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Efficient learning of robust multigait quadruped locomotion for minimizing the cost of transport

Key words: Reinforcement learning; Locomotion; Motor learning; Energy efficiency

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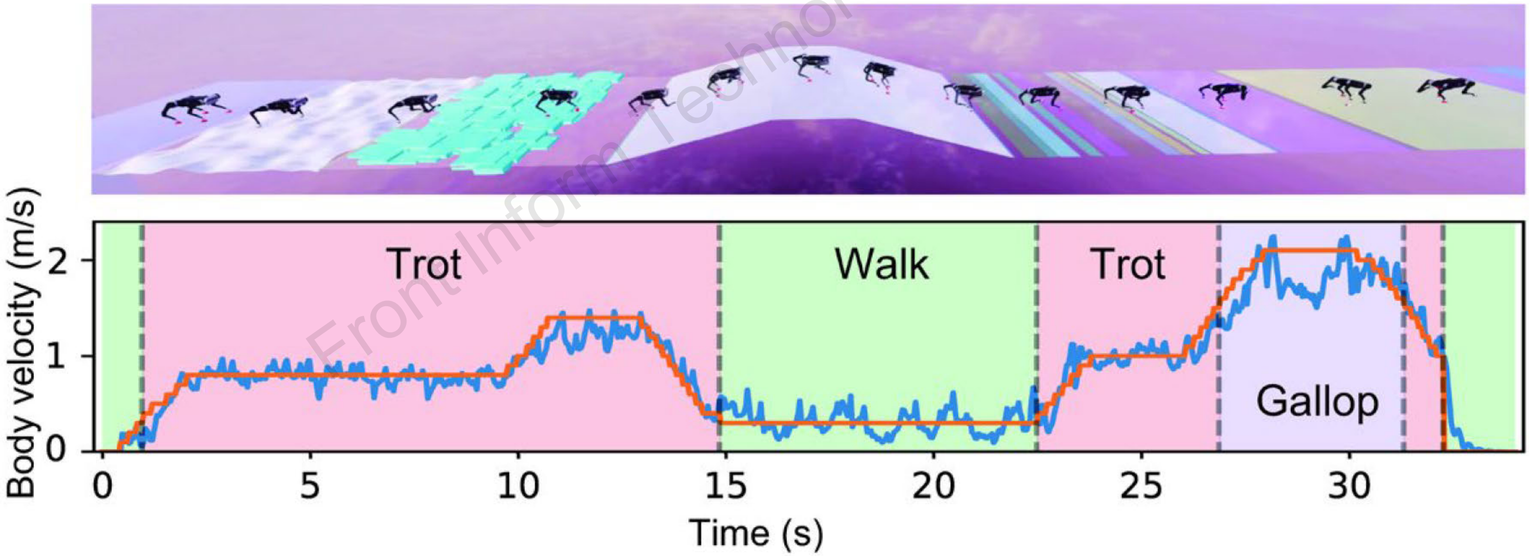
Motivation

