The 44th Chinese Control Conference

THE UNIVERSITY of ADELAIDE

From Model-based to AI-Empowered Cyber-Physical Multi-Agent Systems

Peng Shi

30 July 2025

Outline

1) Introduction and Challenges of CPMAS

2) Model-Based Control in CPMAS

3) AI-Empowered Approaches for CPMAS

4) Future Research Directions in CPMAS

Outline

1) Introduction and Challenges of CPMAS

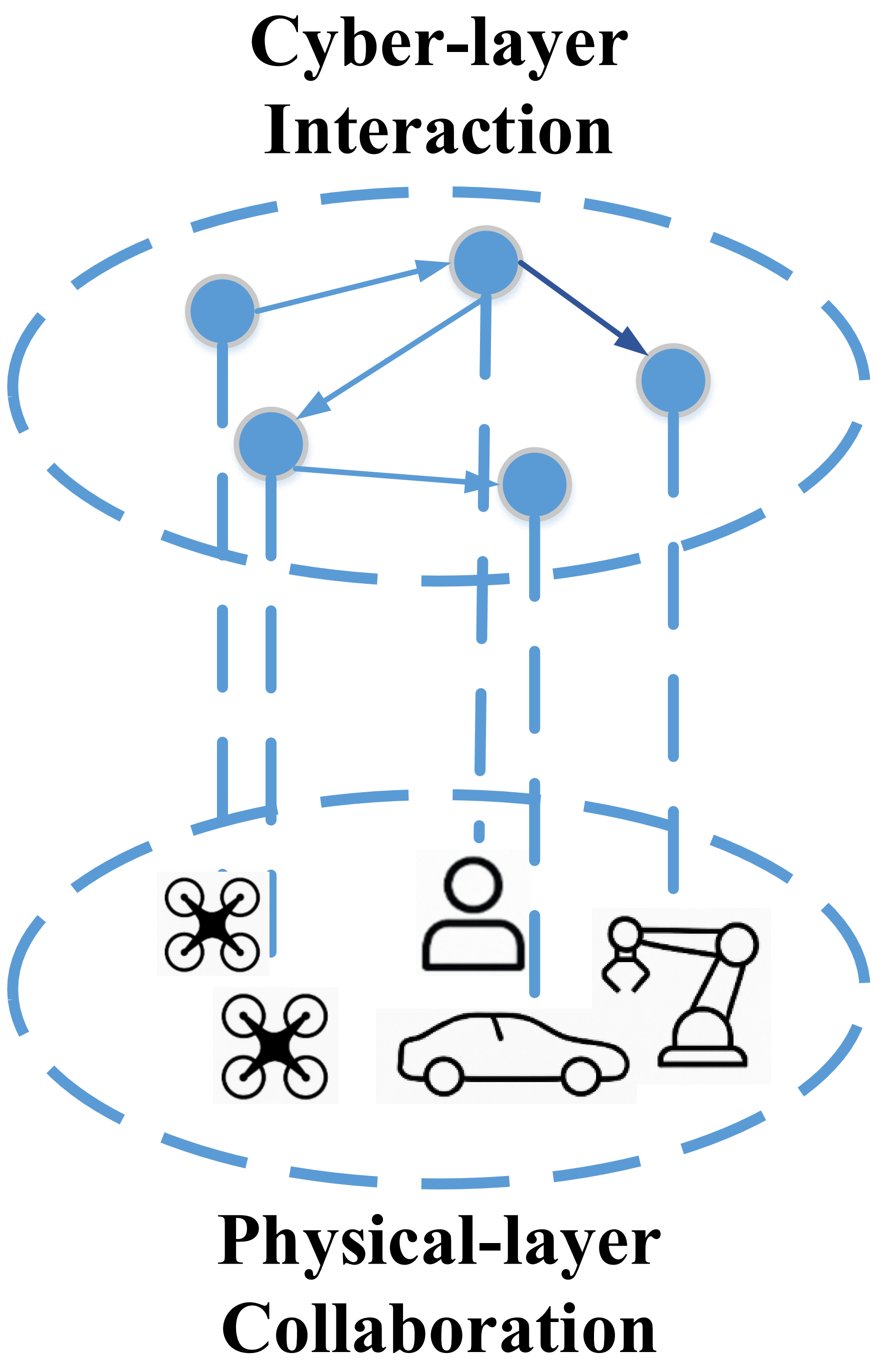
2) Model-Based Control in CPMAS

3) AI-Empowered Approaches for CPMAS

4) Future Research Directions in CPMAS

1.1 Cyber-physical Multiagent Systems (CPMAS)

CPMAS integrates cyber and physical layers across multiple intelligent agents to enable resilient, cooperative behaviour in dynamic, real-world environments



System Type	Key Focus	Strengths & Weaknesses
MAS	Distributed coordination	✓ Decentralized, scalable ✗ Limited physical interaction
CPS	Cyber-physical coupling	✓ Real-time control ✗ Centralized or partially distributed, less adaptive
CPMAS	Cyber-physical-agent collaboration	✓ Adaptive, robust in complex environments ✓Wider application

THE UNIVERSITY of ADELAIDE

1.2 Examples of CPMAS

UAV formations

Heterogeneous satellite system

Autonomous cars in intersection

Human-machine collaboration

1.3 Advantages of CPMAS

Save average energy

Improve survivability

Complete complex tasks

Extend functions

Source from: https://www.youtube.com/watch?v=i3ernrkZ91E

THE UNIVERSITY of ADELAIDE

1.4 Significance - Frontier Field

125 Questions from Science

125 QUESTIONS: EXPLORATION AND DISCOVERY

Artificial Intelligence

Could we integrate with computers to form a human–machine hybrid species?

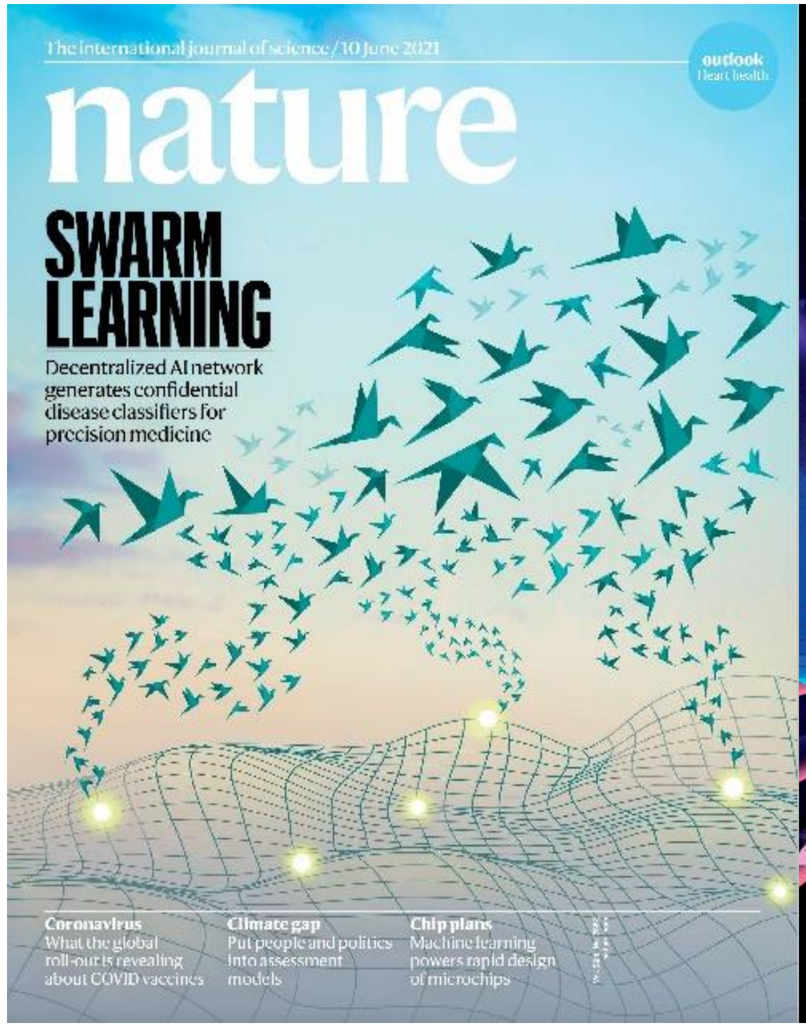
We are on the cusp of human-machine hybrids, especially given advancements in smart exoskeletons and prosthetics, implantable sensors and chips, AI, and genomic editing technologies.

How does group intelligence emerge?

Group or collective intelligence occurs when individuals come together and collaborate. In his book *Social Media Security*, Michael Cross discusses how groups collectively solve problems through interaction and competition between individuals within the group. Through consensus, ideas that detract from the solution are resolved and discarded. This phenomenon is not limited to human–human interaction. Scientists at the MIT Center for Collective Intelligence are exploring "how people and computers can be connected so that—collectively—they act more intelligently than any person, group, or computer has ever done before." The team's multidisciplinary insights can offer a window into how group intelligence emerges, using methods

How does group intelligence emerge?

Covers from Science and Nature



Swarm learning, AI, etc.

