Design and Control Co-Optimization for Automated Design Iteration of Dexterous Anthropomorphic Soft Robotic Hands

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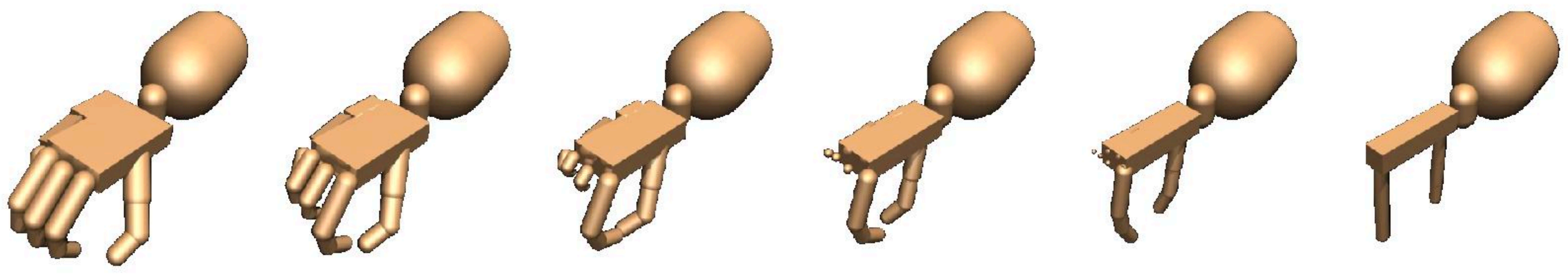
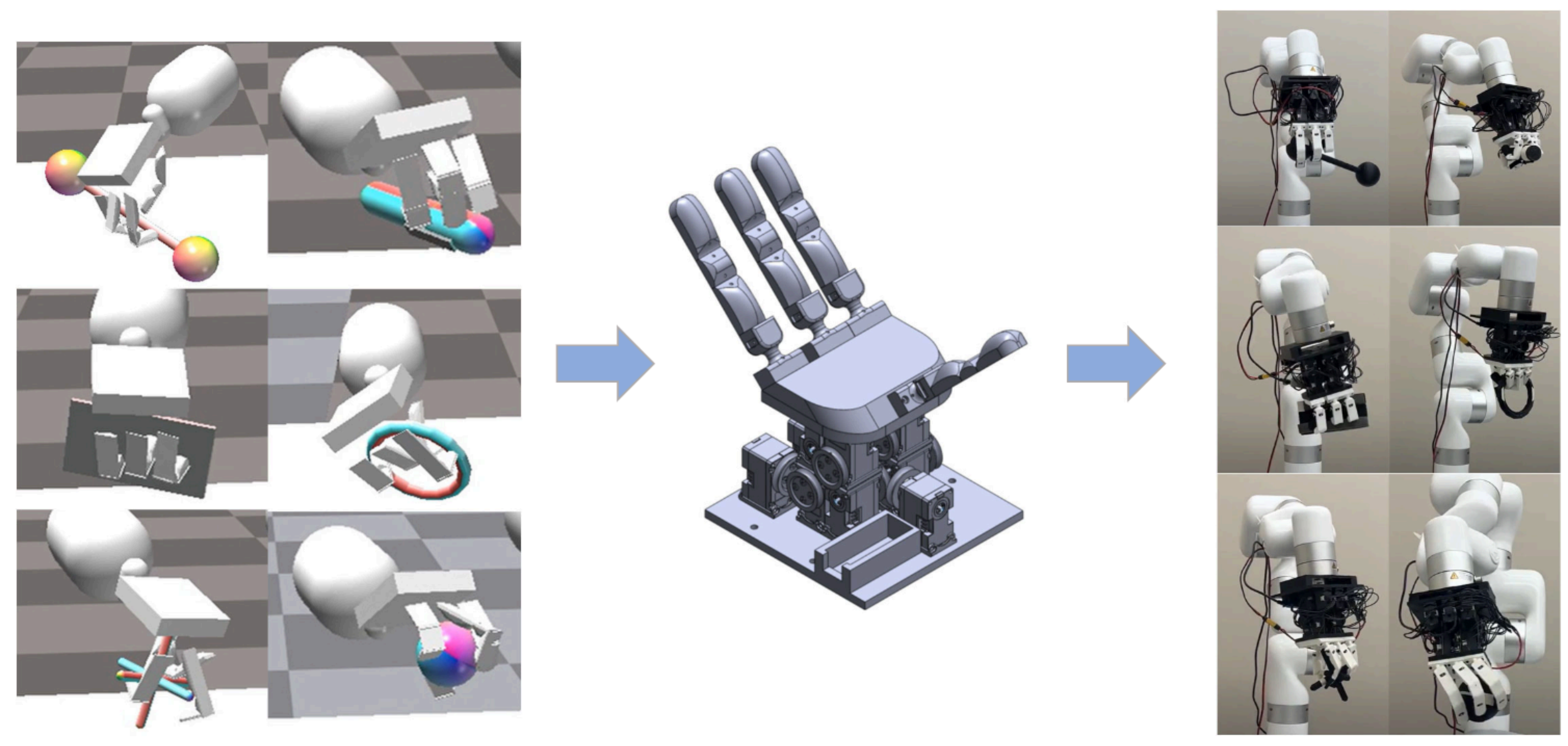
Policy Transfer and Robot Evolution



Xingyu Liu et al. REvolveR: Continuous Evolutionary Models for Robot-to-robot Policy Transfer. ICML 2022.

- Simulation helps avoid testing many designs in the real world
- Related work has efficiently transferred policies to intermediate robots
- Co-optimize design and control of dexterous robotic hands in simulation and test them in the real world using teleoperation



hand design optimization ⟶ 3D printing ⟶ teleoperation evaluation

Design and Control Co-Optimization in Isaac Gym

- 6 test objects: barbell, pen, board, ring, cross3d, and sphere at 3 scaled sizes (0.75x, 1.0x, 1.25x)
- Nearly 400 robotic hand designs evaluated on picking up and reorienting objects in-hand with added external disturbance forces up to 1 N
- Each object evaluated on 256 randomized goal poses
- Evaluation metric is the average success rate under different external force magnitudes
- Built two optimized hand designs, v6 and v7, where v7 is #1 optimized hand design in sim
- Tested optimized hands against v1-v5, our manually design iterated hands from prior work

Algorithm 1 Design and Policy Co-Optimization

1: **Notation Summary:** $\theta_i \in \mathbb{R}^D, i = 1, 2, \dots, C$: design parameter of i-th candidate robot; $\pi^*_{\theta_i}$: expert policy on i-th candidate robot; $\xi \in \mathbb{R}^+$: evolution step size; $q \in \mathbb{R}$: reward threshold; $\mathcal{D}_e$: the set of robots with expert policy; $\theta_M \in \mathbb{R}^D$: element-wise mutation range. $\theta_U, \theta_L \in \mathbb{R}^D$: element-wise upper and lower bounds of design parameter.