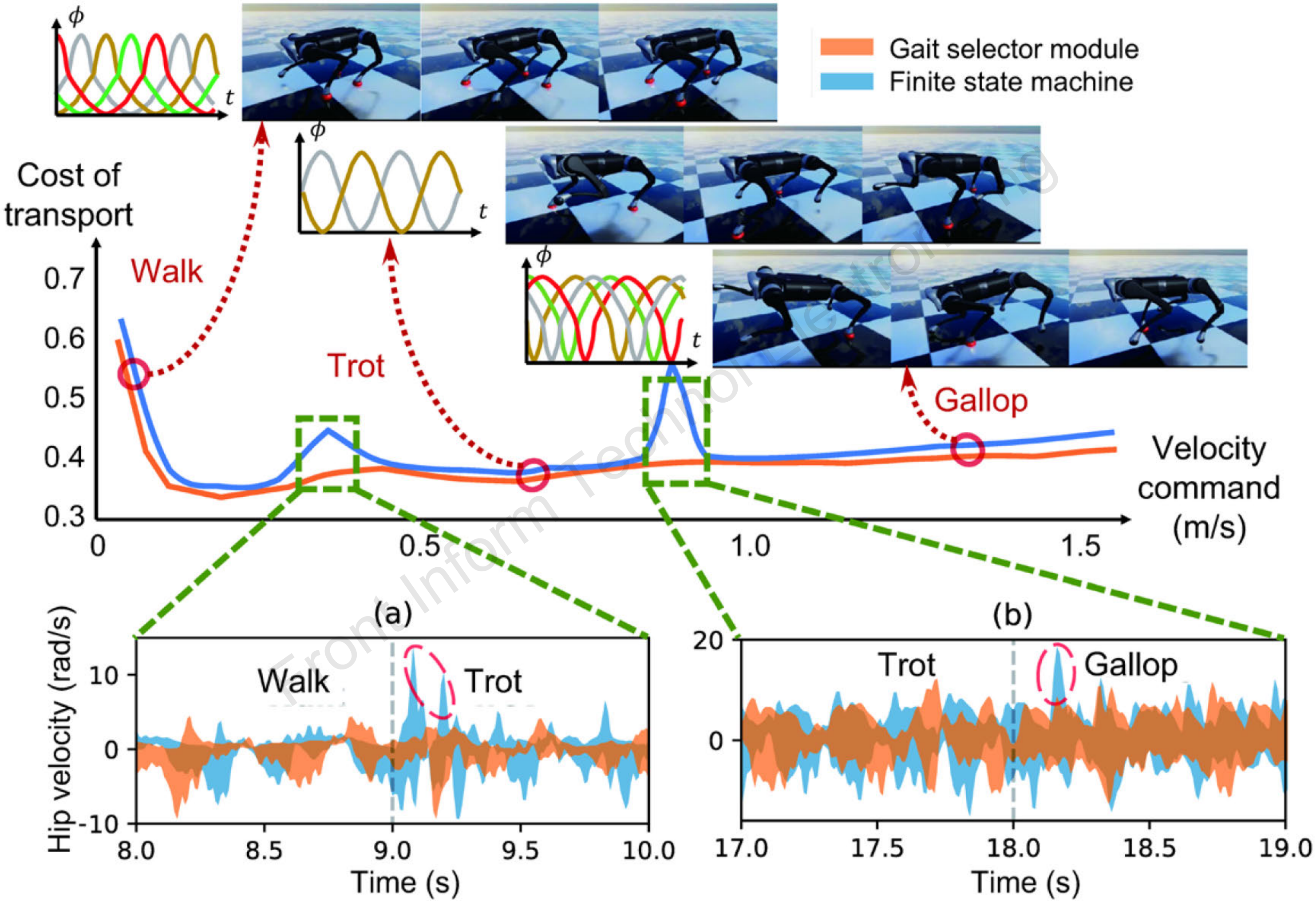
- Quadruped robots have been deployed to various application scenes. However, their locomotion behavior still lacks adaptability and energy efficiency compared to animals.
- Existing methods fix to one gait or leave gait choice uncontrolled, which leads to poor efficiency and controllability.
- We still need a framework for smooth, energy-efficient, and robust multigait locomotion.

Main idea

Develop a reinforcement-learning-based multigait locomotion framework that enables controllable, smooth, and energy-efficient gait switching.



Framework



Overview of the efficient gait-conditioned locomotion learning framework

Method

1. Gait pattern generator design

To achieve controllable gait patterns within a unified framework, we design a phase generator that yields periodic signals based on sine waves to specify gait phase commands. By modulating the period and offset of every leg, the robot can learn to perform any desired gait.

$$\phi_i = \begin{cases} \dfrac{\pi}{\gamma_i\, T_i} t + \Delta\phi_i & 0 \leq\ mod(t, T_i)\ < \gamma_i \\ \dfrac{\pi t}{(1-\gamma_i)T_i} + \dfrac{1-2\gamma_i}{1-\gamma_i}\pi + \Delta\phi_i & \gamma_i \leq mod(t, T_i) <\ T_i \end{cases}$$