THE UNIVERSITY of ADELAIDE

1.4 Significance - Strategic Needs


中华人民共和国中央人民政府
www.gov.cn

国务院印发《新一代人工智能发展规划》

2017-07-20 17:12 来源：新华社 字号：默认 大 超大 | 打印

新华社北京7月20日电 国务院近日印发《新一代人工智能发展规划》（以下简称《规划》），提出了面向2030年我国新一代人工智能发展的指导思想、战略目标、重点任务和保障措施，部署构筑我国人工智能发展的先发优势，加快建设创新型国家和世界科技强国。

《规划》指出，要全面贯彻党的十八大和十八届三中、四中、五中、六中全会精神，深入学习贯彻习近平总书记系列重要讲话精神和治国理政新理念新思想新战略，坚持科技引领、系统布局、市场主导、开源开放等基本原则，以加快人工智能与经济、社会、国防深度融合为主线，以提升新一代人工智能科技创新能力为主攻方向，构建开放协同的人工智能科技创新体系，把握人工智能技术属性和社

China

USA

Australia

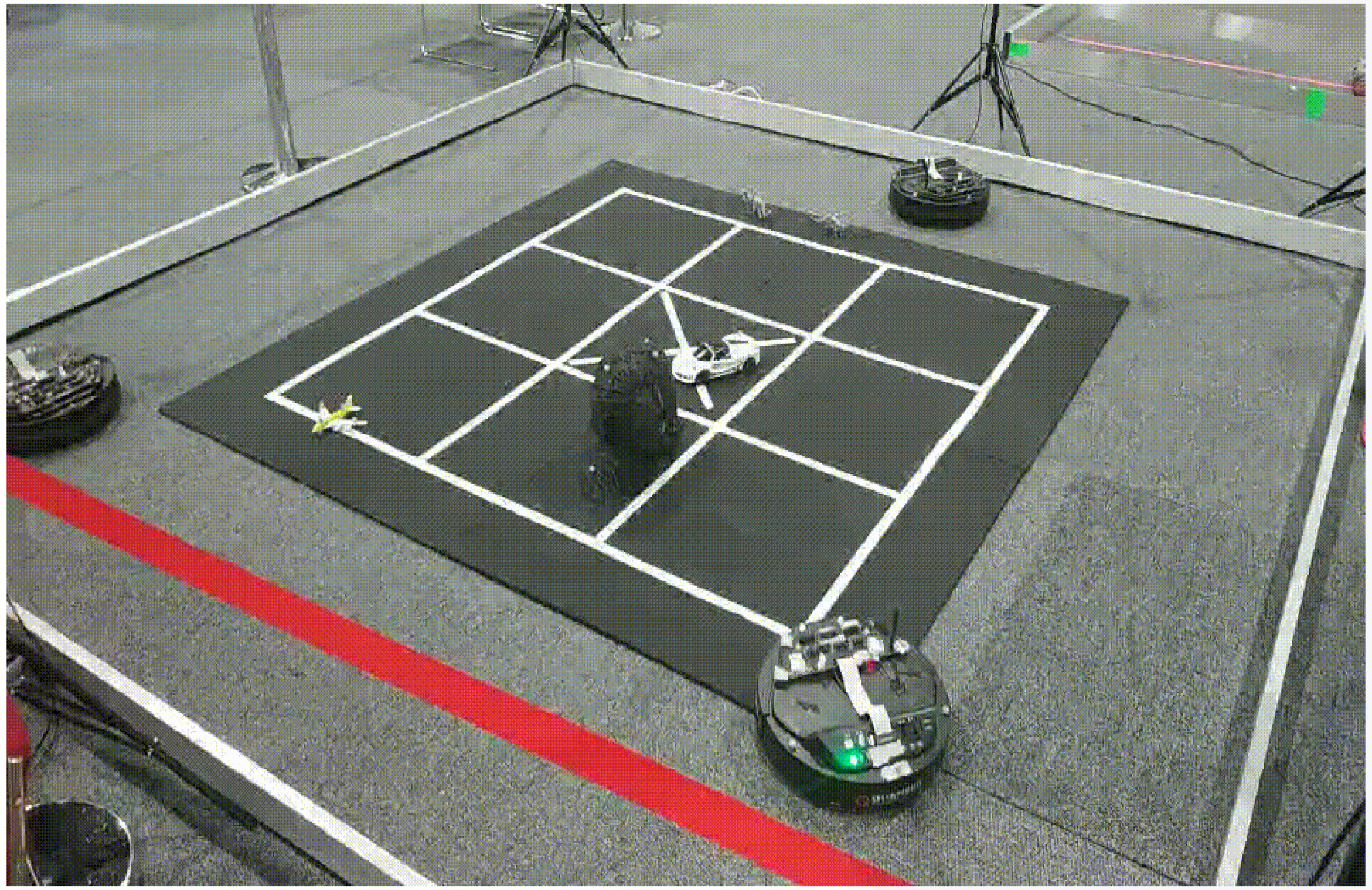
UK

THE UNIVERSITY of ADELAIDE

1.5 Applications - Intelligent Transportation

- Traffic signal control, reducing congestion and optimizing traffic flow
- Autonomous parking systems, optimizing decision-making

Intelligent transportation systems-self-drive AlphaBus



Autonomous parking system (University of Adelaide (UoA))

Source from: https://news.sina.cn/2017-12-05/detail-ifyphtze4406603.d.html

THE UNIVERSITY of ADELAIDE

1.5 Applications - Defense

- Autonomous attack and defense, enhancing combat efficiency while reducing human involvement in dangerous environments

Unmanned vehicle formations for attack and defense

Israel-Iran conflict

Source from: https://news.sina.cn/2017-12-05/detail-ifyphtze4406603.d.html

THE UNIVERSITY of ADELAIDE

1.5 Applications - Defense

- Autonomous attack and defense, enhancing combat efficiency while reducing human involvement in dangerous environments

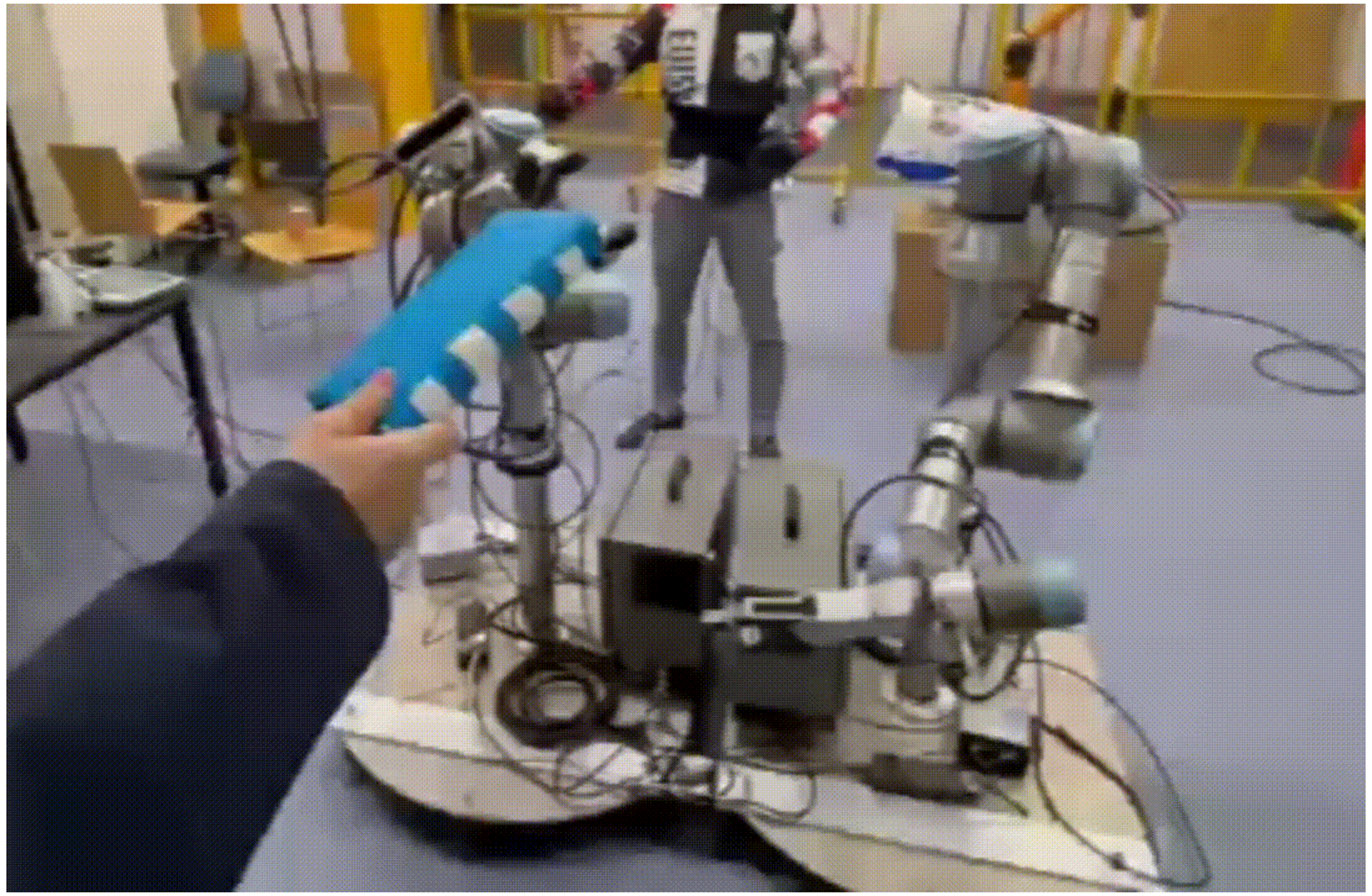
MineSwarm for efficient detection of land mines (UoA)

Ground-air switching vehicle tracking a target drone (UoA)