```
2: D_e ← {θ_1, θ_2, ..., θ_C};
3: for i in 1, 2, ..., N do
4:    // sample new robot design candidate
5:    Sample θ_1, θ_2 ~ D_e, mutation noise n ~ U([−θ_M, θ_M]);
6:    θ_new ← random_crossover(θ_1, θ_2) + n;
7:    θ_new ← MAX(MIN(θ_new, θ_U), θ_L); // stay in bound
8:    // find closest source robot to transfer policy from
9:    θ_s ← argmin_{θ∈D_e} ||θ − θ_new||;
10:   θ ← θ_s, π* ← π*_{θ_s};
11:   // transfer the policy by robot interpolation
12:   while ||θ − θ_new|| < ε do
13:      θ ← θ + ξ · (θ_new − θ)/||θ_new − θ||;
14:      train expert policy π*_θ ← argmax_π E[ρ^{π,θ}] by initializing
         policy with π*;
15:      π* ← π*_θ
16:      if E[ρ^{π*_θ,θ}] > q then
17:         D_e ← D_e ∪ {θ}; // only keep elite robot candidates
18: return {(θ, π*_θ) | θ ∈ D_e};
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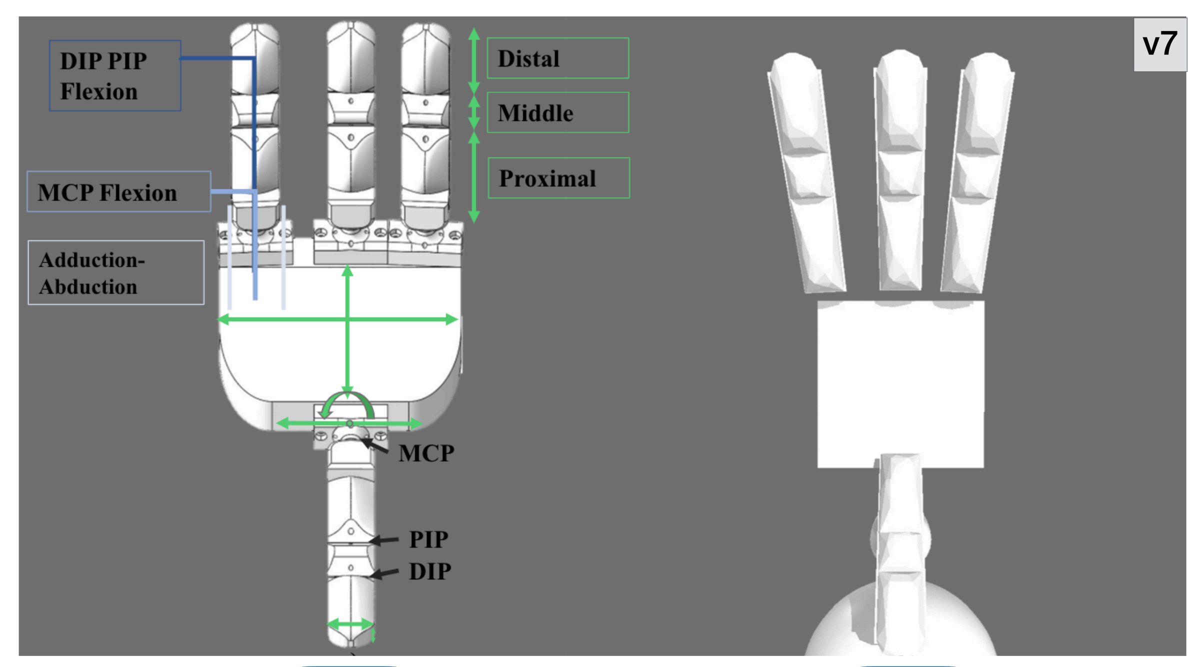
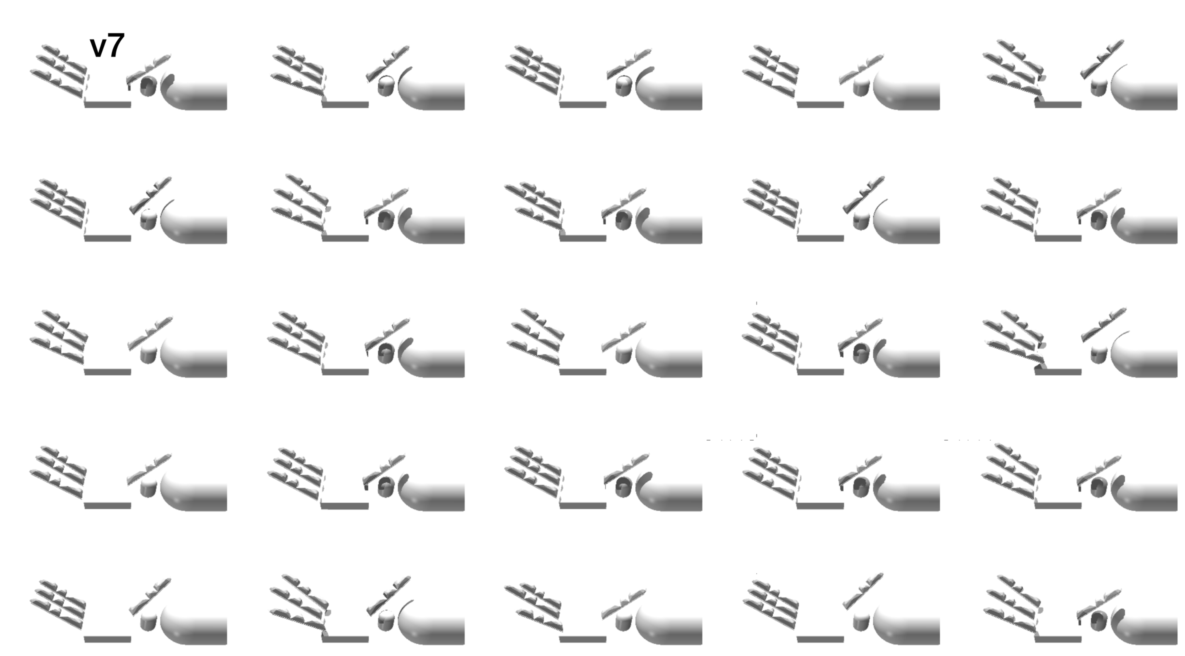
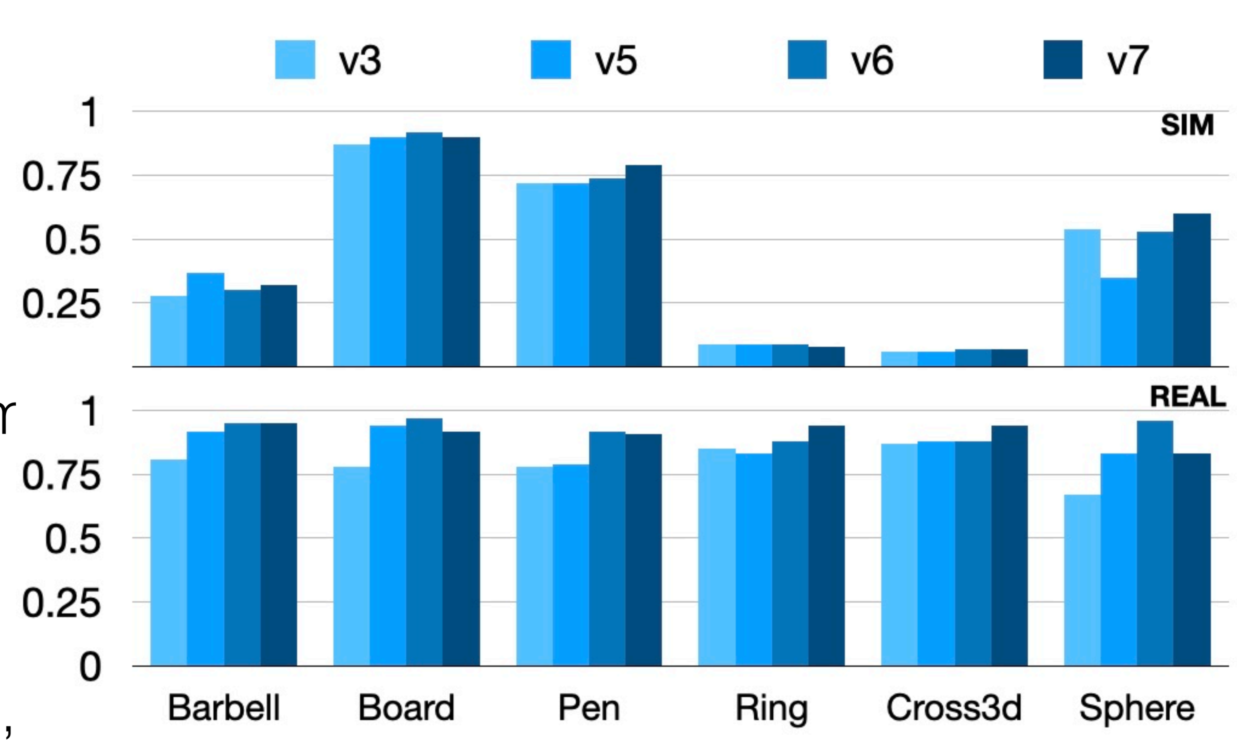


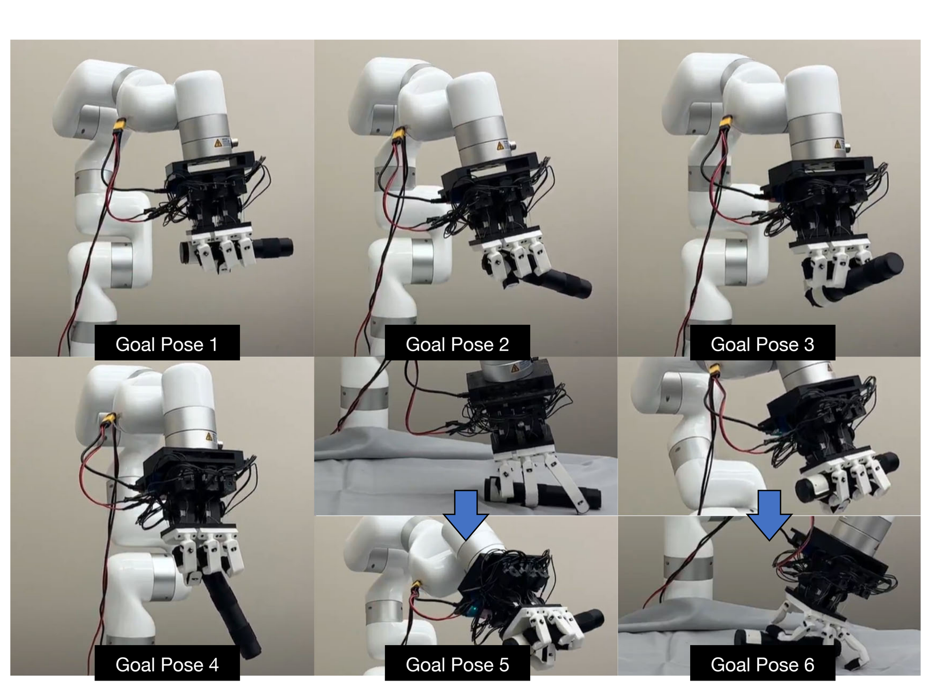
Real Sim



Real World Teleoperation Evaluation Experiments

- Sim to real gap of simulating rigid hands and testing tendon driven soft hands in real world
- Optimized hands outperformed previous hand designs on the same 6 objects in sim and real
- Tested generalization of optimized hand design v7 on a different task set DASH-30, which outperformed previous designs and Allegro Dexterous Hand.
- Tested two different fingertip shapes, rounded and wedge-like fingertip, and found that simulation preferred round fingertips and real world experiments preferred thinner fingertips





Goal Pose 1-5 evaluation metric

1	stable grasp (unmovable by small disturbance force)
0.75	object moves by disturbance force but will not drop
0.5	object can be moved and dropped by disturbance force
0.25	grasp fragile and will not be able to carry object
0	grasping or achieving goal pose failed

Goal Pose 6 evaluation metric

1	graceful placement of object on table within 3cm drop height
0.5	object initially contacts table and falls greater than 3cm
0	object falls from hand greater than 3cm height with no initial contact with table

	Allegro	v1	v2	v3	v4	v5	v7
Tasks with 5/5 success (out of 30)	7	10	14	16	17	19	23
Overall success (out of 150)	60%	70%	82%	83%	75%	87%	95%