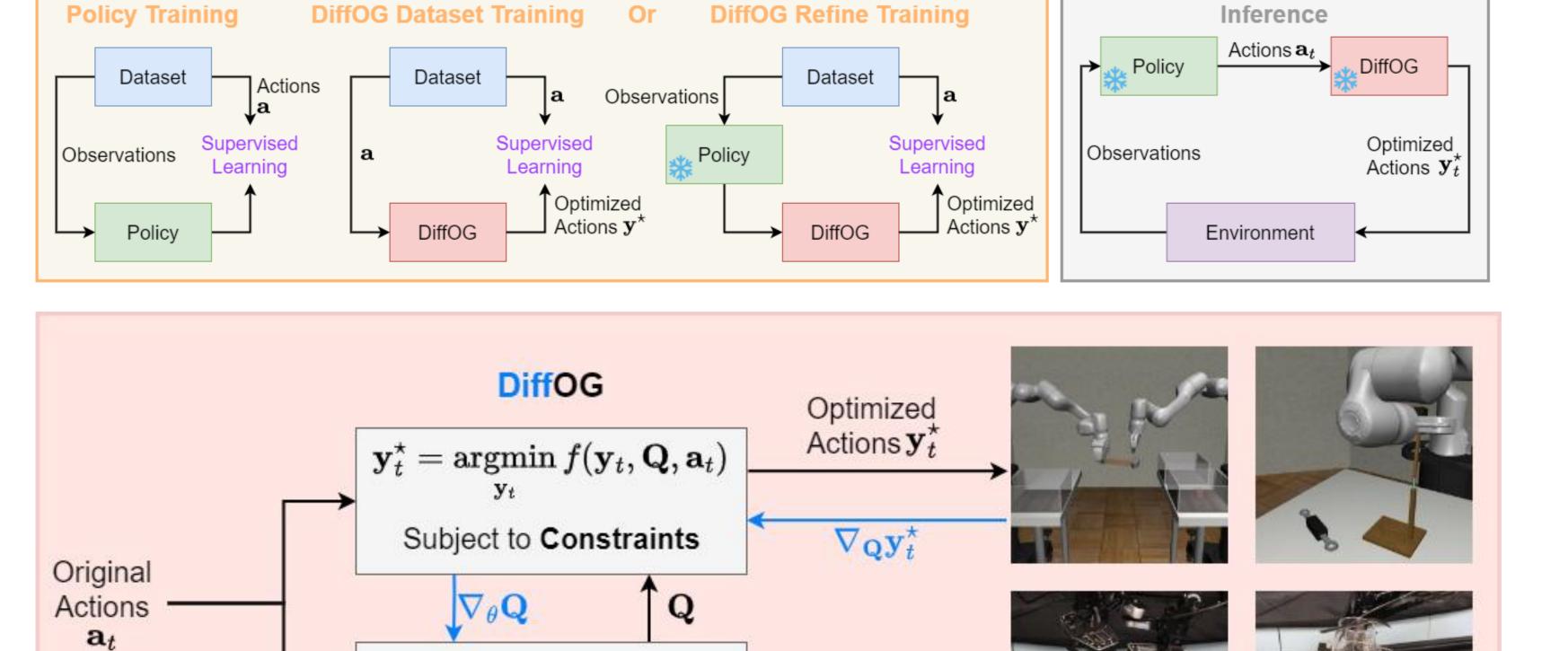
DiffOG: Differentiable Policy Trajectory Optimization with Generalizability

