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Multi-agent reinforcement learning behavioral control for nonlinear second-order systems

Key words: Reinforcement learning; Behavioral control; Second-order systems; Mission supervisor

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Motivation

1. Reinforcement learning mission supervisor can be used for only single-agent applications, since it is modeled through Markov decision processes. As a result, any cooperative behavior cannot be implemented, which greatly limits the swarm intelligence.
2. Although reinforcement learning behavioral control guarantees the convergence of position error signals, it is not enough for second-order systems. Generally, second-order systems require both position and velocity error signals to converge.
3. Reinforcement learning controller (RLC) does not have input saturation constraints, and thus the control input may exceed the physical limit of the actuator. Particularly, if behavior priorities are switched, the problem of excessive control input may be aggravated.

Main idea

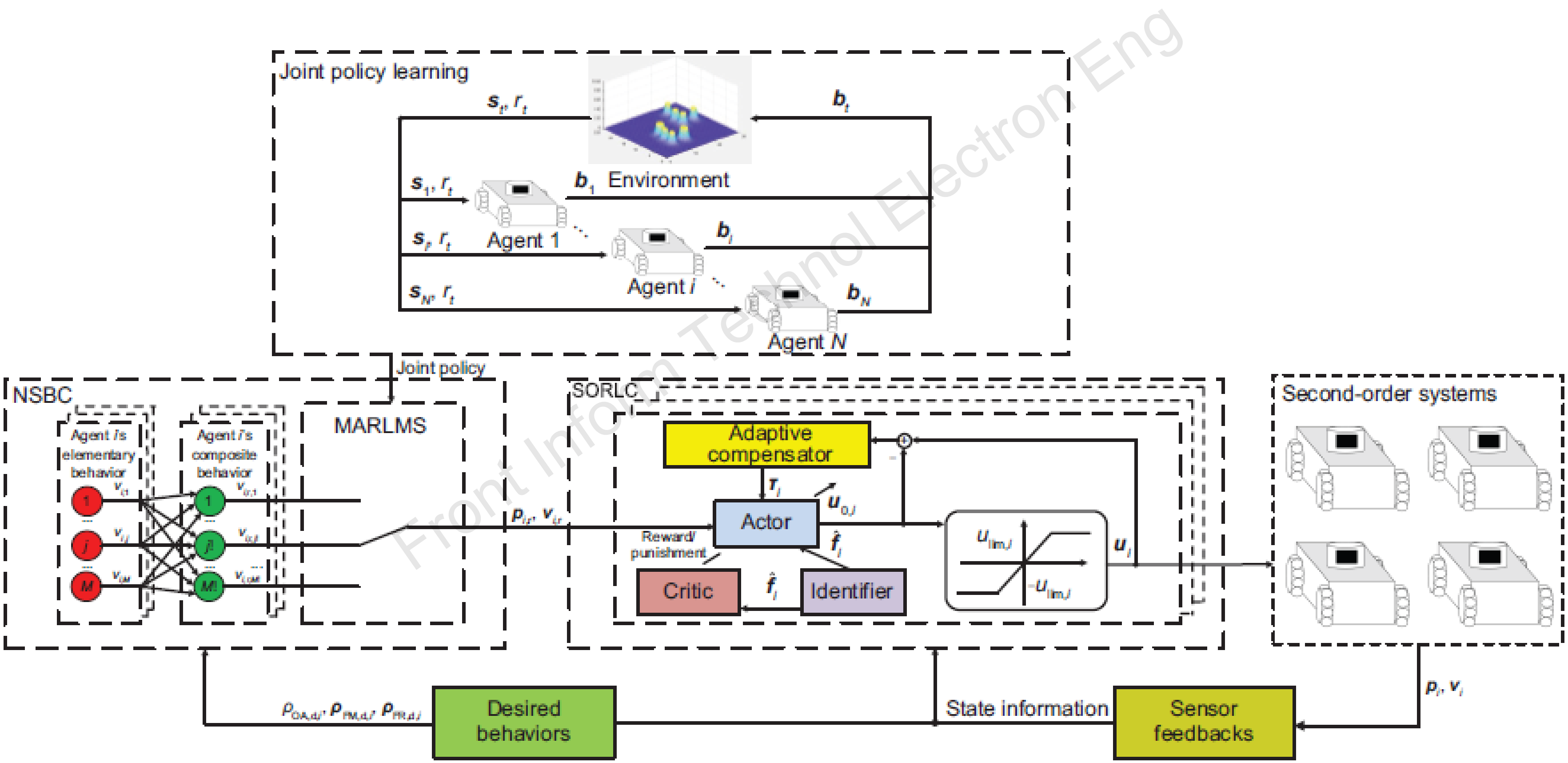
1. A multi-agent reinforcement learning mission supervisor (MARLMS) is proposed to learn the optimal joint behavior priority policy. Through learning a joint behavior priority policy, the switching frequency of behavioral control is reduced significantly.

