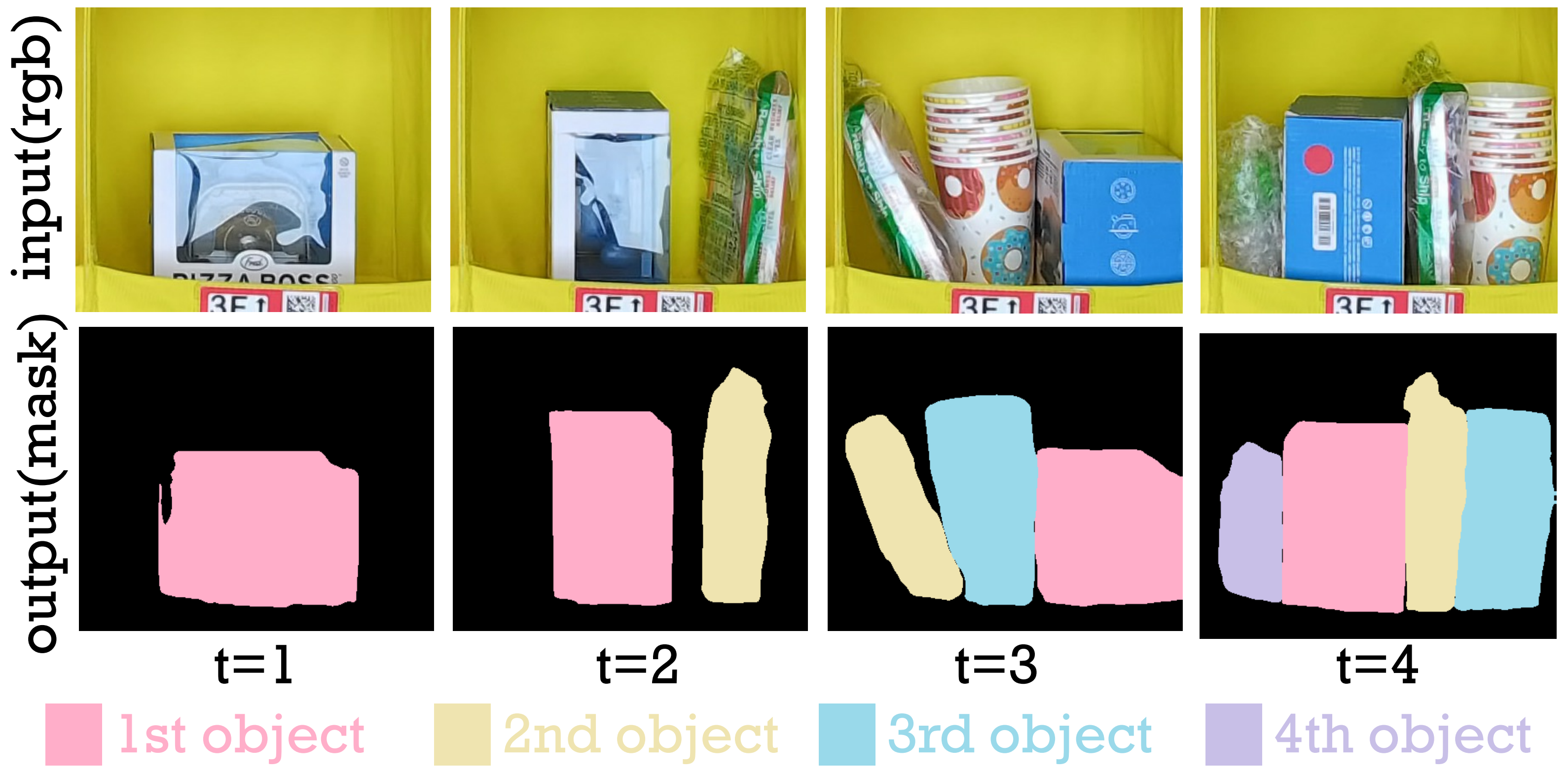
CODE, DATA AND MORE

SCAN ME

Task Formulation

- ◆ A cluttered shelf contains diverse objects
- ◆ objects may be rearranged
- ◆ camera may be occluded
- ◆ The goal is to pick an object based on its given order index in the bin.