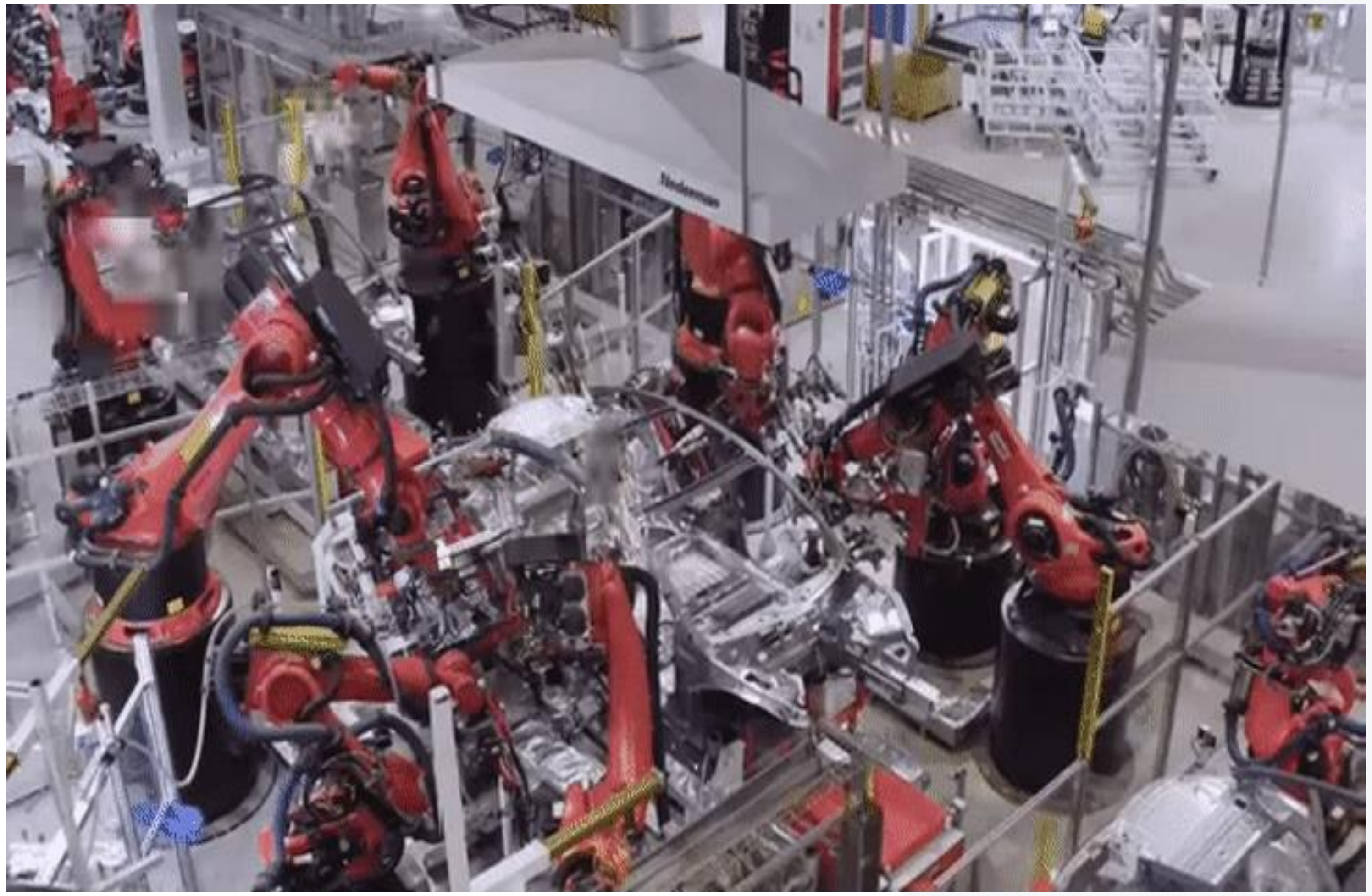
THE UNIVERSITY of ADELAIDE

1.5 Applications - Industrial Automation

- Collaborative manufacturing, handling, and inspection, enabling real-time optimization on complex production lines



Show robot human-machine smart manufacturing (UoA with Australian Meat Processor Corporation)



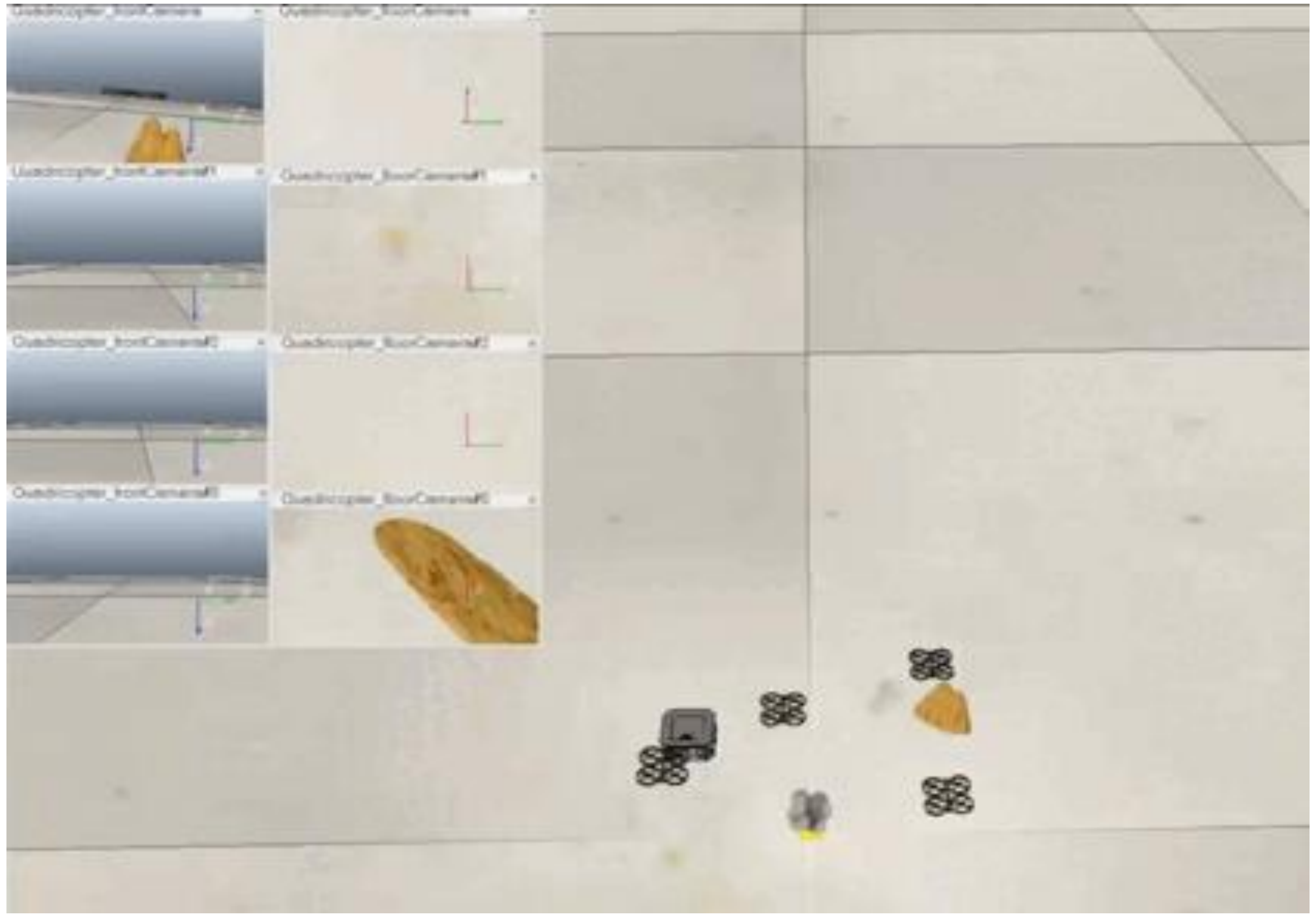
Tesla's automated vehicle production

THE UNIVERSITY of ADELAIDE

Source from: https://www.tesla.cn/; https://www.iimt.org.cn/h-nd-611.html

1.5 Applications - Environmental Monitoring

- Collaborative environmental data collection, disaster assessment, improving real-time monitoring performance and area coverage



Australian bushfire monitoring (UoA)

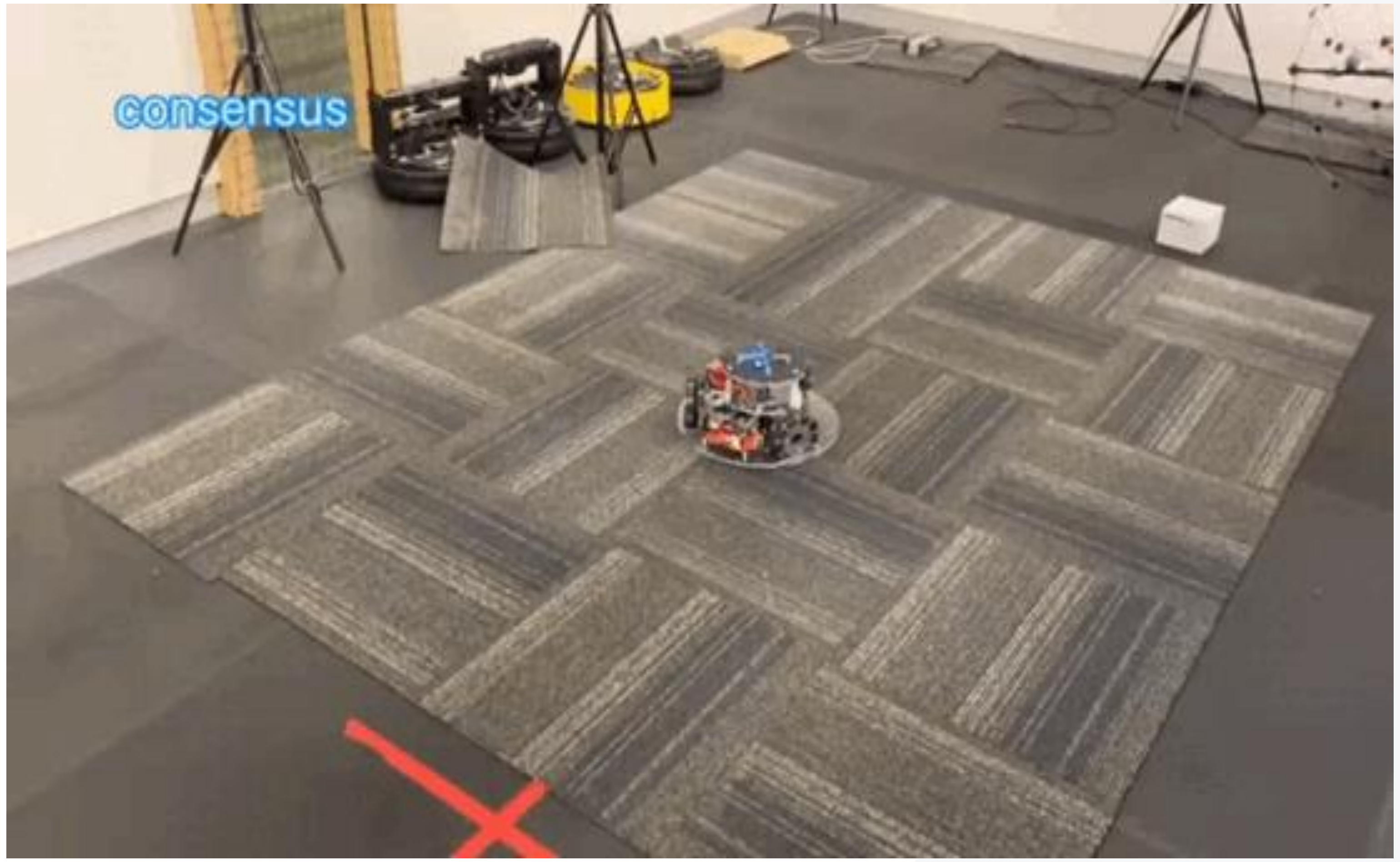
Multi-UAV agricultural monitoring and irrigation

