SafeDiffuser Safe Planning with Diffusion Probabilistic Models

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Previous Paper Presentation Review

Paper Name: OpenVLA: An Open-Source Vision-Language-Action Model

Motivation

- Existing VLA models are large (~55B parameters), closed-source, and lack fine-tuning studies
- OpenVLA is 7B parameters, fully open-source, and supports efficient fine-tuning and quantization

• Key Results

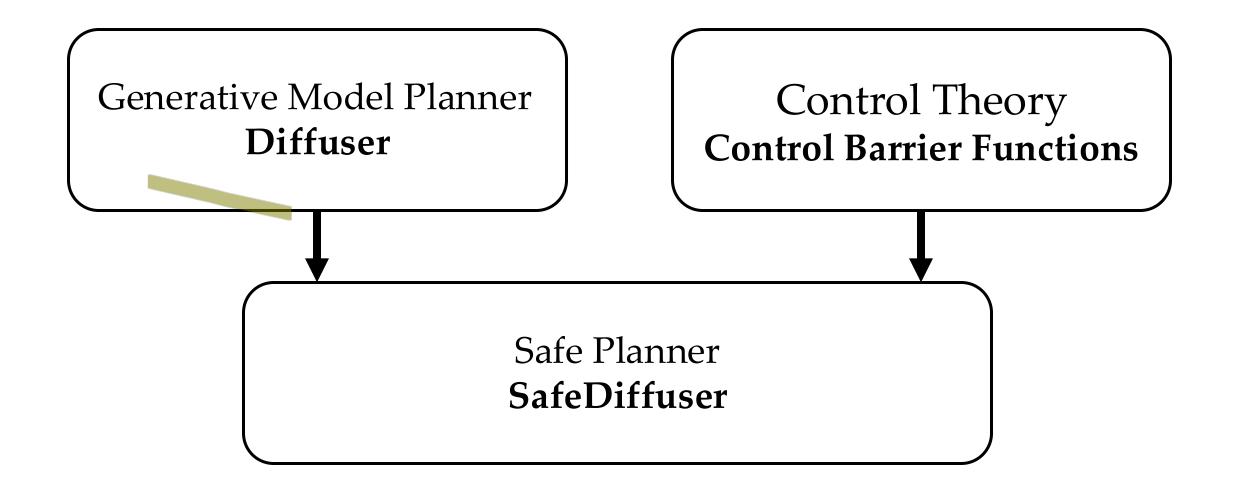
- **Generalization**: Outperforms RT-2-X (55B) by 16.5% on 29 tasks with fewer parameters
- **Fine-tuning**: Fast adaptation to new setups with just 10–150 demos
- Quantization: Reduce memory with minimal performance loss



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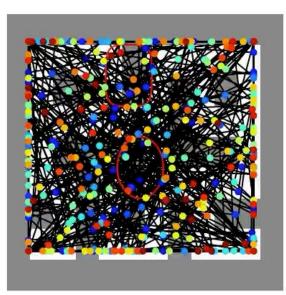
- 1. Overview of SafeDiffuser
- 2. Generative Model Planner: Diffuser
- 3. Control Barrier Functions
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- 6. Quiz



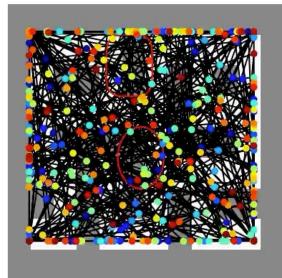




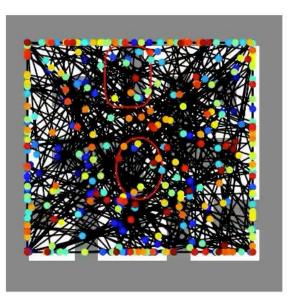
Overview of SafeDiffuser: Comparison



Diffuser



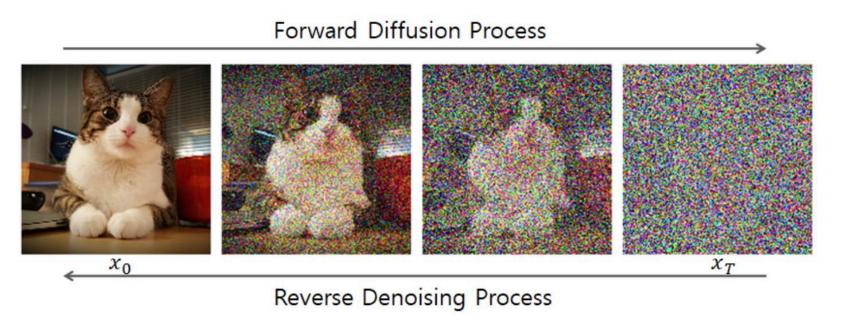
Classifier Guidance (Potential-based)