$$\mathcal{I} = \{I_1, I_2, \cdots, \boxed{I_T} \mid I_t \in \mathbb{R}^{H\times W\times C_I}\}$$

T: num of frames
K_I: num of objects

$$\mathcal{M}_t = \{M_t^1, M_t^2, \cdots, M_t^{K_I} \mid M_t^i \in \{0,1\}^{H\times W}, i = 1, 2, \cdots, K_I\}$$

Challenges

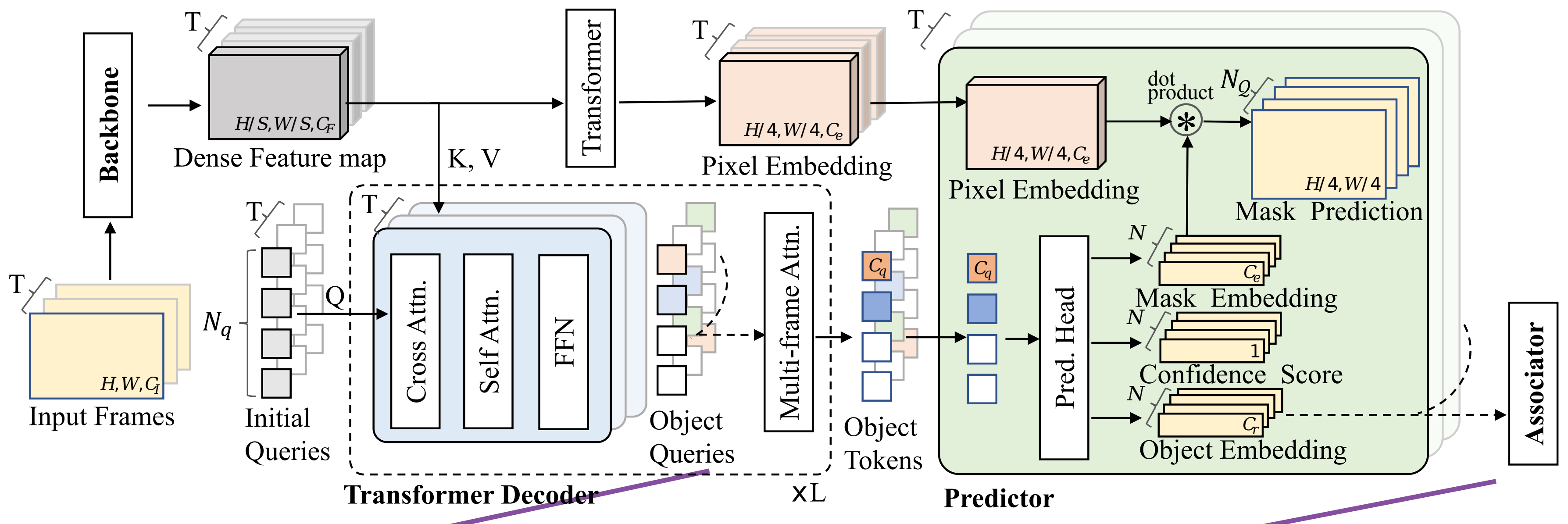
Unseen Objects

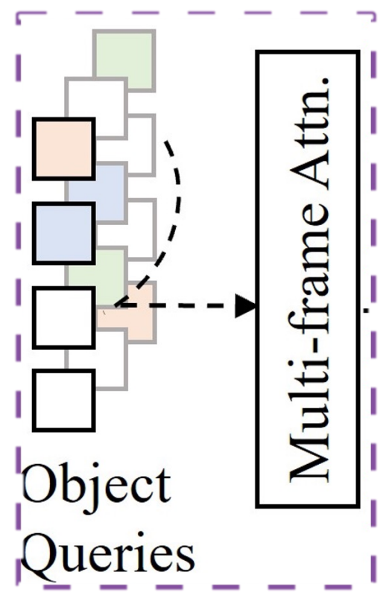
- Vast number of categories
- Limited synthetic models
- Ambiguous border
- Transparent parts
- Plastic wrapper