Source from: https://www.youtube.com/watch?v=jcbJTiimO-w

1.5 Applications - Smart logistics

- Collaborative logistics, optimizing goods distribution and logistics operations

Unmanned warehouse



UAV-UGV consensus (UoA)

Source from: https://www.youtube.com/watch?v=oBlmGOwxHsE

THE UNIVERSITY of ADELAIDE

1.6 Current Challenges

Chall. 1 Unstable communication networks

Traditional cooperation struggles with limited network resources and malicious attacks

→ Cyber-layer: insecure interaction

Chall. 2 Multi-physical constraints

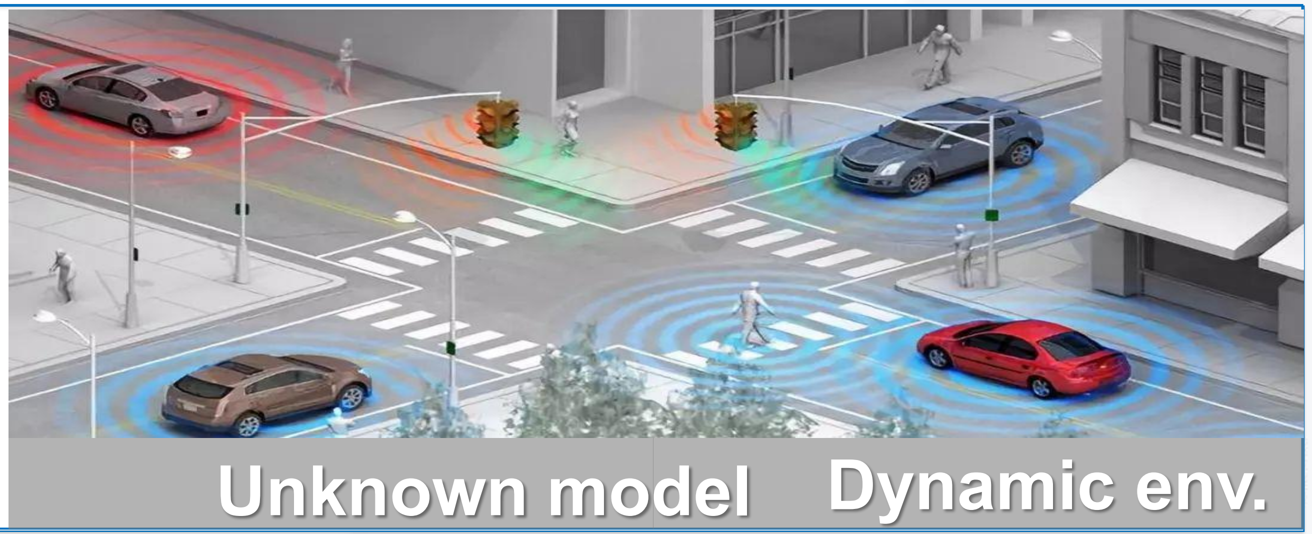
Existing cooperative methods fail under heterogeneity, non-cooperative obstacles, and faults

→ Physical-layer: unsafe cooperation

Chall. 3 Complex and unknown environment

Most methods are model-sensitive and have limited autonomy in complex dynamic environment

→ Both layers: low autonomy



Source from： https://www.guancha.cn/society/2018_05_02_455570.shtml; https://blog.csdn.net/FEISILAB_2022/article/details/130678377; https://bigsuperzzzx.github.io/

1.7 Solution

From model-based to AI-empowered cooperative control

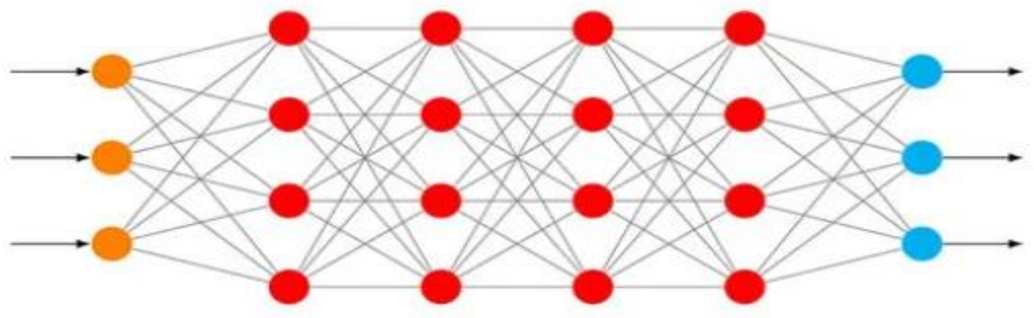
Model-based cooperative control

$$\begin{cases} F_x = (\dot{u} + wq - vr)m \\ F_y = (\dot{v} + ur - wp)m \\ F_z = (\dot{w} + vp - up)m \end{cases}$$

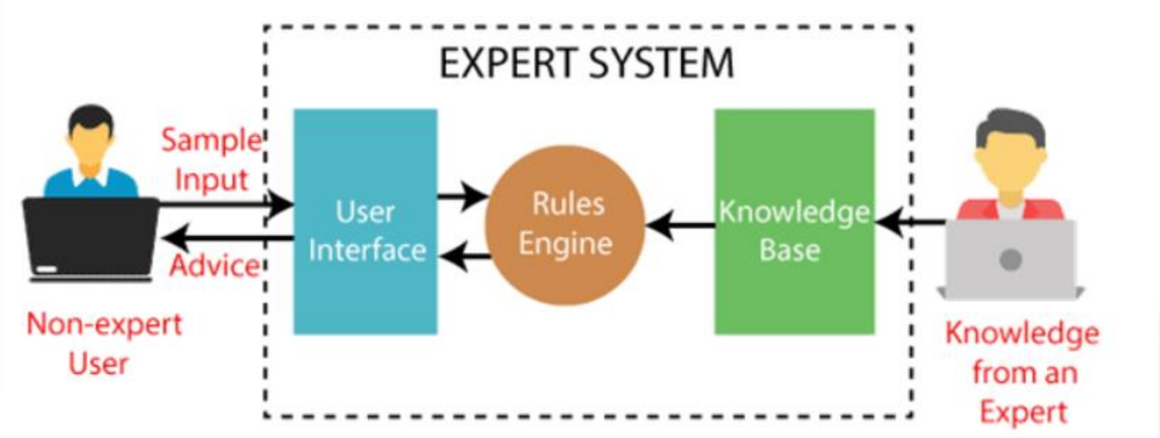
$$\begin{cases} \dot{x} = v\cos\theta \\ \dot{y} = v\sin\theta \\ \dot{\theta} = \frac{v}{L}\tan\delta \end{cases}$$

- Safety-critical applications
- Known or partially known model
- Good theoretical guarantee

AI-empowered cooperative control



Neural network



Expert system

- Partially known/unknown environment
- Complex environment
- Data-rich environment

Outline

1) Introduction and Challenges of CPMAS

2) Model-Based Control in CPMAS

3) AI-Empowered Approaches for CPMAS

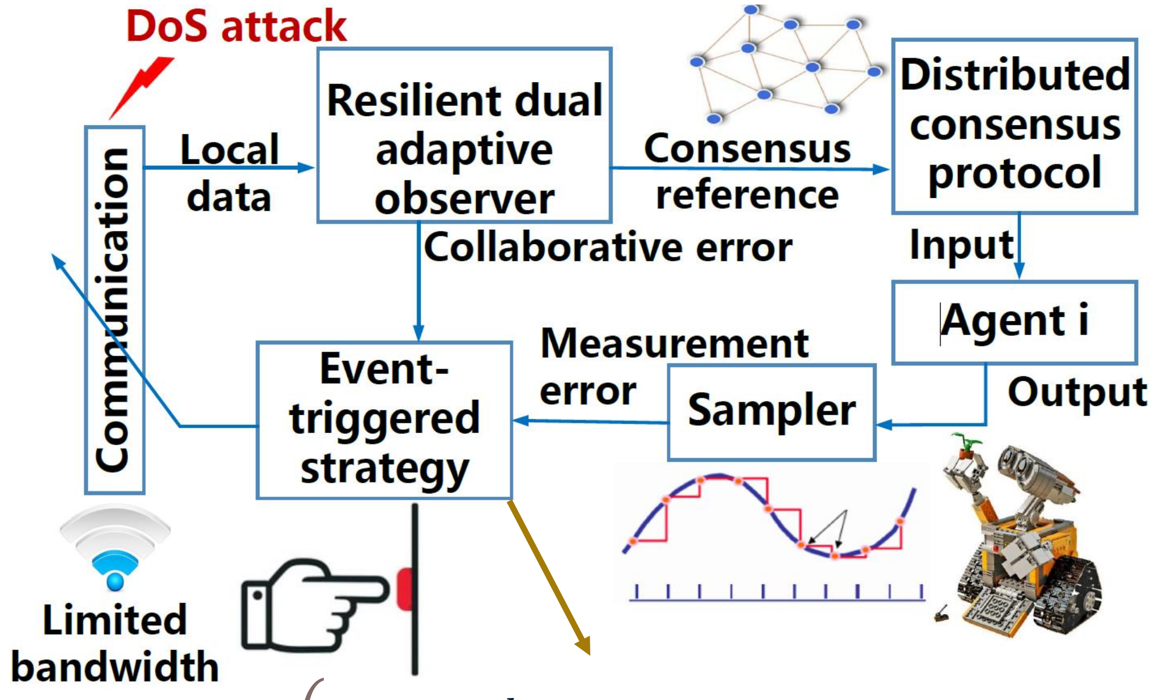
4) Future Research Directions in CPMAS

2.1 Model-Based Control under Cyber-Layer Constraints

(1) Distributed resilient consensus under limited bandwidth and DoS attacks

Technical Hurdles
- Limited communication and local information hinder timely cooperation
- DoS attacks disrupt links and threaten consensus resilience