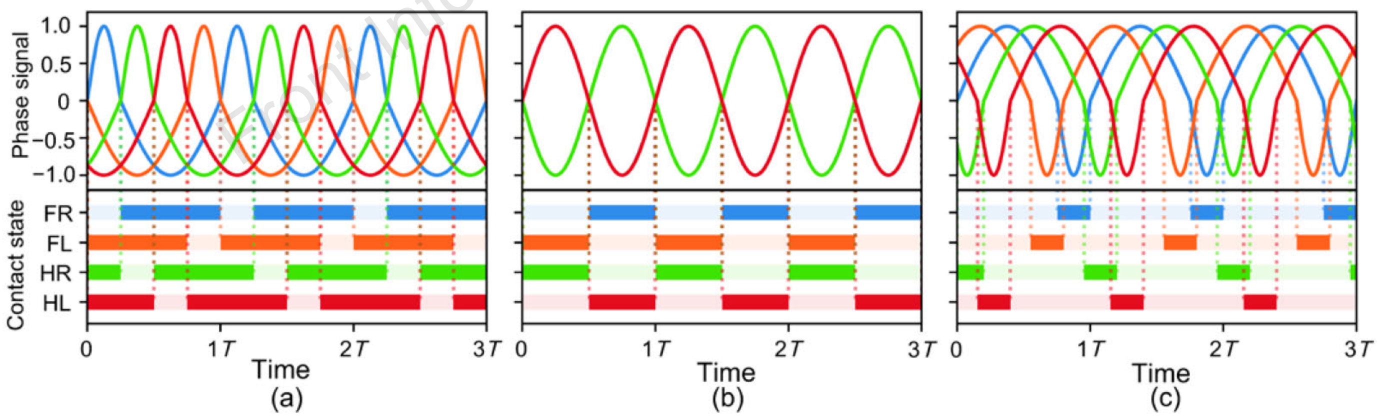


Fig. 3 Gait phase signals and foot contact sequence of different gaits: (a) quasi-static walk; (b) trot; (c) gallop

Method

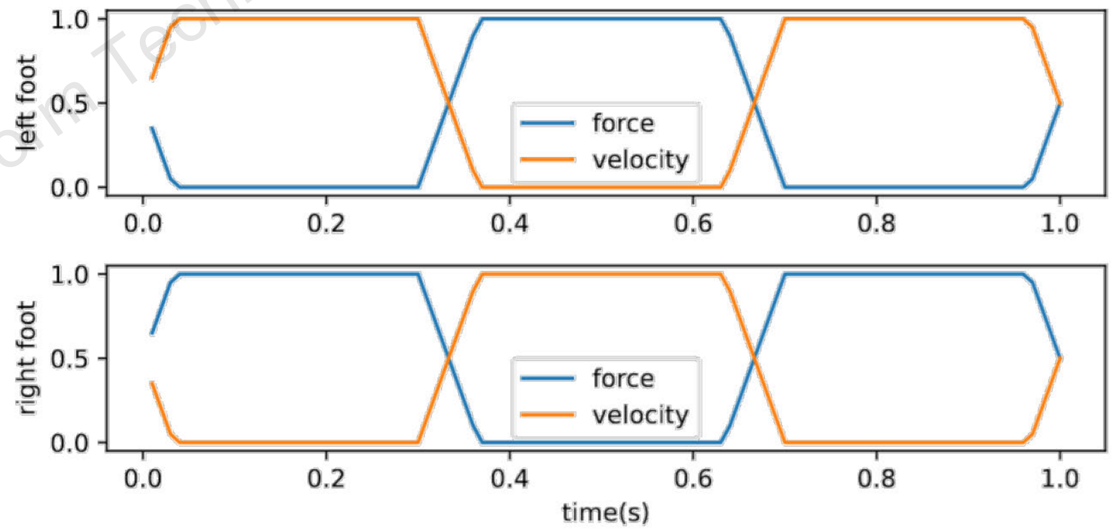
2. Gait-encouraging reward design

To make sure the robot perform accurate gait as commanded, a pair of rewards is designed. It penalizes contact force on end effectors during the expected swing phase and penalizes relative movement to the terrain during the expected stance phase.