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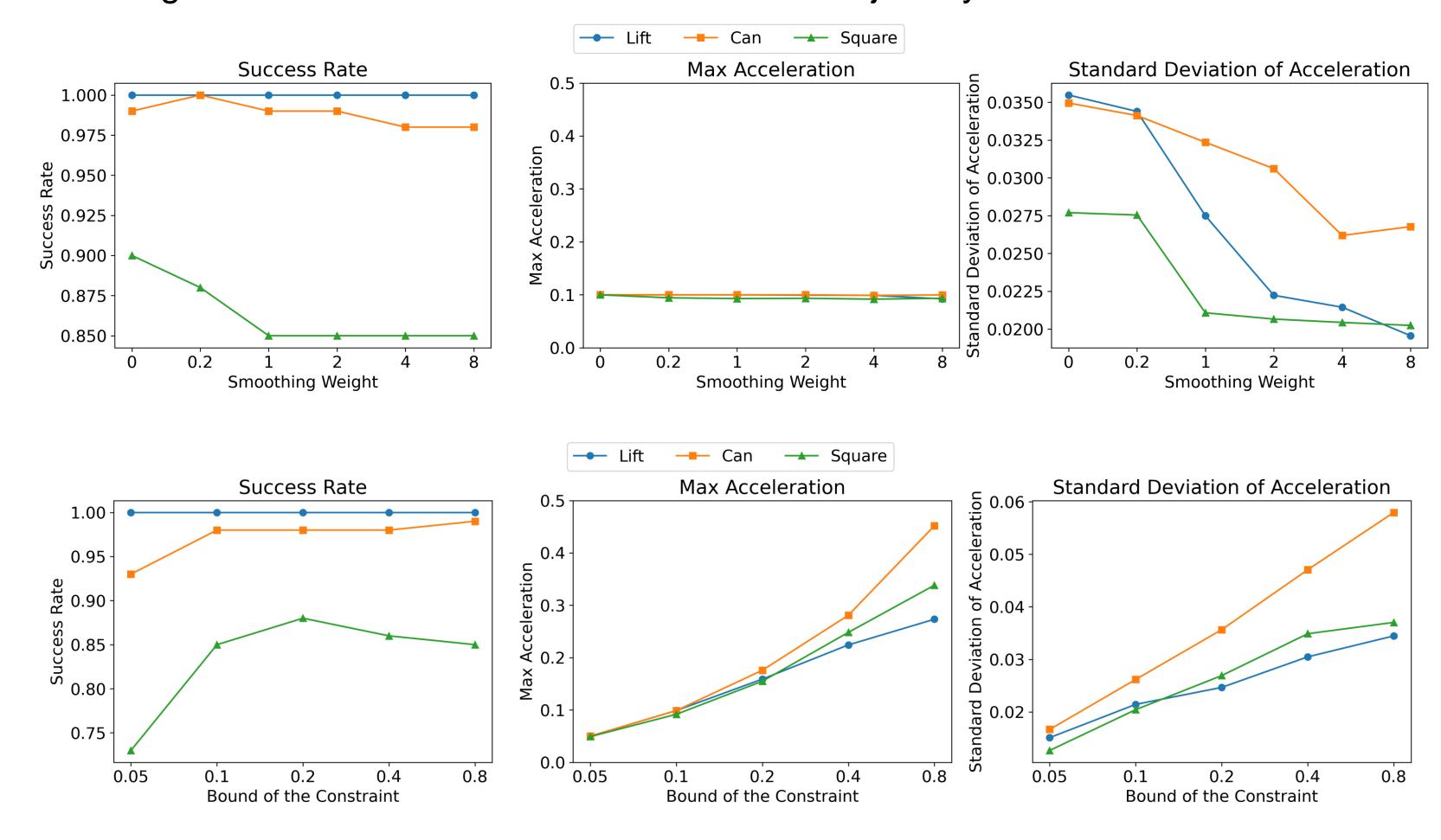
Method

We introduce DiffOG, a learning-based trajectory optimizer that enhances visuomotor policies by integrating a differentiable transformer-based optimization layer. DiffOG produces smoother, constraint-compliant, and more interpretable action trajectories.



Adjustability of Trajectory

Visuomotor policies typically lack mechanisms for directly influencing the properties of the generated actions through parameter adjustment. DiffOG offers interpretability, enabling flexible and direct modulation of action trajectory characteristics.