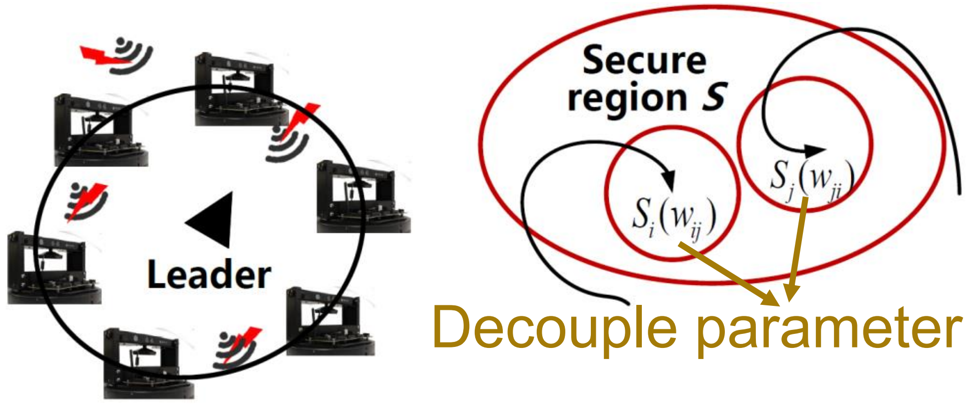
Adaptive and Event-based Scheme



$$t_i^{k+1} = \begin{cases} t_i^k + \Delta^*, if \ \ k \in \mathcal{F}_i \\ \{t \,|\, > t_i^k \,|\, \boxed{\phi_i \ \ \theta_i} \, e_{\chi_i}^T e_{\chi_i} > \psi_i^T \psi_i\} \end{cases}$$

Dual adaptive laws

Distributed Resilient Control



Distributed convergence to each agents' secure regions

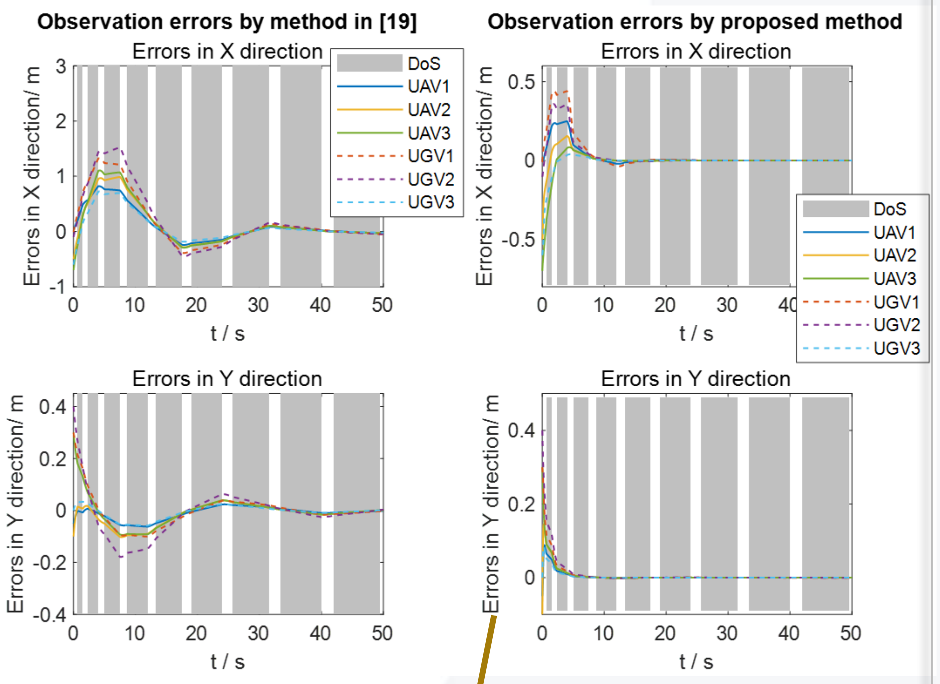
- Fast convergence without DoS:

$$A_i^{\eta} u_i^{\nu} + d_{ij}^{\nu} b_{ij}^{\eta} < d_{ij}^{\nu} \overline{\delta_{\nu}}, j \in \mathcal{N}_i, \beta_1 > 0$$

- Slow divergence with DoS:

$$\eta_i^T \left((A^{\nu})^T P + P A^{\nu} - \beta_2 P \right) \eta_i < \delta_{\nu}, \beta_2 > 0$$

Experimental Results



Improved convergence speed
almost twice under DoS attack

Enable resilient interaction under cyber-layer constraints

IEEE TSMCS, 2024, 54(8): 4876–4886; IEEE TCYB, 2024, 54(10): 6244–6255; Automatica, 2020, 122, 109223

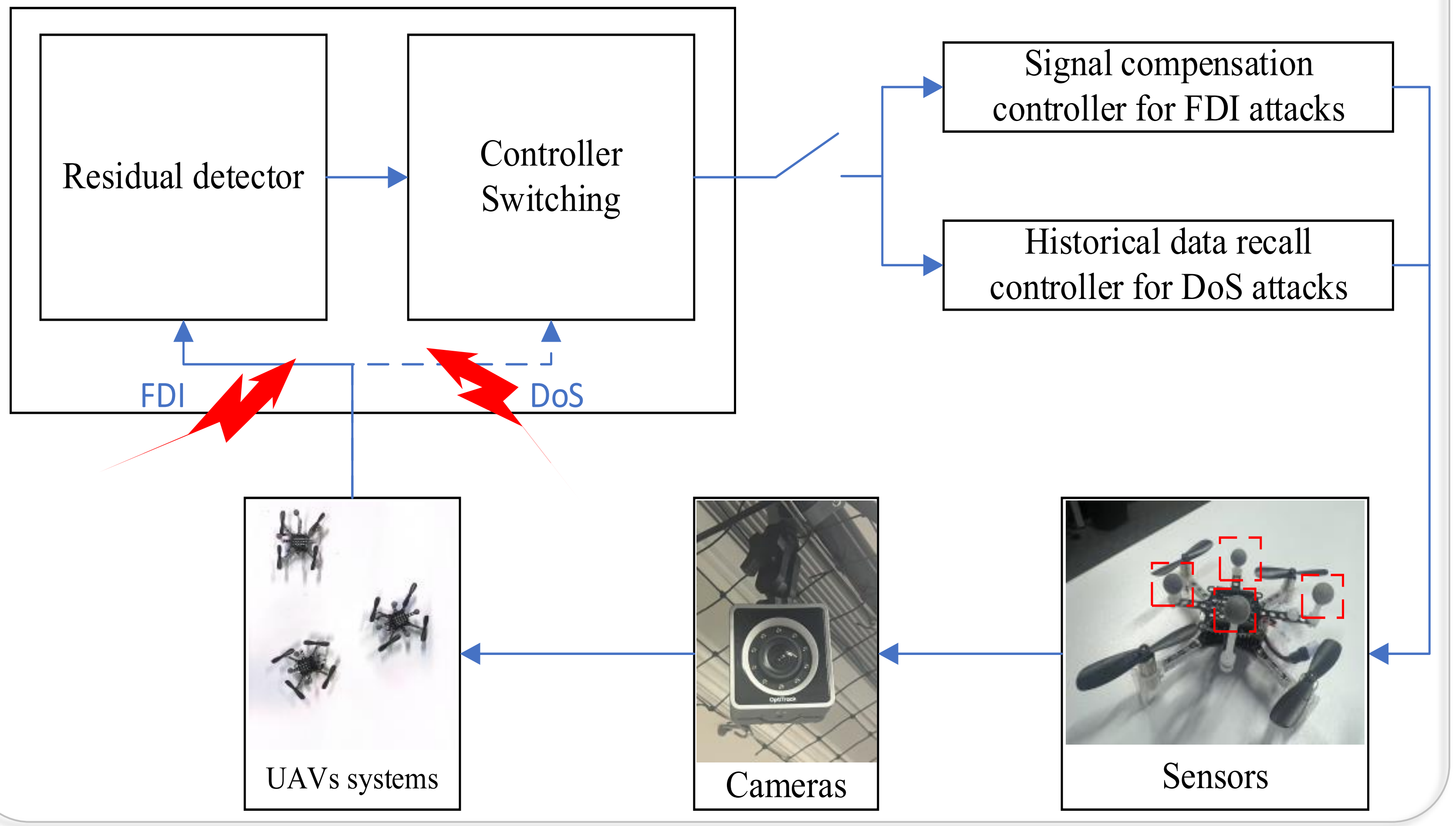
2.1 Model-Based Control under Cyber-Layer Constraints