$$R_{swing} = F_{\alpha_1,\beta_1}\left(\sum_i C_i \|F_i\|\right)$$

$$R_{stance} = F_{\alpha_2,\beta_2}\left(\sum_i (1 - C_i)\|v_i\|\right)$$

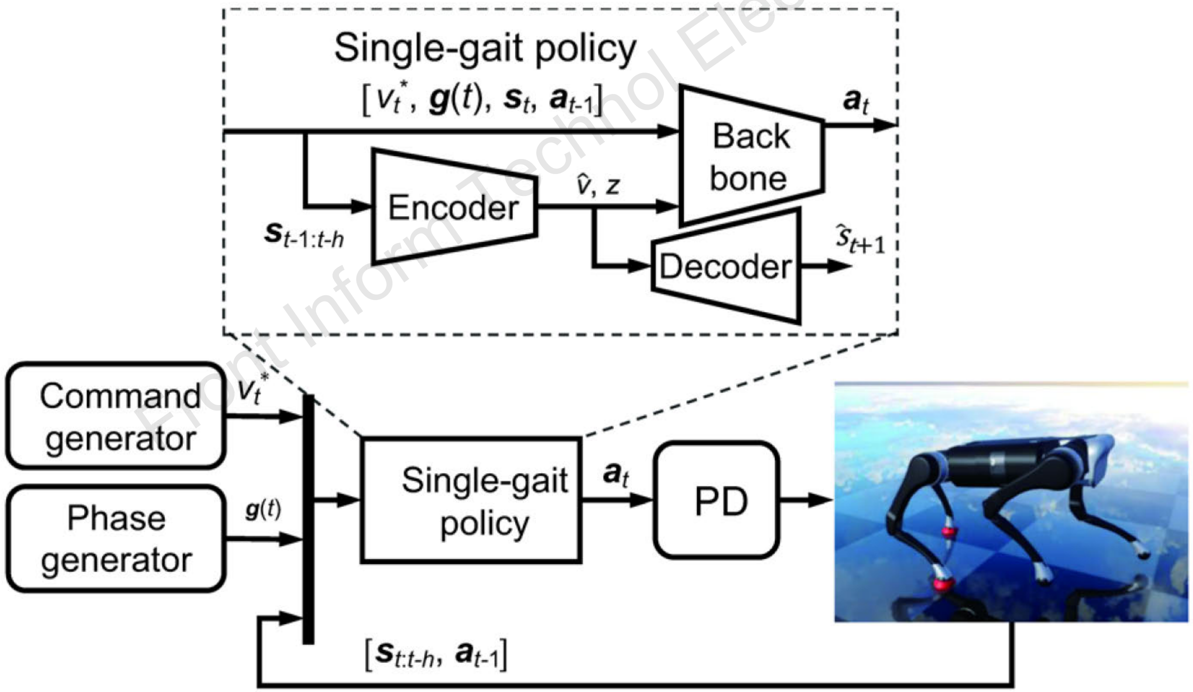
$$F_{\alpha,\beta}(x) = \alpha \exp\left(-\frac{x}{\beta}\right)^2$$



