Reinforcement Learning with Self-Supervised 3D Representation for Motor Control

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Our 3D method trained in simulation

could transfer zero-shot to the real robot setup.

Lift





Ours (3D Pretrain)



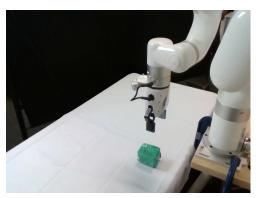


Lift



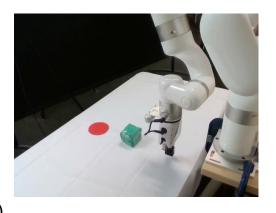


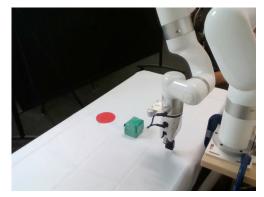
MoCo Pretrain





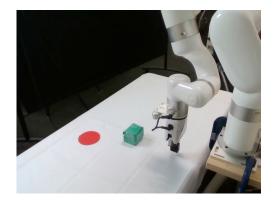
Push



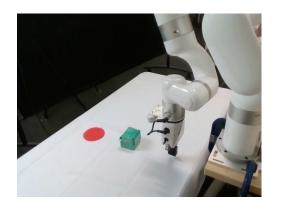


Ours (3D Pretrain)





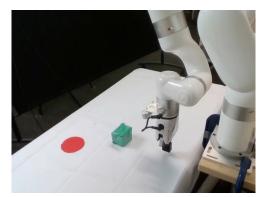
Push





MoCo Pretrain





Peg in Box





Ours (3D Pretrain)





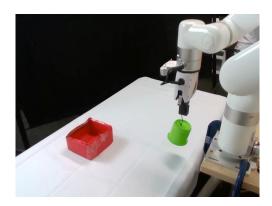
Peg in Box



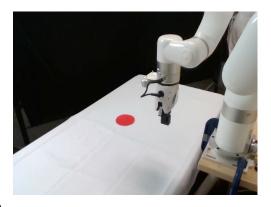


MoCo Pretrain





Reach





Ours (3D Pretrain)





Reach





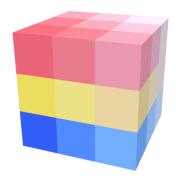
MoCo Pretrain





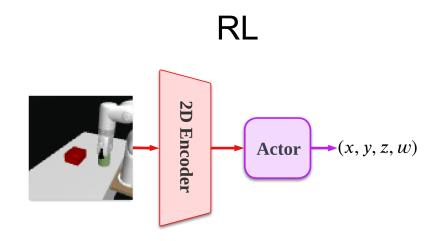
Our Method

We use a voxel-based 3D scene representation.

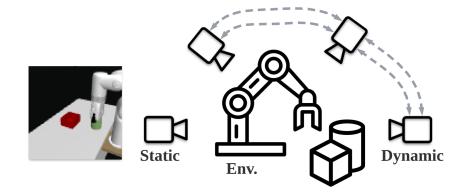


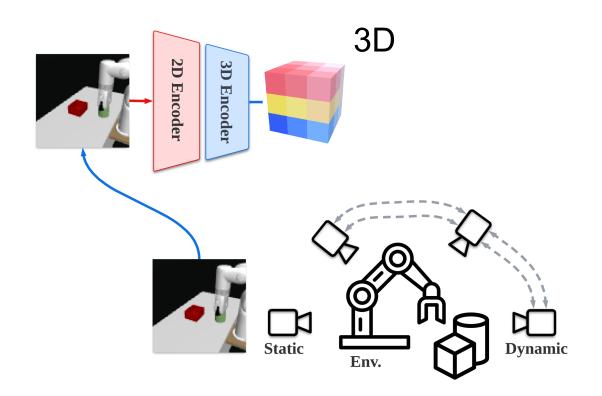
We first pretrain our visual representation on CO3D dataset, using a view synthesis task with autoencoder.