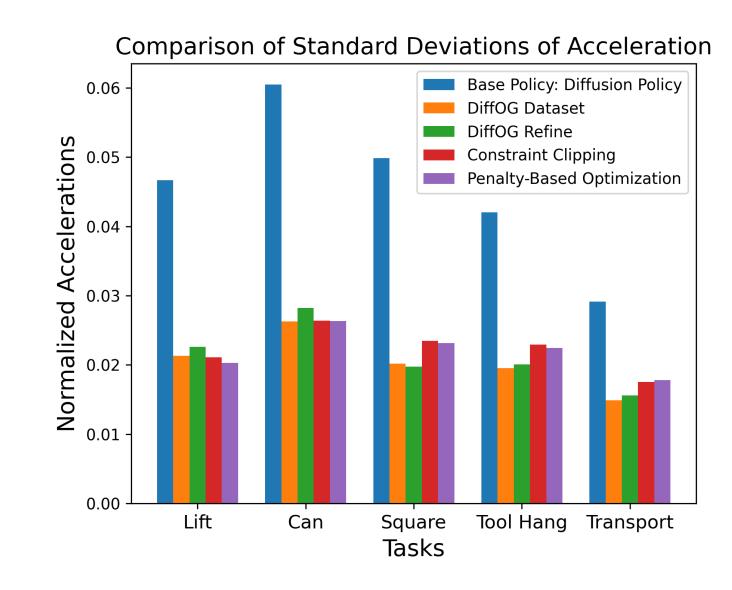
Benchmark Results

Transformer Encoder $E_{\theta}(\mathbf{a}_t)$

Interpretable, Constrained, Generalizable

Benchmark on Visual Imitation learning

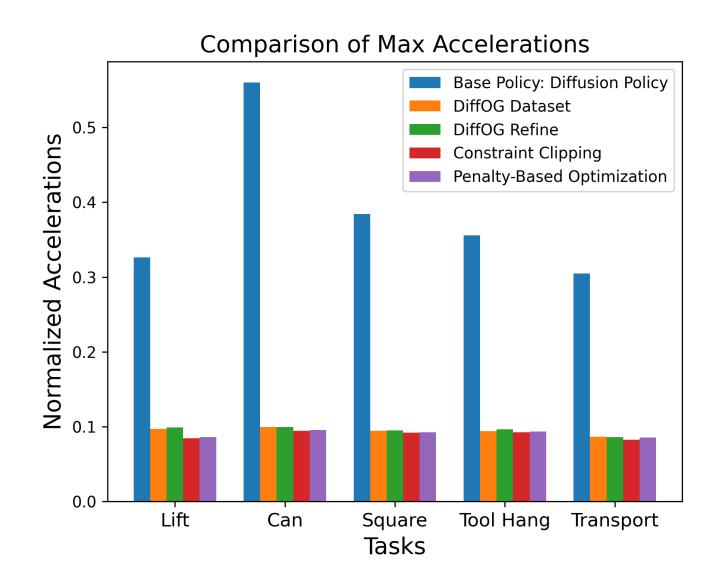
	Lift	Can	Square	Tool Hang	Transport	Push-T
Base Policy: Diffusion Policy	1.00 ± 0.00	0.98 ± 0.01	0.91 ± 0.01	0.83 ± 0.03	0.91 ± 0.01	0.84 ± 0.03
DiffOG Dataset (Ours)	1.00 ± 0.00	0.98 ± 0.01	0.87 ± 0.02	0.82 ± 0.02	0.89 ± 0.02	0.83 ± 0.02
DiffOG Refine (Ours)	1.00 ± 0.00	$\textbf{0.98} \pm \textbf{0.01}$	0.90 ± 0.01	0.81 ± 0.02	0.91 ± 0.03	0.80 ± 0.02
Constraint Clipping	1.00 ± 0.00	0.93 ± 0.04	0.78 ± 0.03	0.59 ± 0.03	0.82 ± 0.02	0.82 ± 0.02
Penalty-Based Optimization	1.00 ± 0.00	0.96 ± 0.02	0.76 ± 0.03	0.79 ± 0.01	0.81 ± 0.02	0.81 ± 0.04