Method

3. Single-gait policy training

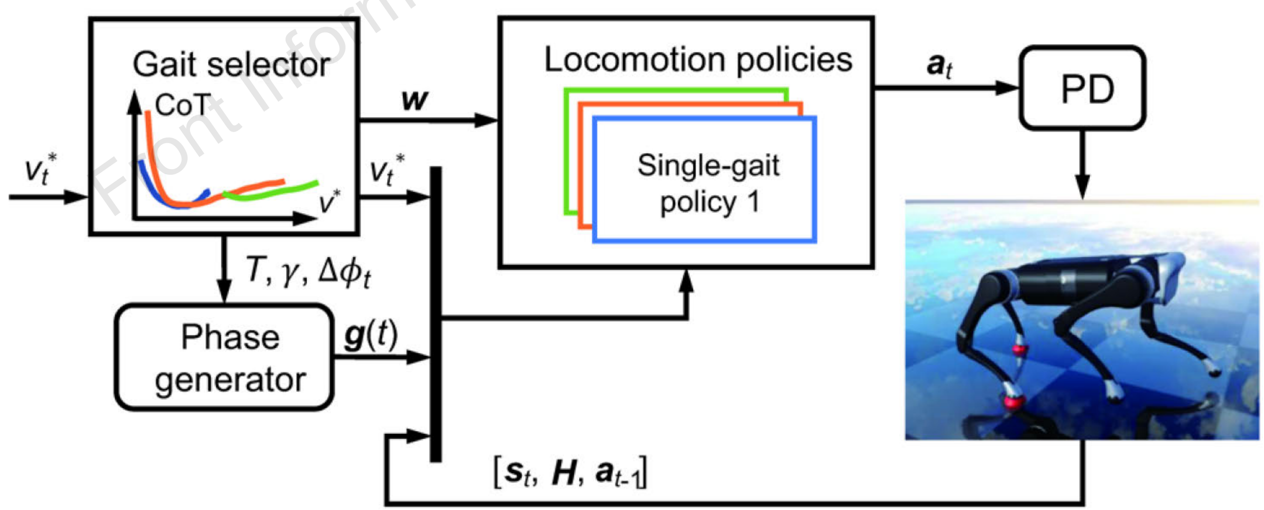
In single-gait training, each gait type is trained as an independent policy, conditioned on velocity commands and gait phase signals.



Method

4. Gait selector module training

The gait selector is trained with reinforcement learning while freezing the single-gait policies, taking as input the velocity command, proprioceptive history, and terrain information. Its reward encourages accurate velocity tracking, smooth parameter transitions, reduced joint velocity spikes, and low energy consumption, enabling adaptive and efficient gait switching.



Major results

Results in the table below demonstrate that all single-gait policies are capable of effectively tracking velocity and gait command signals, highlighting the robustness of our training framework in enabling the policies to master locomotion skills. Meanwhile, each single-gait policy exhibits trade-offs across different metrics.

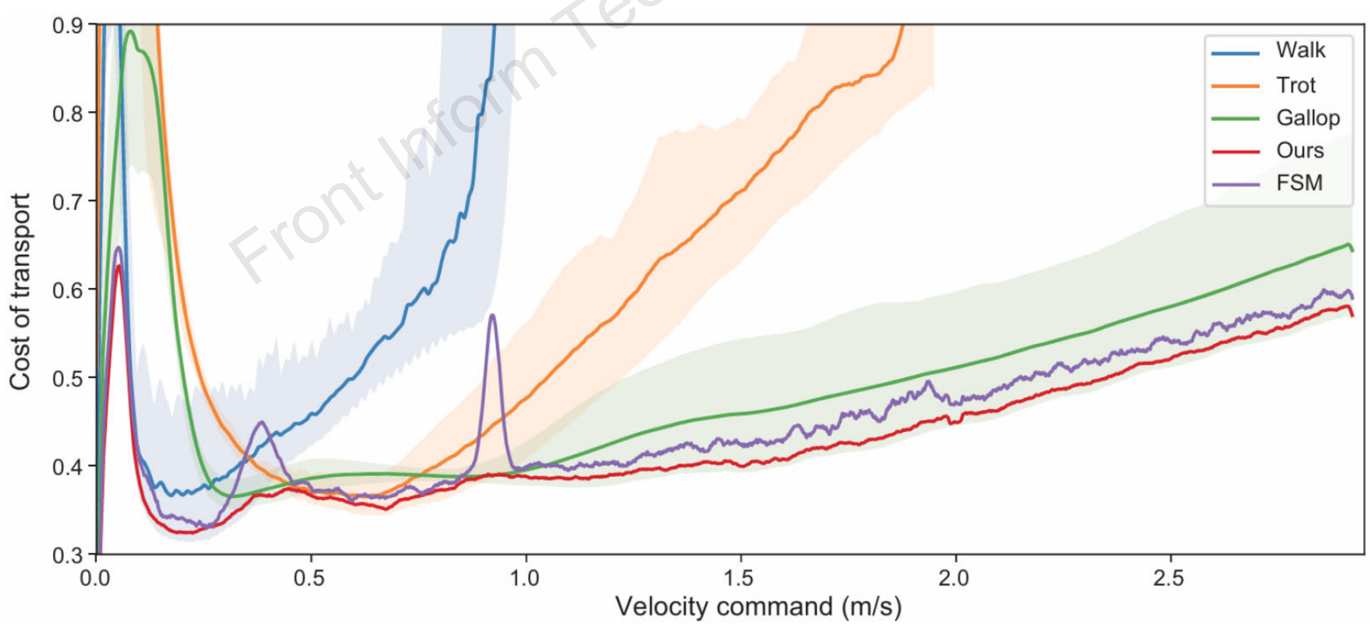
Table 6 Performance summary under different conditions