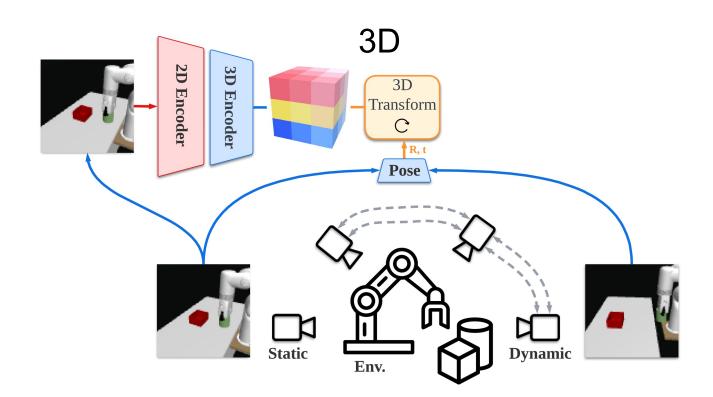


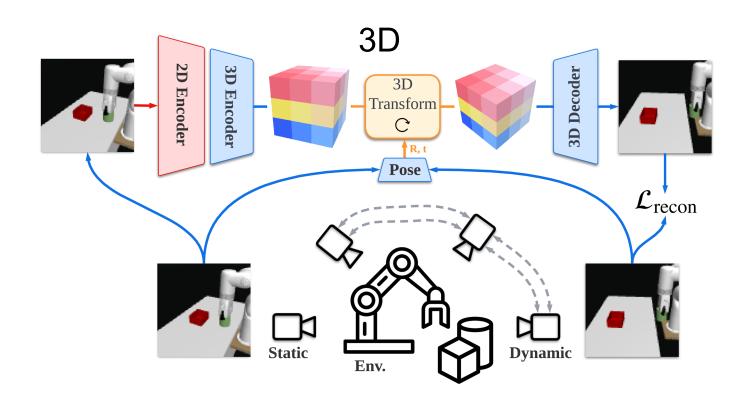


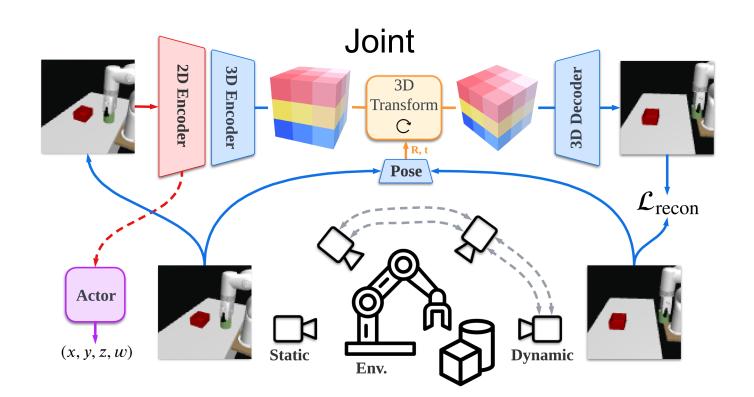
3D



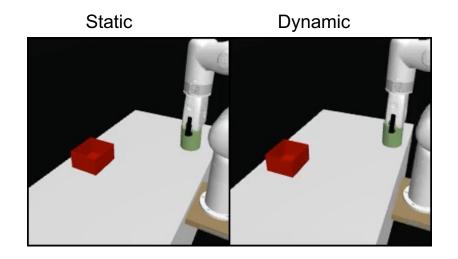


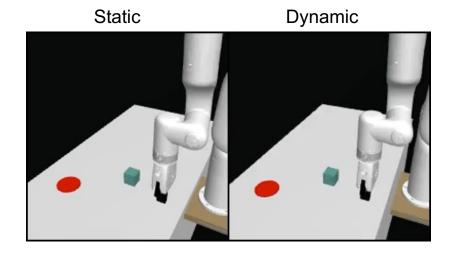






To achieve this, we need at least two cameras for RL tasks. We design one static camera and one dynamic camera.





Only trained in simulation, our method enjoys good performance when transferred to real.

Sim-to-real results.

Real	Scratch	ImageNet	MoCo	3D (ours)
Reach	$84{\pm}12$	$96{\pm}4$	$80{\pm}11$	$96{\pm 4}$
Push	$2{\pm}2$	$22{\pm}10$	$22{\pm}7$	$48{\pm}9$
Peg in Box	$40{\pm}14$	$62{\pm}20$	50 ± 15	$\textbf{76} {\pm} \textbf{19}$
Grasp	$44{\pm}14$	20 ± 10	38 ± 10	$62 {\pm} 14$
Lift	30 ± 15	$2{\pm}2$	20 ± 5	$46 {\pm} 19$

Thanks!