Discrete frames

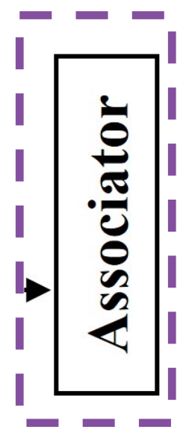
- Caused by heavy occlusion
- Drastic appearance change
- Large movement between frames
- Little information from context

Method





- Multi-frame attention
- On object queries from different frames
- Inside decoder block
- Efficient inter-frame reasoning

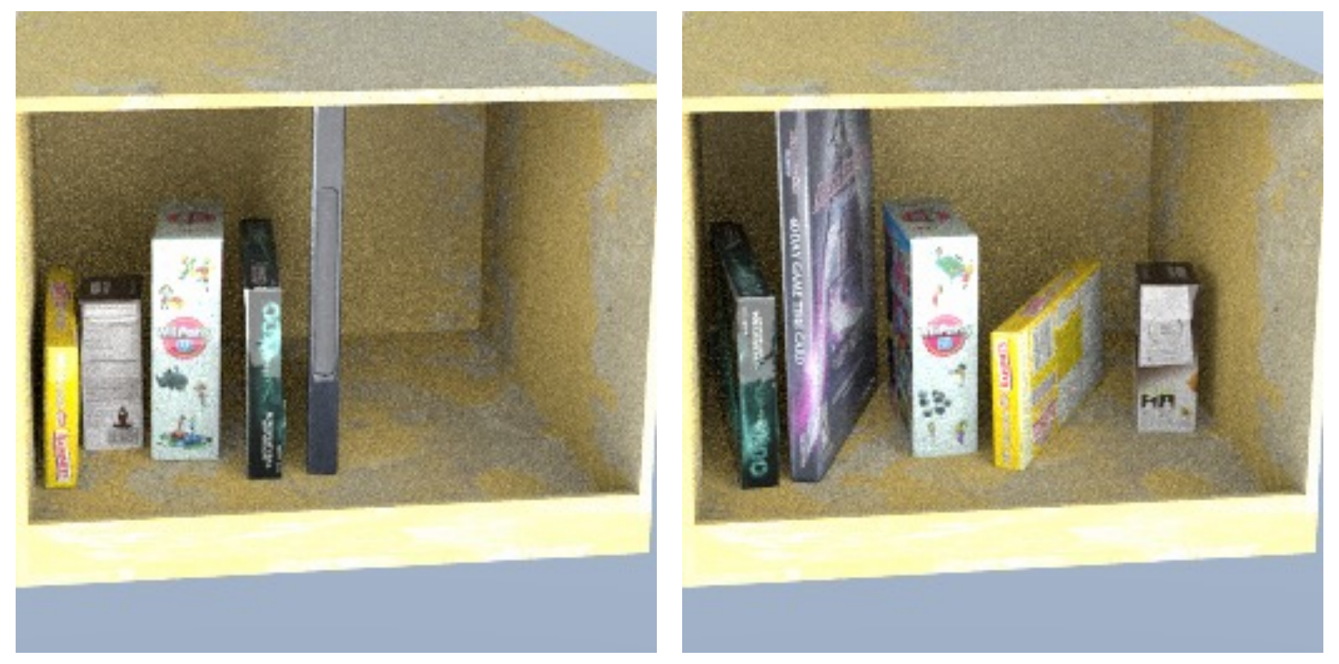


- Hungarian matching
- Embeddings for tracking
- From each frame
- Disentangles tracking from detection