Parameter	Walk		Trot		Gallop		FSM	Ours
	0.8 Hz	1.6 Hz	1.2 Hz	2.4 Hz	2.0 Hz	3.2 Hz		
RMSE(Δv_{L})	0.1034	**0.0920**	0.0954	0.0982	0.0966	0.0941	0.1125	0.0929
RMSE(Δv_{M})	0.3768	0.1430	0.1365	0.0860	0.0621	0.0625	0.0827	**0.0620**
RMSE(Δv_{H})	0.8916	0.4997	0.3042	0.0880	0.0760	**0.0500**	0.0650	0.0522
$\mathrm{CoT}_{\mathrm{avg}}$	0.7241	0.4733	0.6886	0.6041	0.5675	0.4514	0.4531	**0.4306**
$\mathrm{TSR}_{\mathrm{fractal}}$	0.90	0.95	**1.00**	**1.00**	0.80	0.85	**1.00**	**1.00**
$\mathrm{TSR}_{\mathrm{slope}}$	0.85	0.85	**1.00**	**1.00**	0.65	0.70	**1.00**	**1.00**
$\mathrm{TSR}_{\mathrm{discrete}}$	0.80	0.95	**1.00**	0.95	0.70	0.60	0.75	**1.00**
$\mathrm{TSR}_{\mathrm{gaps}}$	0.80	0.80	0.90	**1.00**	0.80	0.80	**1.00**	0.95
$\mathrm{TSR}_{\mathrm{projectile}}$	0.95	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**