2. A group of second-order reinforcement learning controllers (SORLCs) with the identifier–actor–critic structure are developed to learn the optimal control policies. As a result, the control cost of behavioral control is reduced significantly.

3. A group of adaptive compensators are designed to maintain the optimal control performance and counteract the saturation effect in real time.

Method

Multi-agent reinforcement learning behavioral control



Major results

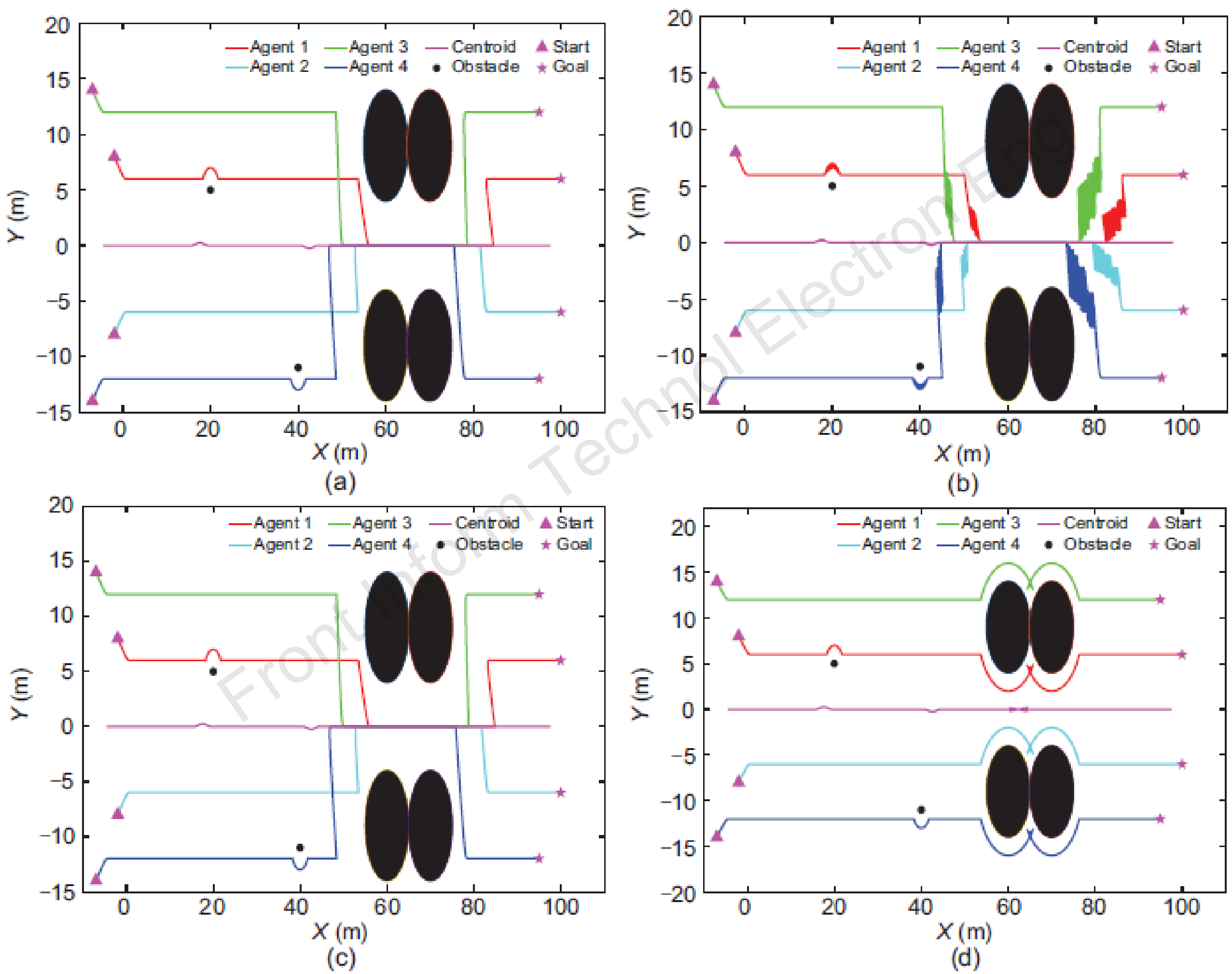


Fig. 2 Trajectories of agents with different mission supervisors: (a) MARLMS; (b) FSAMS; (c) MPCMS; (d) RLMS

Major results (Cont'd)