SafeDiffuser



Generative Model Planner: Diffuser



Forward process (adding noise):

$$q(x_t \mid x_{t-1}) = \mathcal{N}(x_t; \sqrt{1-eta_t} x_{t-1}, eta_t I)$$

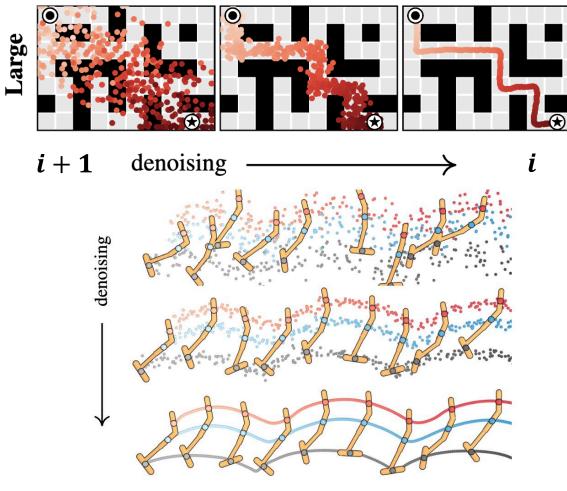
Reverse process (denoising):

$$p_{ heta}(x_{t-1} \mid x_t) = \mathcal{N}(x_{t-1}; \mu_{ heta}(x_t, t), \Sigma_{ heta}(x_t, t))$$



Generative Model Planner: Diffuser

• Diffuser^[1]



$$\dot{x}^{i} = \lim_{\Delta x \to 0} \frac{x^{i} - x^{i+1}}{\Delta t}$$

[Diffuser Dynamics]

* *i* is denosing step.



Preliminaries for Control Barrier Functions

• Def. Control affine system:

 $\dot{x} = f(x) + g(x)u$

where *x* is a state, *u* is a control input, and *f* and *g* are locally Lipschitz continuous function that describe the system dynamics.

• Def. Set Invariance:

A set $C \subset \mathbb{R}^n$ is **invariant** if:

 $x(0) \in C \to x(t) \in C, \forall t \ge 0$

The system **remain inside** the set for all future time.

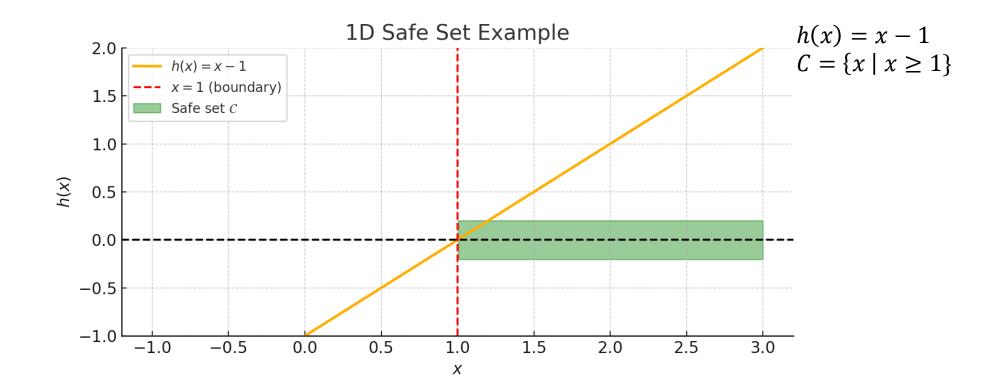


Control Barrier Functions

• Def. Safe Set:

Define a continuously differentiable function $h: \mathbb{R}^n \to \mathbb{R}$

 $C = \{x \in \mathbb{R}^n | h(x) \ge 0\}$





Control Barrier Functions

- The idea is to make sure that, **over time**, h(x) **doesn't drop below zero**.
- This means **the system should stay within the safe set**. To enforce this, this inequality should be satisfied:

$$\dot{h}(x) = \nabla_x h \cdot \dot{x} \ge -\alpha h(x)$$

1D Safe Set Example (x) = x - 1**Example** (the system is $\dot{x} = u$, and choose $\alpha = 1$) = 1 (boundary) 1.5 If the state is in unsafe set $C_{unsafe} = \{x | h(x) < 0\}$: Safe set C $\dot{h}(x) = 1 \cdot u \ge -h(x)$ 1.0 h(x) = x - 1(X)ل 0.5 If the state is at the boundary $\partial C = \{x | h(x) = 0\}$: $C = \{x \mid x \ge 1\}$ $\dot{h}(x) = 1 \cdot u \ge 0$ 0.0 -0.5If the state is in safe set $C' = \{x | h(x) > 0\}$: $\dot{h}(x) = 1 \cdot u \ge -h(x)$ -1.0-1.0-0.51.5 2.0 2.5 3.0 0.0 0.5 1.0 Х



where $\alpha > 0$.

Control Barrier Functions

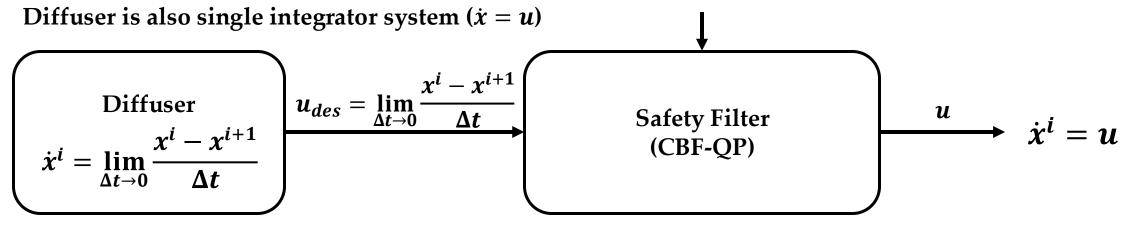
• Goal: Design a control input *u* that:

- Keeps the system **safe** using a Control Barrier Function.
- Follows a desired control input u_{des} as closely as possible.

Optimization: CBF-QP

$$\min_{u} \|u - u_{des}\|^2$$

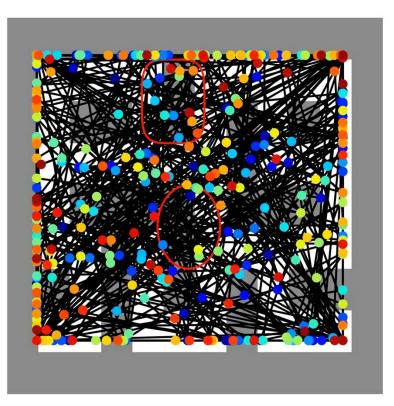
s.t. $\nabla_x h(x) \cdot u + \alpha h(x) \ge 0$





SafeDiffuser: Local Traps

• Local traps occur when trajectories are safe but unable to reach the goal.





SafeDiffuser: Local Traps

• They add relaxation term in the optimization problem, to allow the planner violates the safety constraint in the early phase of planning.

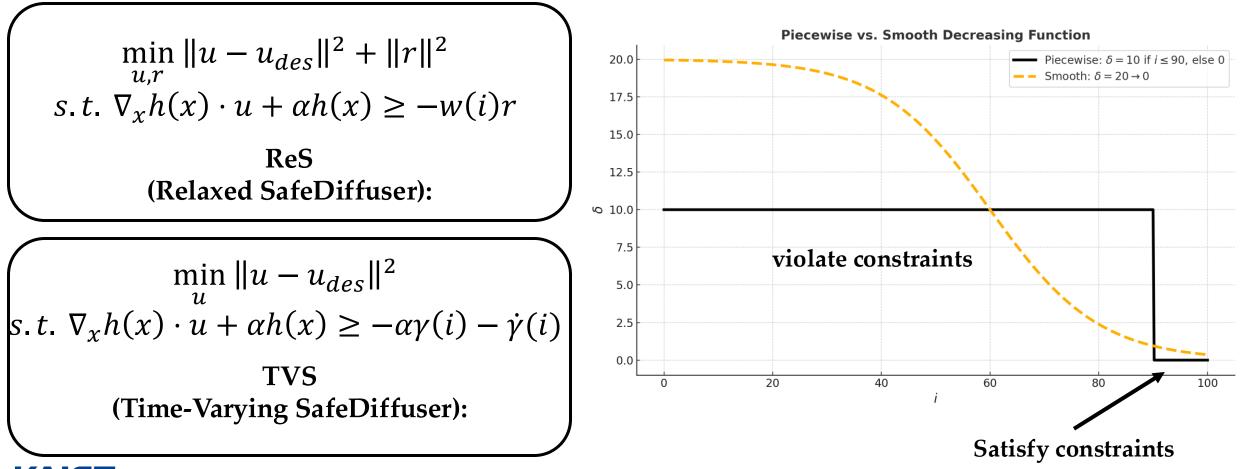
Constraint:
$$\nabla_x h(x) \cdot u + \alpha h(x) \ge 0$$