Dataset

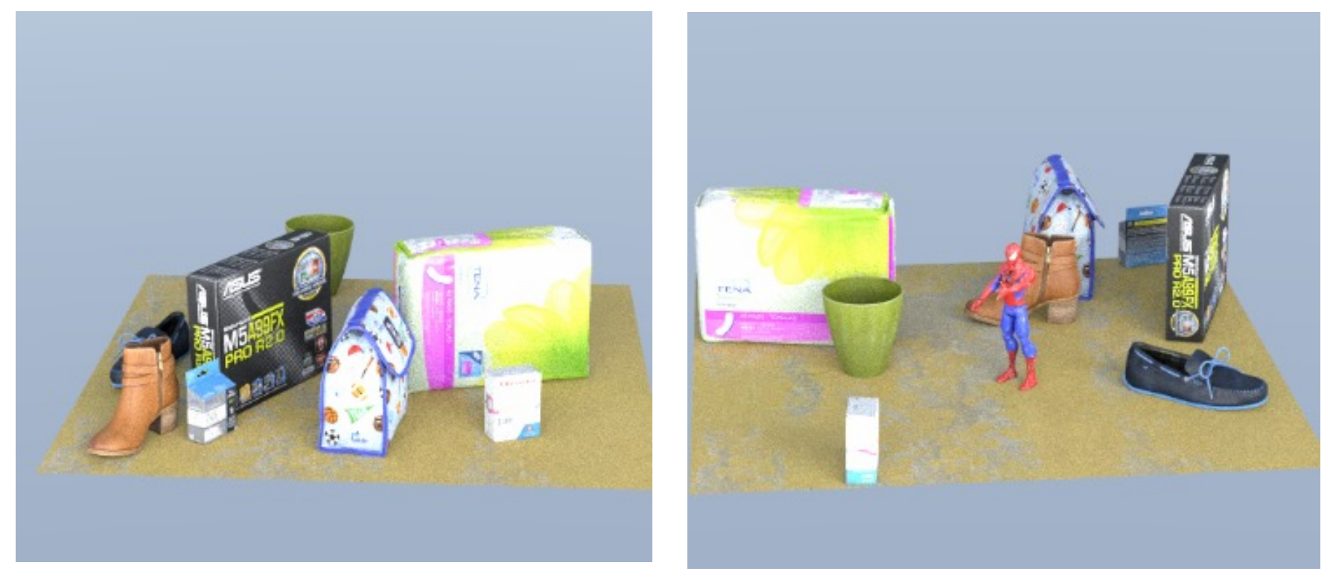
Synthetic Data (train & val)
GoogleScanned objects
~900 for train, ~100 for test

shelf



10k sequences
2 frames for each sequence

tabletop



2k sequences
15 frames for each sequence

Real Data (test)
~ 150 real objects
manual annotation

44 sequences of bins
220 images in total

20 sequences
280 images in total

Results

Method	Shelf		Tabletop	
	AP@all	AP@0.5	AP@all	AP@0.5
MinVIS	6.3	21.2	0.7	0.0
Mask2Former Video	35.0	66.1	27.7	56.7
VITA	42.7	70.1	26.6	55.0
STOW (Ours)	**55.6**	**81.3**	**49.7**	**75.4**

- Comparison with STOA VIS methods
- Train on synthetic data and test on real data
- All using RN50 backbone with same number of iteration

multi frame	shelf		tabletop	
	AP@all	AP@0.5	AP@all	AP@0.5
-	51.8	78.7	44.4	68.5
✓	**55.6**	**81.3**	**49.7**	**75.4**

- Ablation study on multi-frame attention layer
- Frame attention layer can boost performance by ~5%

method	synthetic		real	
	AP@all	AP@0.5	AP@all	AP@0.5
MinVIS	0.3	2.6	0.7	0.0
M2F-V	71.6	83.7	27.7	56.7
VITA	69.4	81.9	26.6	55.0
STOW (Ours)	**74.1**	**89.3**	**49.7**	**75.4**

- Better performance handling Sim2Real Gap
- Train on synthetic and test on synthetic and real

Real Robot Experiments

82 trials, involving >100 objects

Method	Success Rate
UCN+SIFT	40.2%
VITA	46.3%
STOW(Ours)	74.4%

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