(2) Distributed formation control for UAVs under DoS and FDI attacks

Technical Hurdles

- Distributed architectures communicate under malicious network attacks
- Attack detection and control switching for nonlinear system models

Distributed Control Framework



Two Controller Designs

- DoS attacks case

$$u_i = -\frac{k_{i1}}{(2\tau_i)^p} x_i^{2p-1} - l_{i1} e_i^a - \frac{1}{2} x_i - \hat{\theta}_{i1}^{\mathrm{T}} \psi_{i1} \boxed{(\xi_i)}$$

Called data

$$\dot{\hat{\theta}}_{i1} = x_i^{\mathrm{T}} \psi_{i1} \boxed{(\xi_i)} - \gamma_{i1} \hat{\theta}_{i1} - \gamma_{i1} \hat{\theta}_{i1}^{2q-1}$$

- FDI attacks case

$$u_i = -c\varphi_i - \varepsilon_i \phi_i - f_i \boxed{(\hat{v}_i)}$$

Compensation data

$$\varphi_i = \sum_{j \in N_i} a_{ij} \left(p_i - p_j \right) + d_i p_i$$

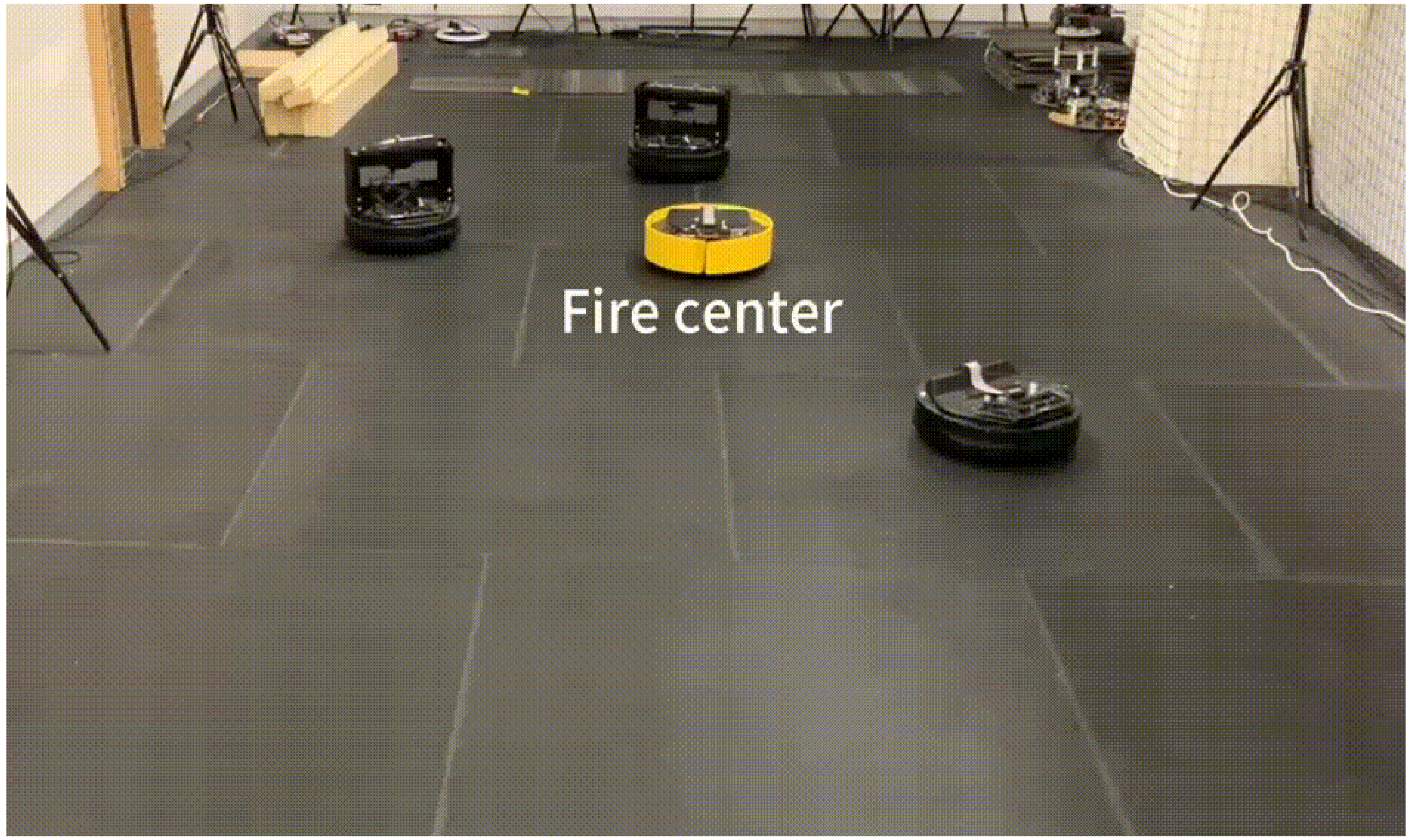
$$\phi_i = \sum_{j \in N_i} a_{ij} \left(h_i - h_j - F_i + F_j \right)$$

Ensure distributed detection and secure communication under hybrid attacks

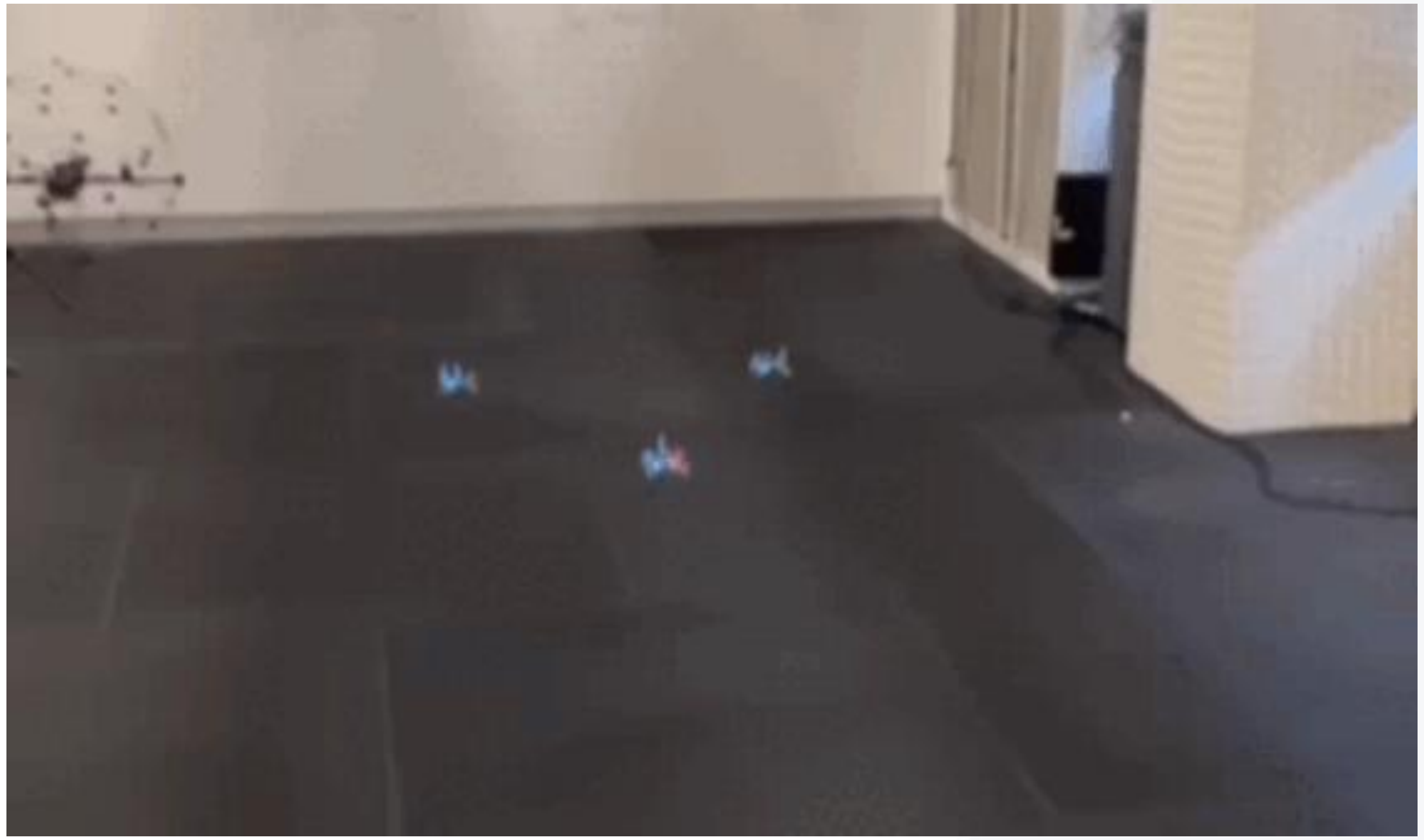
IEEE TITS under review Jul. 2025

2.1 Model-Based Control under Cyber-Layer Constraints

- **Verifications — applied to build information security for UGVs and UAVs**



Collaborative target tracking and patrolling under communication constraints and DoS