Constraint: $\nabla_x h(x) \cdot u + \alpha h(x) \ge -\delta(i)$
where $\delta(i) \ge 0$



SafeDiffuser: Local Traps

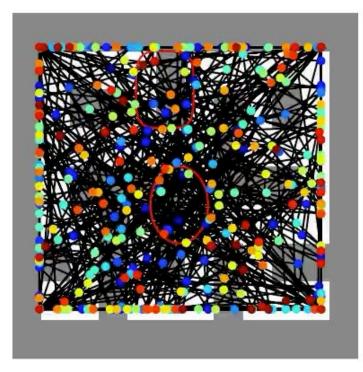
• Relaxed and time-varying SafeDiffuser help the planner escape local traps.

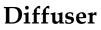


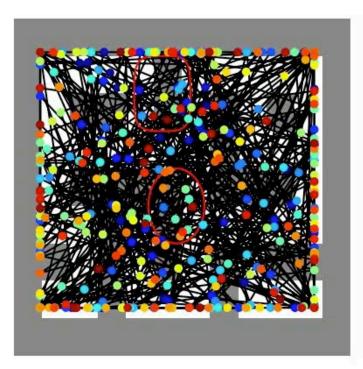
KAIST

Experiment Results: Maze2D

- Diffuser cannot generate safe path.
- Basic SafeDiffuser can avoid safety constraints, but local traps occur.





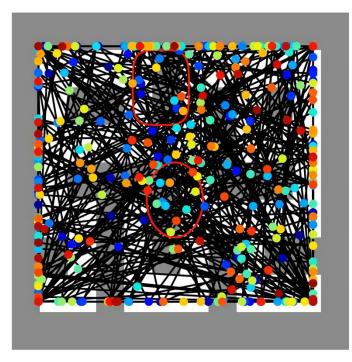


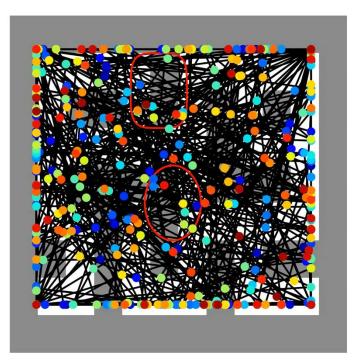
SafeDiffuser: RoS (Basic version - Local trap occurs)



Experiment Results: Maze2D

• Relaxed SafeDiffuser and Time-varying SafeDiffuser can resolve local trap problems.





ReS





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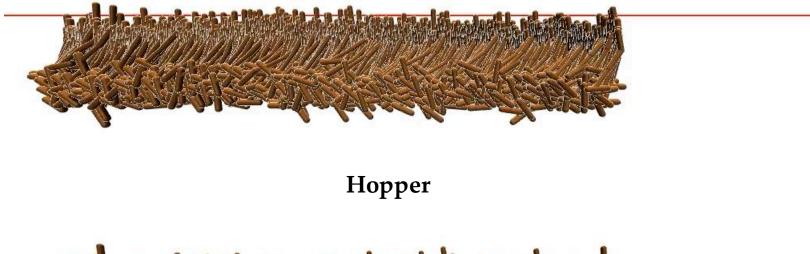