The best results are in bold

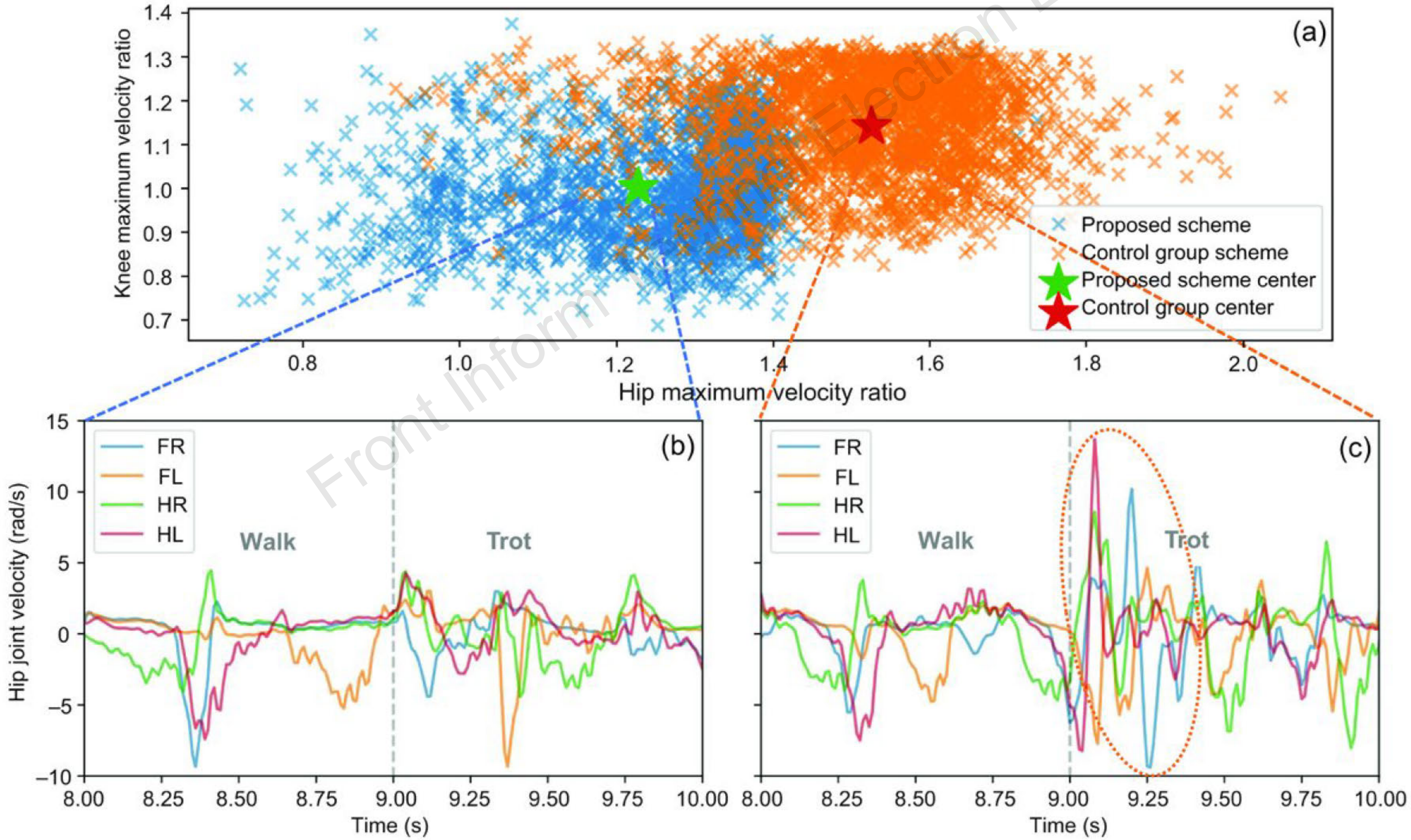
Major results

Both the proposed method and the finite state machine (FSM) effectively leverage the advantages of all single-gait policies. The velocity tracking accuracy of both groups is comparable to that of the best-performing single-gait policies, with the proposed method slightly outperforming FSM. Additionally, the proposed policy demonstrates superior adaptability to challenging terrains compared to FSM.



Major results

The proposed method is safer than FSM since the results show that the proposed method causes less joint fluctuation during gait switching.



Conclusions

We present a learning framework for training and organizing robust gait-conditioned policies, revealing the relationship between velocity command and energy efficiency across different gaits. Based on these findings, an adaptive multimodal locomotion controller is developed, and it outperforms single-gait policies in terms of velocity tracking accuracy, cost of transport (CoT), and robustness.

Zhicheng Wang is a Ph.D. candidate with the Robotics & Machine Intelligence Lab at Zhejiang University (ZJU), China since 2020. She received the B.S. degree in Automation from ZJU in 2020. Between 2022 and 2023, she worked as a research assistant at the Institute for Infocomm Research (I2R), Agency for Science, Technology and Research (A*STAR), Singapore. Her research focuses mainly on learning-based locomotion for legged robots, especially humanoids. Supervised by Dr. Qiuguo Zhu, she participated in the Wukong project since 2019 and helped develop and build the Wukonmg-IV humanoid.

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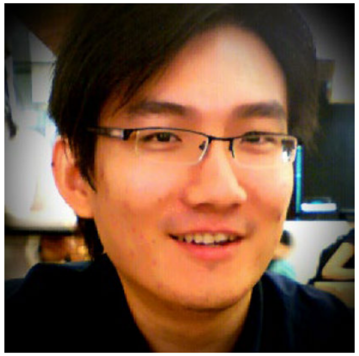

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