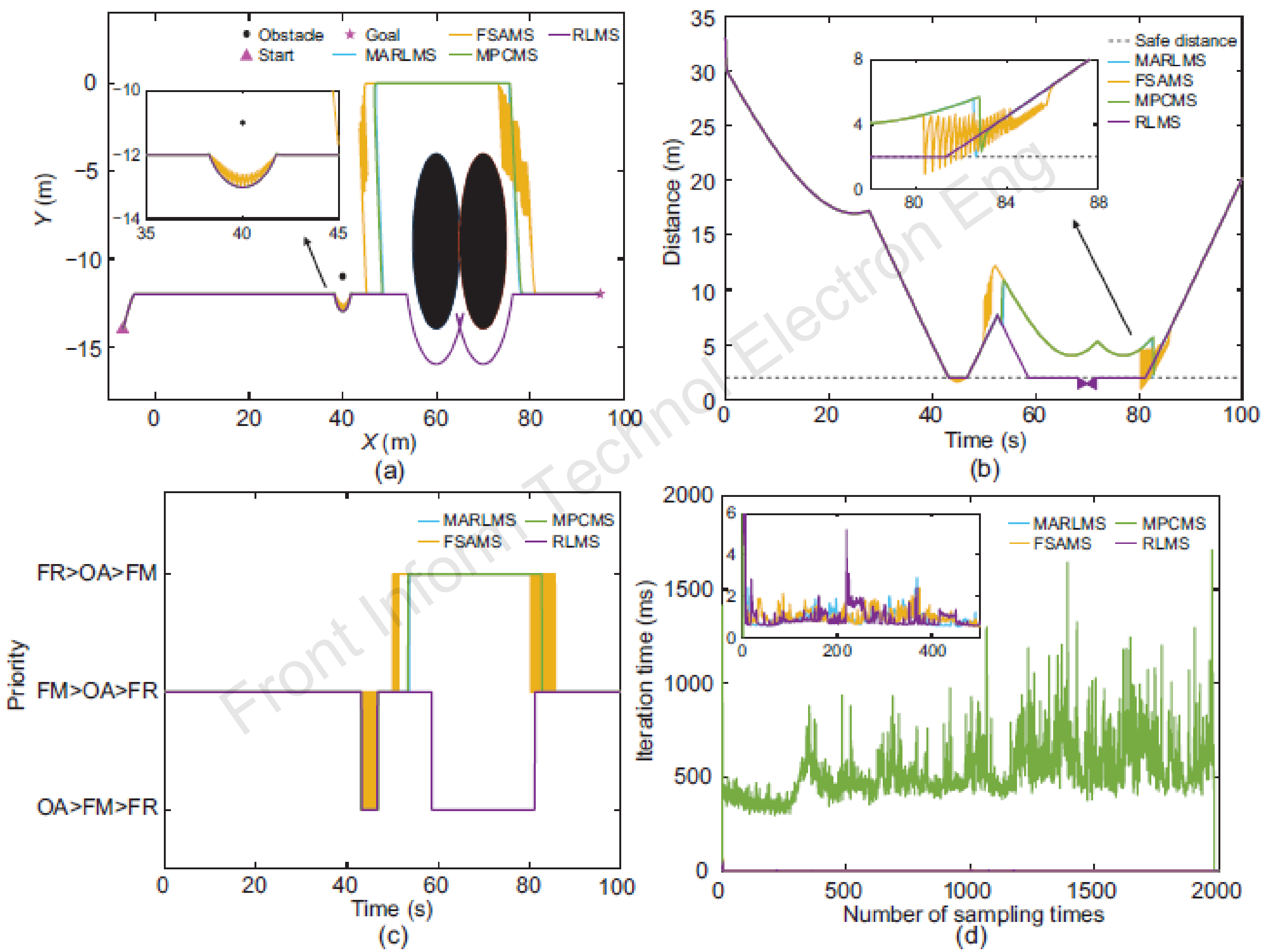


Fig. 3 Results of the 4th agent with different mission supervisors: (a) trajectories; (b) distances between the agent and obstacles; (c) behavior priorities; (d) iteration time

Major results (Cont'd)