Метнор	$\begin{array}{c} \text{S-SPEC}(\uparrow \\ \& \geq 0) \end{array}$	$\begin{array}{c} \text{C-SPEC}(\uparrow \\ \& \geq 0) \end{array}$	Score (\uparrow)	TIME	NLL	Trap rate 1 (↓)	Trap rate 2 (↓)
DIFFUSER JANNER ET AL. (2022)	-0.983	-0.894	$1.598{\pm}0.174$	0.006	$4.501 {\pm} 0.475$		
TRUNC. BROCKMAN ET AL. (2016)	$-1.192e^{-7}$	-0.759	1.577 ± 0.242	0.024	4.494±0.465		
CG DHARIWAL & NICHOL (2021) CG- ε DHARIWAL & NICHOL (2021)	-0.789 -0.853	-0.979 -0.995	$0.384{\pm}0.020$ $0.383{\pm}0.017$	$\begin{array}{c} 0.053 \\ 0.061 \end{array}$	6.962 ± 0.350 6.975 ± 0.343		
INVODE XIAO ET AL. (2023B)	14.000	$1.657e^{-5}$	-0.025 ± 0.000		-		
RoS-DIFFUSER (OURS)	0.010	0.010	1.519 ± 0.330	0.106	4.584 ± 0.646	100%	100%
RoS-DIFFUSER-CF (OURS)	0.010	0.010	$1.536 {\pm} 0.306$	0.007	4.481 ± 0.298	100%	100%
ReS- DIFFUSER (OURS)	0.010	0.010	$1.557 {\pm} 0.289$	0.107	$4.434{\pm}0.561$	46%	17%
ReS-DIFFUSER-CF (OURS)	0.010	0.010	$1.544{\pm}0.280$	0.007	4.619 ± 0.652	36%	16%
TVS-DIFFUSER (OURS)	0.003	0.003	$1.543 {\pm} 0.303$	0.107	4.533 ± 0.494	47%	21%
TVS-DIFFUSER-CF (OURS)	0.003	0.003	$1.588{\pm}0.231$	0.007	4.462 ± 0.431	48%	18%
RES-DIFFUSER-L10 (OURS)	0.010	0.010	$1.527{\pm}0.291$	0.011	4.571±0.693	39%	8%

[Results of SafeDiffuser]



Experiment Results: Hopper





Safe Hopper



[Inference Result of SafeDiffuser^[2] in Mujoco]

Experiment Results: Walker2D



Walker2D



Safe Walker2D



[Inference Result of SafeDiffuser^[2] in Mujoco]

Experiment Results: Hopper and Walker2D

Experime	NT METHOD	$S-SPEC(\uparrow \& \ge 0)$	$ ext{C-SPEC}(\uparrow \& \geq 0)$	Score (\uparrow)	TIME
WALKER2	DIFFUSER JANNER ET AL. (2022)	-9.375	-4.891	0.346 ± 0.106	0.037
	TRUNC. BROCKMAN ET AL. (2016)	0.0	×	0.286 ± 0.180	0.105
	D CG DHARIWAL & NICHOL (2021)	-0.575	-0.326	0.208 ± 0.140	0.053
	ROS-DIFFUSER (OURS)	0.000	0.010	0.312 ± 0.165	0.183
	ROS-DIFFUSER-CF (OURS)	0.000	0.010	0.321 ± 0.119	0.040
Hopper	DIFFUSER JANNER ET AL. (2022)	-2.180	-1.862	0.455 ± 0.038	0.038
	TRUNC. BROCKMAN ET AL. (2016)	0.0	×	0.436 ± 0.067	0.046
	CGDHARIWAL & NICHOL (2021)	-0.894	-0.524	0.478 ± 0.038	0.047
	ROS-DIFFUSER (OURS)	0.000	0.010	0.430 ± 0.040	0.170
	ROS-DIFFUSER-CF (OURS)	0.000	0.010	0.464 ± 0.028	0.040

[Results of SafeDiffuser]



References

- 1. Janner, Y. Du, J. Tenenbaum, and S. Levine. Planning with diffusion for flexible behavior synthesis. In International Conference on Machine Learning, pages 9902–9915. PMLR, 2022.
- 2. Wei, W. Tsun-Hsuan, G. Chuang, H. Ramin, L. Mathias, and R. Daniela. Safediffuser: Safe planning with diffusion probabilistic models. IEEE, 2025.
- 3. Lipman, R. T. Chen, H. Ben-Hamu, M. Nickel, and M. Le. Flow matching for generative modeling. arXiv preprint arXiv:2210.02747, 2022.
- 4. P. Bhat and D. S. Bernstein. Finite-time stability of continuous autonomous systems. SIAM Journal on Control and optimization, 38(3):751–766, 2000.



Thank you