Formation control of micro-UAVs under DoS and FDI attacks

Efficient Interaction

Overcome

Chall.1 Cyber-Layer: insecure interaction

THE UNIVERSITY of ADELAIDE

2.2 Model-Based Control under Physical-Layer Constraints

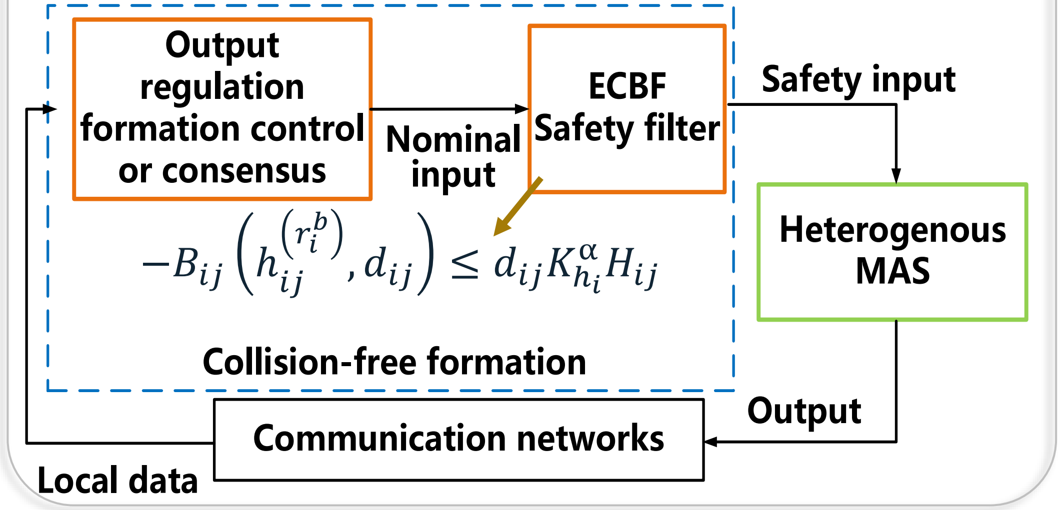
(1) Safe heterogeneous formation control via exponential control barrier function (ECBF)

Technical Hurdles
- Heterogeneous agents with different-order and nonlinear dynamics
- Non-cooperative dynamic obstacles causing unpredictable collisions

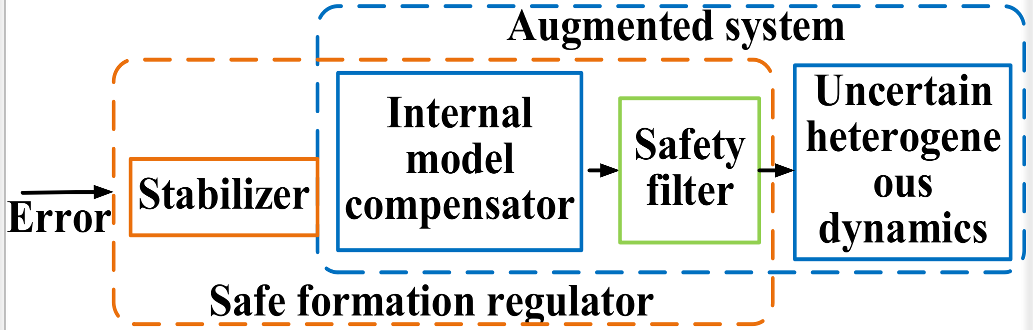
ECBF-based Formation control

Non-cooperative obstacles

Safety region $h_{ij}(x_i, x_j, u_i) > 0,\ \forall j \in O_{ij}$



Safe heterogeneous control



- Heterogenous nonlinear CPMAS

$$\dot{x}_i = \boxed{\tilde{f}_i(x_i) + \tilde{g}_i(x_i)} u_i,$$

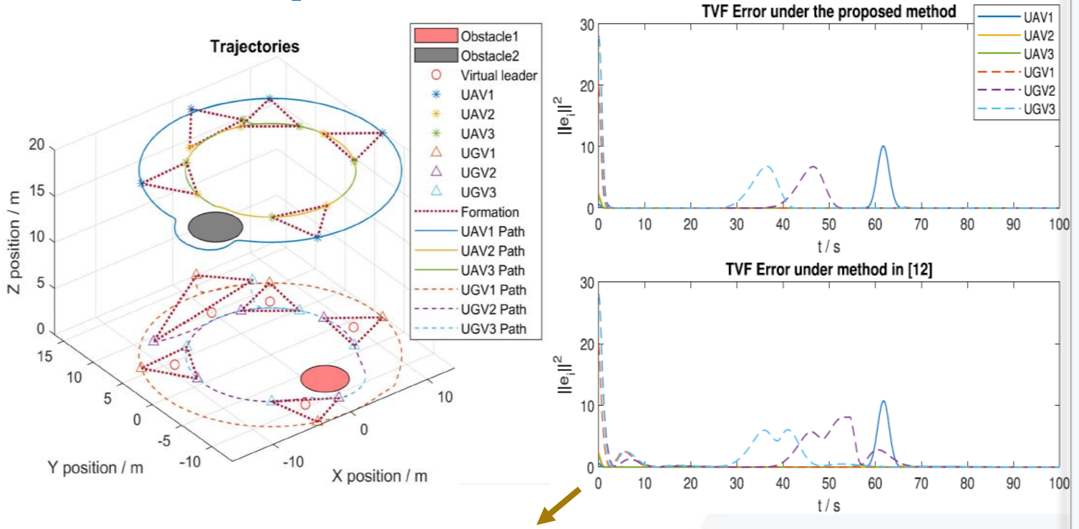
Different order & dynamics

$$y_i = \tilde{h}_i(x_i), \quad i = 1,2,\ldots,n$$

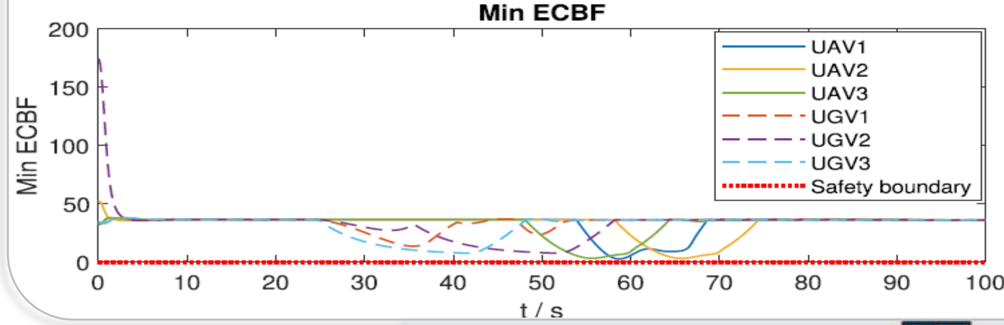
- Internal model compensator

$$\dot{z}_i = \Sigma_{i1} z_i + \Sigma_{i2} \hat{e}_i \quad \hat{e}_i = y_i - C_i^{\eta} \hat{\eta}_i - C_i^f f_i$$

Experimental Results



Achieved faster convergence within distributed safety region



Empower safe cooperation for heterogeneous CPMAS in obstacle-rich environments

IEEE TASE, 2022, 19(4): 2788–2800; IEEE TCYB, 2024, 54(10): 6244–6255

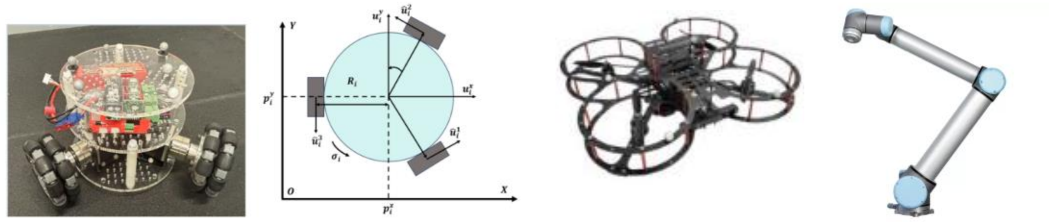
2.2 Model-Based Control under Physical-Layer Constraints

(2) Distributed fault-tolerant cooperative output regulation

Technical Hurdles

- Traditional methods require agents to access full exosystem information – unrealistic
- Existing protocols cannot convergence within a desired time, especially under multi-faults

Fixed-Time Observer & Control



Efficiency Loss | Outage Fault | Bias Fault

Exosystem → Fixed-Time Observer 1 → Fixed-Time Observer 2 → Adaptive Fault-Tolerant Controller

Multi-agent system ↔ Adaptive Fault-Tolerant Controller

Guarantee that the multiagent networks can achieve output regulation control despite the impact of faults

Fault-Tolerant Control Strategy

- Observer 1: Estimate the matrix *S*

$$\dot{S}_i^{lk}(t) = -c_1\mathrm{sign}(\eta_i(t)) - c_2\mathrm{sig}(\eta_i(t))^2$$

- Observer 2: Estimate the state *v(t)*

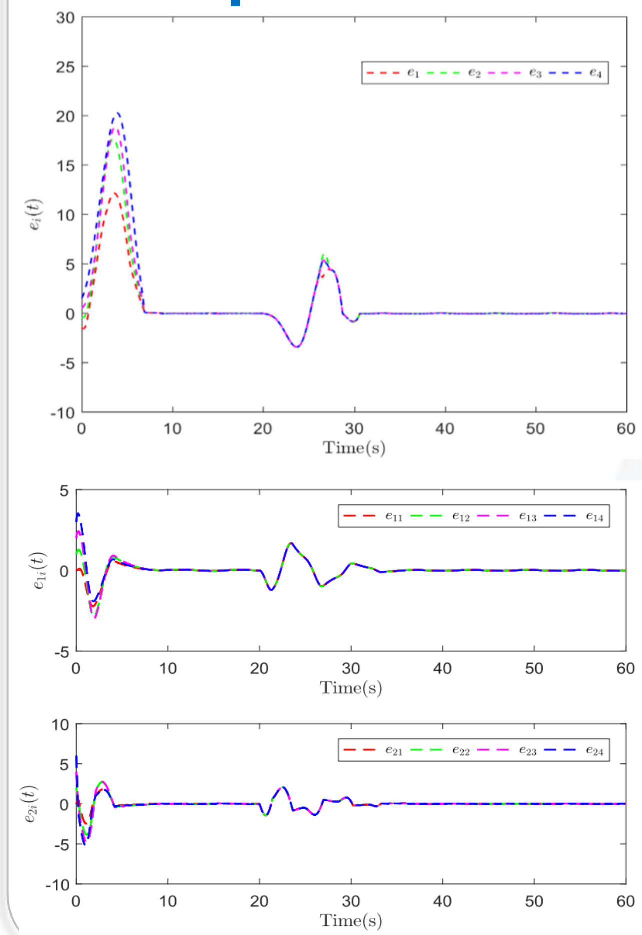
$$\dot{v}_i(t) = S_i(t)v_i(t) - c_3K\xi_i(t)$$
$$-c_4 sign\big(K\xi_i(t)\big) - c_5 sig\big(K\xi_i(t)\big)^2$$