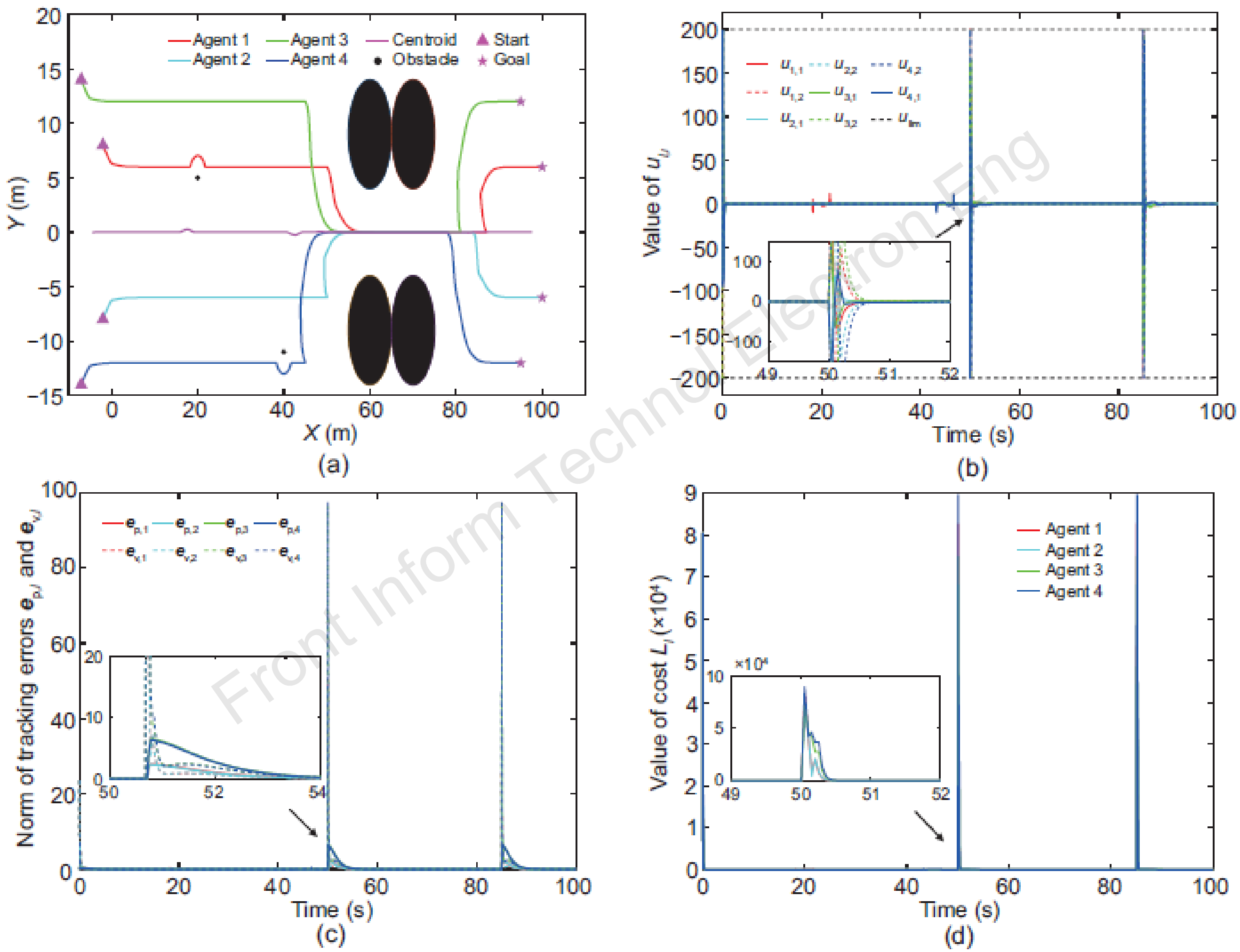


Fig. 6 Control performance of the proposed SORLC: (a) trajectories; (b) control inputs; (c) tracking errors; (d) costs

Major results (Cont'd)

