2025中国自动化大会

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LLM-DiSC: LLM-enabled Distributed and Safe Coordination of Multi-Robot Systems using Control Barrier Functions

Qingqing Yang[1], Guoxiang Zhao[1,*], Xiaoqiang Ren[1], Xiaofan Wang[2]

[1]Shanghai University [2]Shanghai Institute of Technology

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Abstract

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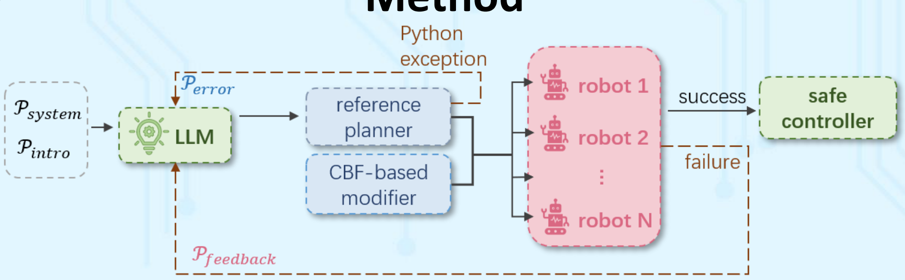
Method



Reference planner:

LLM generates the reference planner in Python, with automatic semantic correction through error feedback to the LLM.

CBF-based modifier:

Unsafe reference signals are corrected by the CBF-based modifier to ensure safety.

Define the safe state set S using a continuously differentiable function $h(\boldsymbol{x})$, $S = \{\boldsymbol{x} \in \mathbb{R}^n : h(\boldsymbol{x}) \geq 0\}$. Given the system's dynamics and the safe state set, h is a CBF if there exists a class $\mathcal{K}$ function α, such that $\forall x_i \in S$:

$$\sup_{\boldsymbol{u}_i \in U} \left[L_f h_i(\boldsymbol{x}_i) + L_g h_i(\boldsymbol{x}_i) \boldsymbol{u}_i + \alpha\left(h_i(\boldsymbol{x}_i)\right) \right] \geq 0.$$

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$$L_f h_{i,k}^o(\boldsymbol{x}_i^t) + L_g h_{i,k}^o(\boldsymbol{x}_i^t) \boldsymbol{u}_i^t + \alpha\left(h_{i,k}^o(\boldsymbol{x}_i^t)\right) \geq 0, \forall k \in \mathcal{O}$$

Planner optimization:

Planner optimization iteratively refines the LLM-generated planner using simulation feedback when robots fail to reach their targets.

Experiments

Experiments were conducted in environments with polygonal obstacles and multiple robots, where the reference planner was generated using OpenAI o1-preview. Performance of the LLM-DiSC was compared against a conventional distributed planner combining A*, Pure Pursuit, and a CBF coordinator.

■ Safety and Scalability

TABLE I: Different robot models and group sizes

Model	Size	Pass@k			Iterations
		k=1	k=5	k=10	
Single Integrator	5	100%	100%	100%	1
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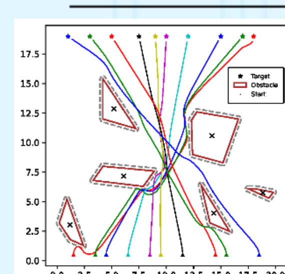

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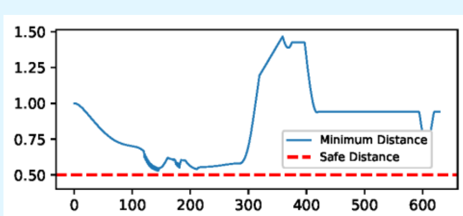

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TABLE II: Near-optimality evaluation

Methods		LLM-DiSC	Conventional
Computations	Offline	**261.98s**	676.03s
	Online	7.85s	7.03s
Execution	Success	**Yes**	No
	Traveling Time	41.10s	40.5s
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LLM Model		o1-preview	GPT-4o	DeepSeek-r1
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Conclusions

By integrating LLM reasoning with CBF safety guarantees, our approach enables collision-free navigation and efficient task execution without relying on extensive training data or expert-designed models. The experimental results validate the superior performance of LLM-DiSC across different dynamic models and group sizes. This accessible solution significantly lowers technical barriers and computational demands for multi-robot motion planning.

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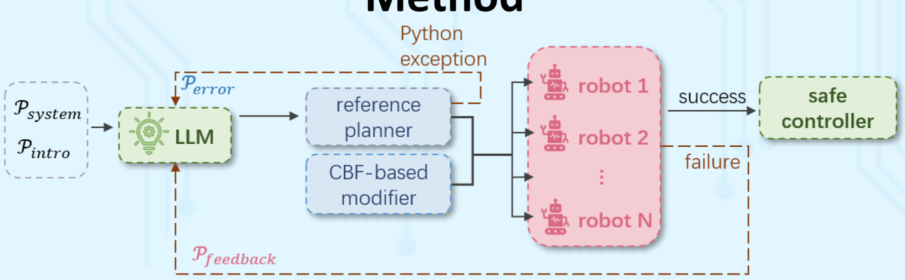

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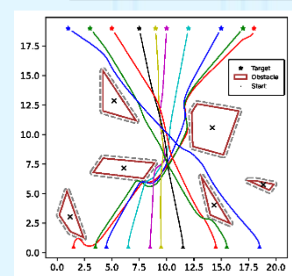

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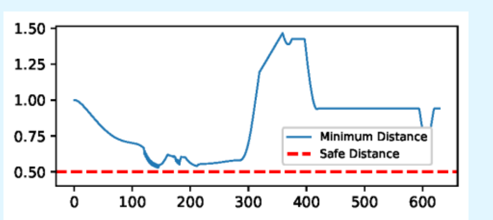

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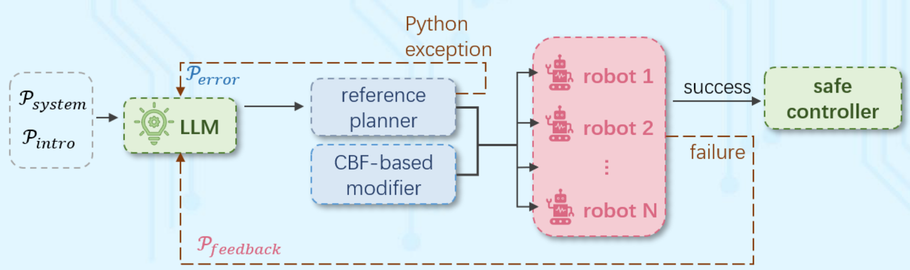

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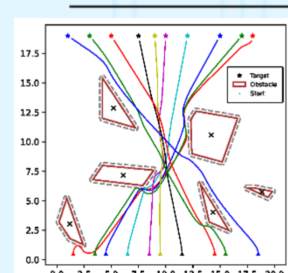

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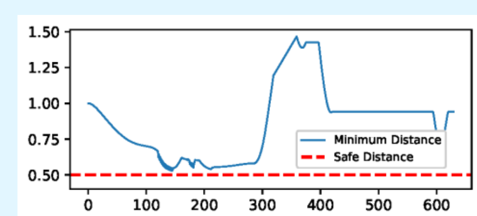

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