Base Policy: Diffusion Policy

9/15

Arrange Desk



Constraint Clipping

2/15

Penalty-Based Optimization

4/15

Benchmark on Real-world Tasks

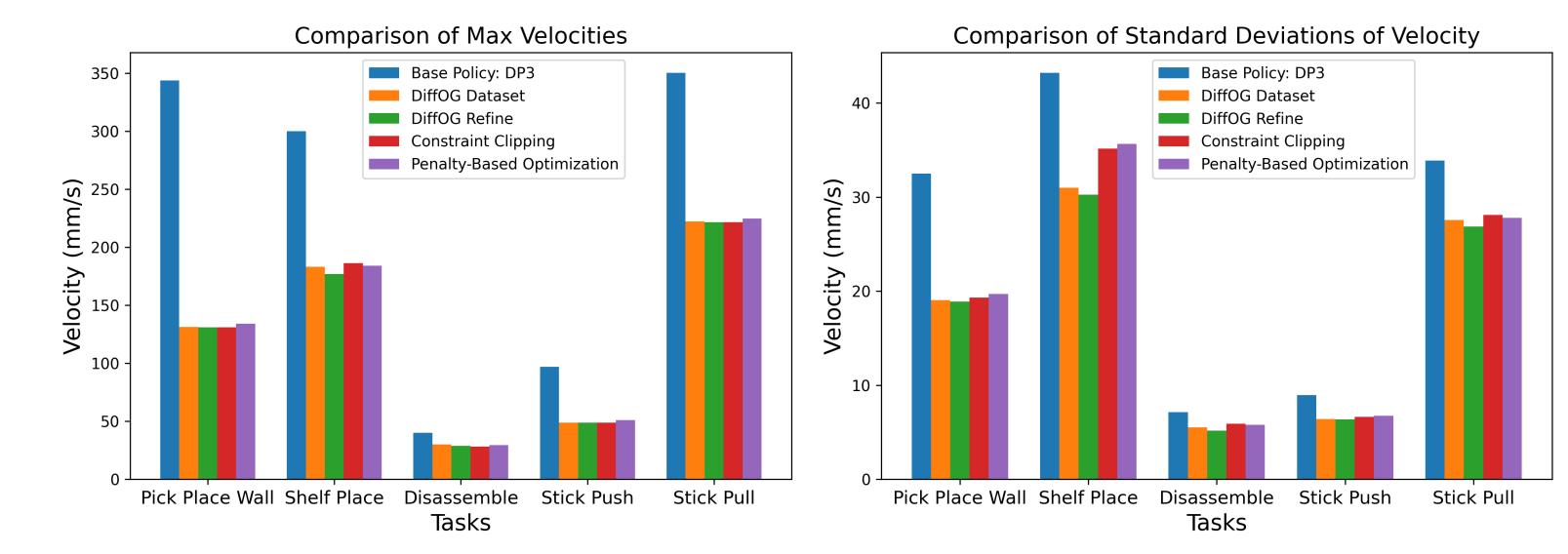
DiffOG Dataset

9/15

	Move the Stack	3/15		10/15 6/15			7/15		
	Base Policy: Diffusion DiffOG Dataset	•	nstraint Clipping nalty-Based Optimizatior	n					
_	Maximum Velociti	es 🛒	Maximum Accelera	ations S	tandard Deviati	ions of Velocit	ty 🤿 Stan	ndard Deviation	ns of Acceleration
Joint Velocity (rad/s) 0 0 1 1 0 2 0 5	9	Joint Acceleration (rad/s²)	9	the Stack (rad/s)	_	Move the Stack	Joint Acceleration (rad/s ² 00 0.0 0.0 00 52 0.0 1	Arrange Desk	Move the Stack
	Tasks Tasks		Tasks		Task	KS		Tas	ks

Benchmark on 3D Imitation learning

	Pick Place Wall	Shelf Place	Disassemble	Stick Push	Stick Pull
Base Policy: DP3	0.98 ± 0.01	0.77 ± 0.04	0.87 ± 0.02	1.00 ± 0.00	0.70 ± 0.02
DiffOG Dataset (Ours)	$\textbf{0.98} \pm \textbf{0.01}$	$\textbf{0.73} \pm \textbf{0.01}$	0.89 ± 0.05	1.00 ± 0.00	0.70 ± 0.03
DiffOG Refine (Ours)	0.98 ± 0.01	0.72 ± 0.02	0.90 ± 0.03	$\textbf{1.00} \pm \textbf{0.00}$	0.68 ± 0.02
Constraint Clipping	$\textbf{0.98} \pm \textbf{0.01}$	0.70 ± 0.01	0.86 ± 0.05	$\textbf{1.00} \pm \textbf{0.00}$	0.69 ± 0.02
Penalty-Based Optimization	$\textbf{0.98} \pm \textbf{0.01}$	0.67 ± 0.03	0.86 ± 0.06	$\textbf{1.00} \pm \textbf{0.00}$	0.70 ± 0.03



We benchmarked DiffOG and several baselines across 13 tasks. DiffOG consistently improves action trajectories, making them smoother and more constrained, while preserving alignment with the original demonstration distribution, thereby preventing policy performance degradation.

Check out the project website!