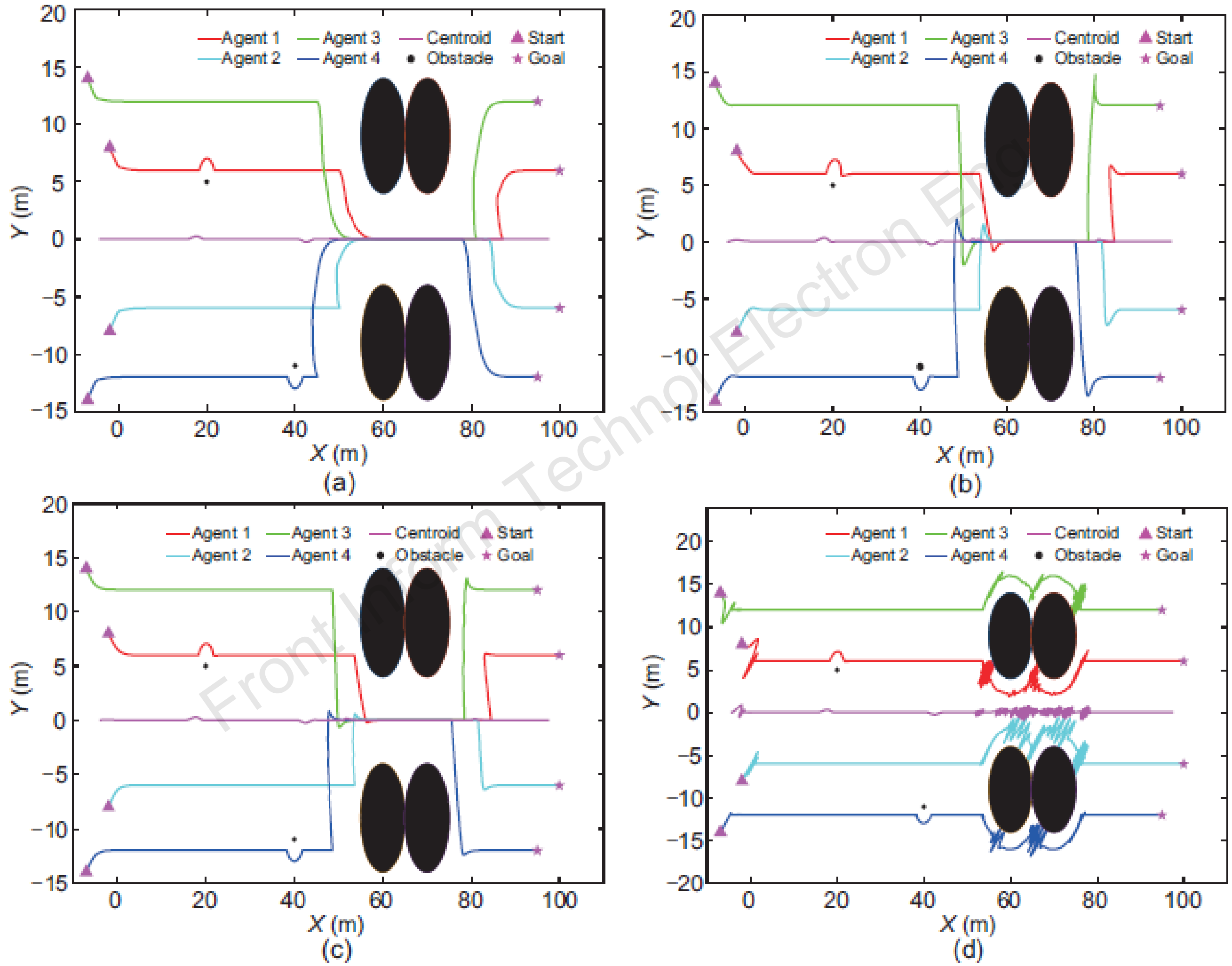


Fig. 8 Trajectories of agents with different NSBC methods: (a) MARLBC; (b) finite-time NSBC; (c) fixed-time NSBC; (d) RLBC

Major results (Cont'd)

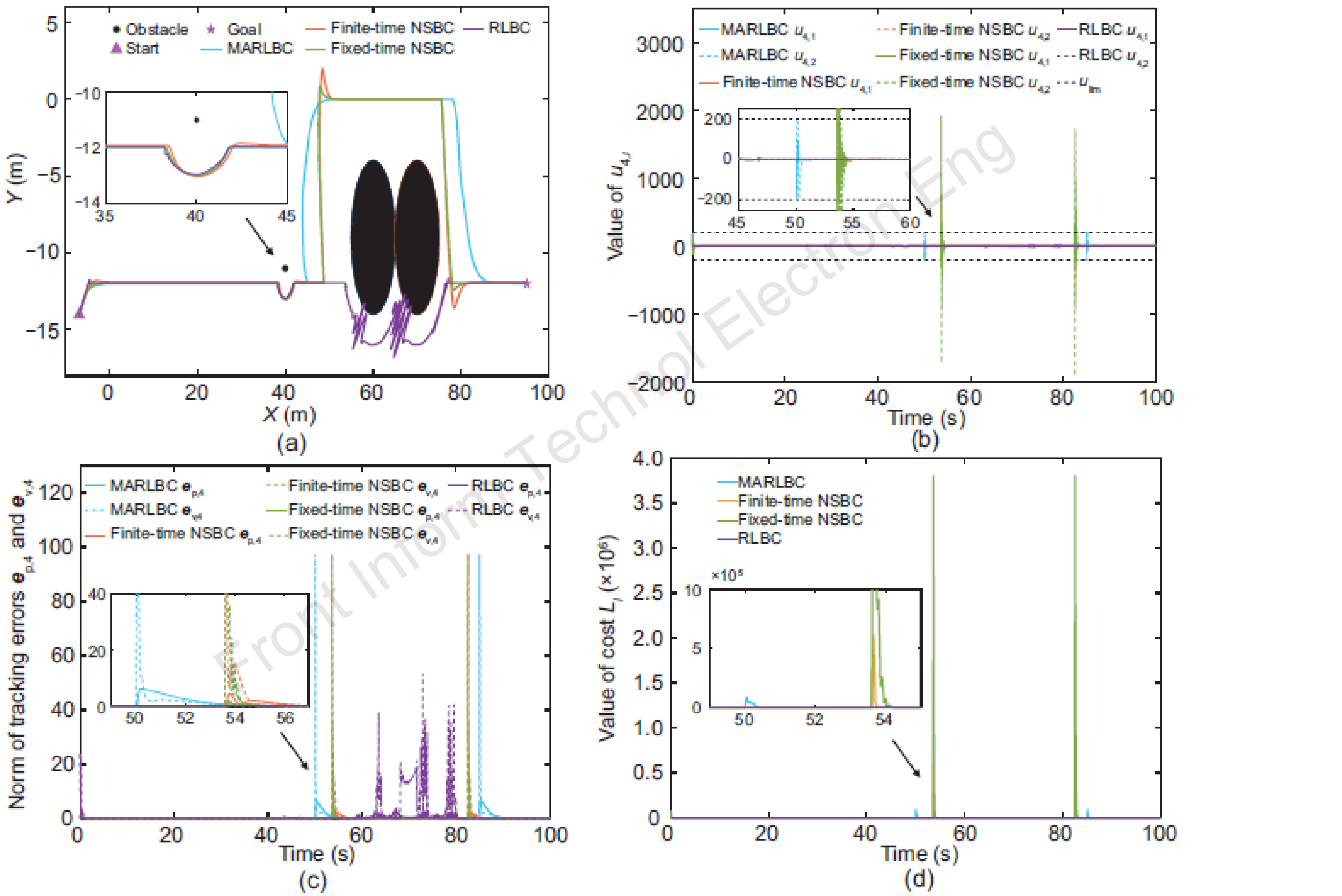


Fig. 9 Control performances of the 4th agent with different NSBC methods: (a) trajectories; (b) control inputs; (c) tracking errors; (d) costs

Major results (Cont'd)

Table 5 Maximum and total control cost values of different NSBC frameworks

Index	Maximum control cost value ($\times 10^4$)			Index	Total control cost value ($\times 10^4$)		
	MARLBC	Finite-time	Fixed-time		MARLBC	Finite-time	Fixed-time
Max-a1	9	17	103	Tot-a1	382	435	518
Max-a2	9	17	115	Tot-a2	364	404	790
Max-a3	9	60	372	Tot-a3	570	1384	1813
Max-a4	9	60	372	Tot-a4	609	1391	1868

Table 6 Maximum and total control input values of different NSBC frameworks

Index	Maximum control input value			Index	Total control input value		
	MARLBC	Finite-time	Fixed-time		MARLBC	Finite-time	Fixed-time
Max-a1	200	384	960	Tot-a1	2210	2756	9127
Max-a2	200	384	1061	Tot-a2	2341	2883	13 370
Max-a3	200	768	1920	Tot-a3	4118	5274	16 112
Max-a4	200	768	1920	Tot-a4	4285	5466	16 646

Conclusions

1. Multi-agent reinforcement learning behavioral control has smaller control input and cost values than the existing null-space-based behavioral control methods of second-order systems when the behavior priorities are switched.

2. Compared with the traditional reinforcement learning behavioral control, the proposed multi-agent reinforcement learning behavioral control allows the implementation of cooperative behavior and ensures the convergence of velocity signals.

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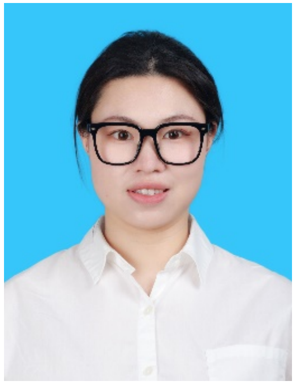

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