- Adaptive Fault-Tolerant Controller

$$\boxed{u_i(t)} = -\frac{\hat{d}_{2i}^2(t)\parallel v_i(t)\parallel^2 B^T P_2\varphi_i(t)}{\hat{d}_{2i}(t)\parallel \varphi_i^T(t)P_2B\parallel\parallel v_i(t)\parallel + \epsilon(t)}$$
$$-\hat{d}_{1i}(t)B^TP_2\varphi_i(t) - \frac{\hat{\hat{f}}_i^2(t)B^TP_2\varphi_i(t)}{\hat{\hat{f}}_i(t)\parallel \varphi_i^T(t)P_2B\parallel + \epsilon(t)}$$

Tolerant multi-faults

Experimental Results



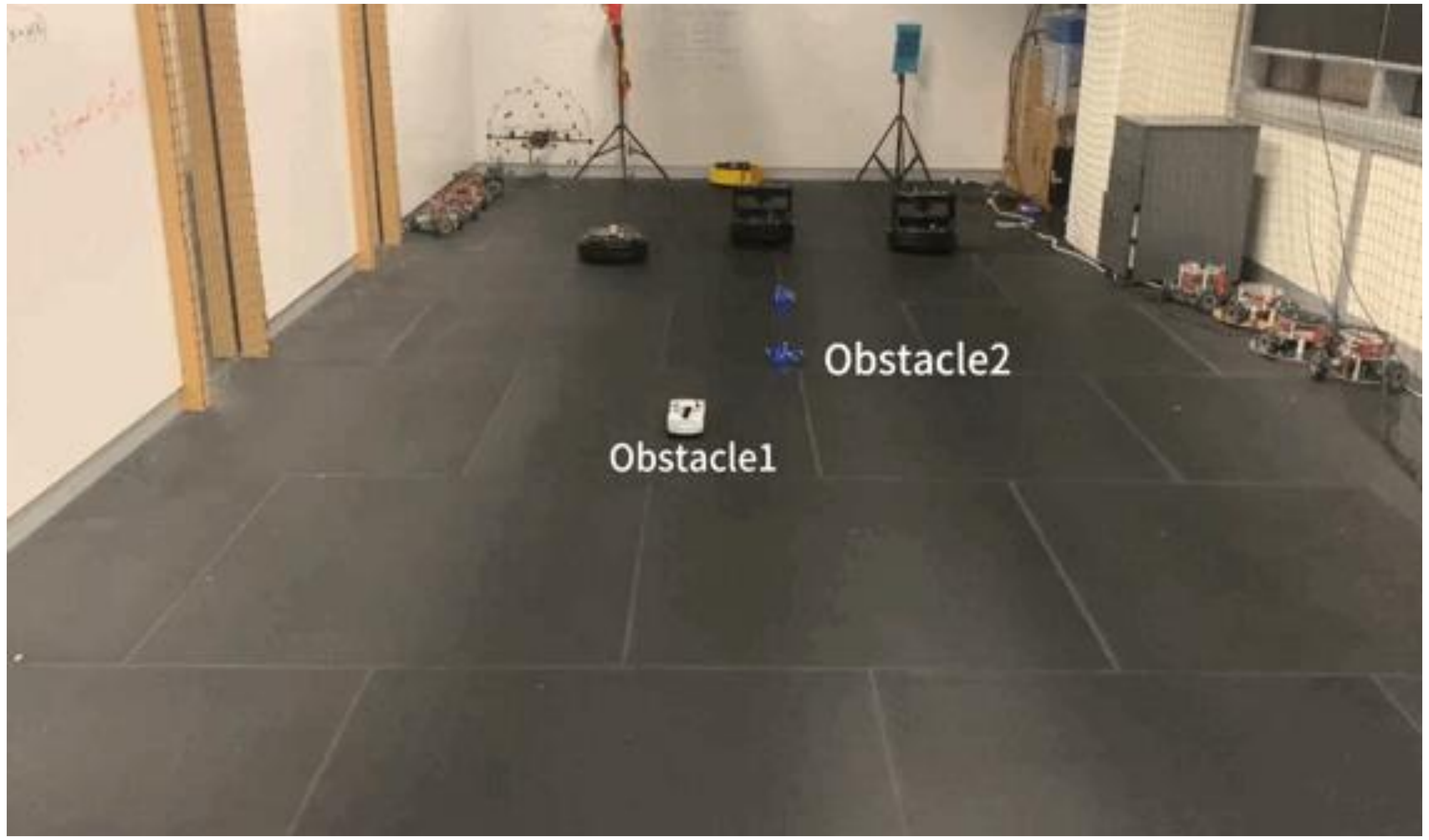
- Improved resilience to **all 3 faults**
- Fixed-time convergence **regardless** of **initial conditions**
- **Quicker** observation speed, **Higher** precision, **More robust**

Enable fast and adaptive fault-tolerant control under multi-faults

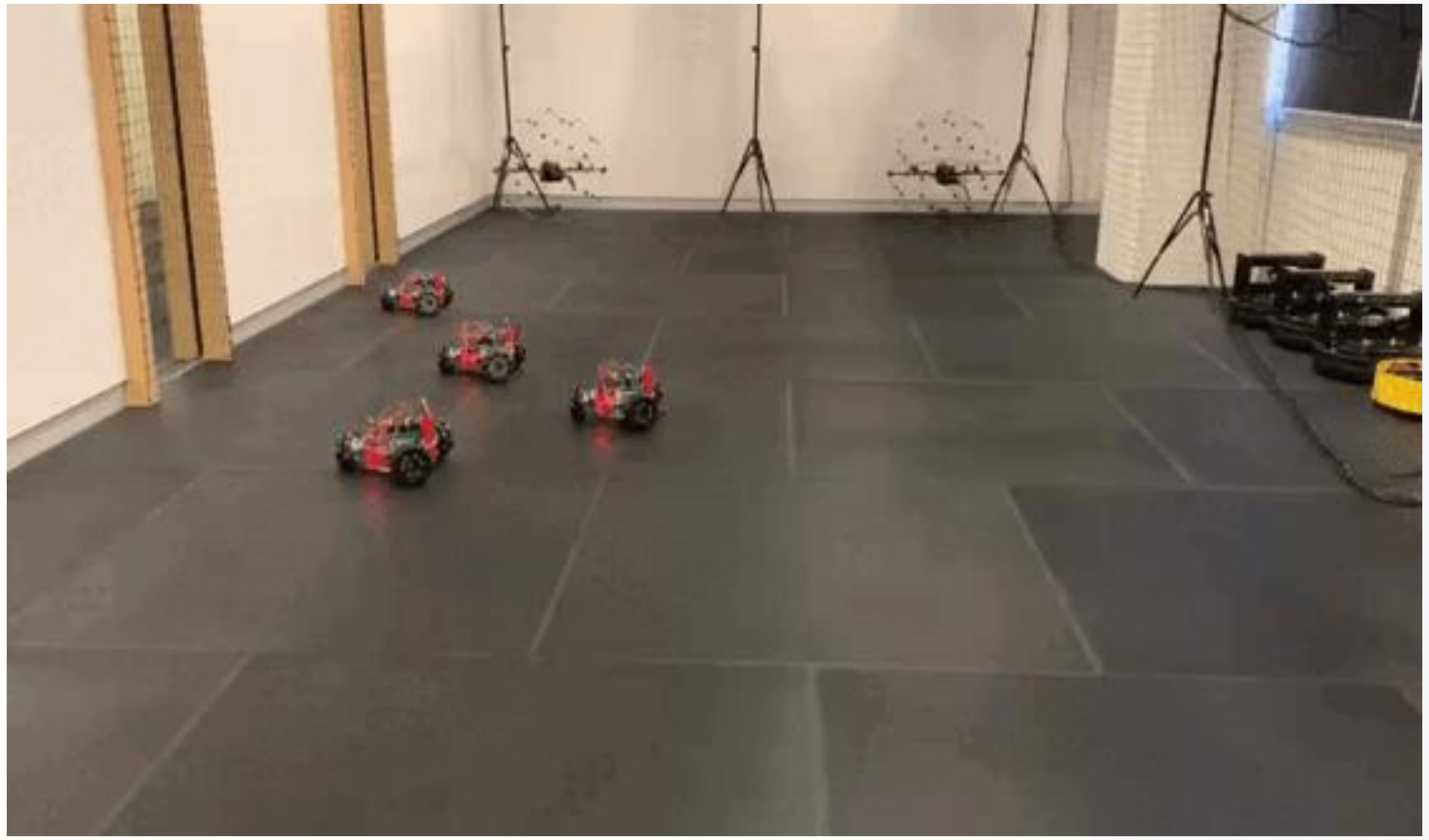
IEEE TCNS, 2022, 9(2): 845-855; JFI, 2019, 356(12):6547-6570

2.3 Model-Based Control under Physical-Layer Constraints

- **Verifications — applied to heterogeneous systems and omnidirectional rovers**



UAV-UGV collaborative area scanning under non-cooperative obstacles



Omnidirectional rover formation for area searching under faults

Reliable Cooperation Overcome → **Chall.2 Physical-layer: Unsafe cooperation**

THE UNIVERSITY of ADELAIDE

Outline

1) Introduction and Challenges of CPMAS

2) Model-Based Control in CPMAS

3) AI-Empowered Approaches for CPMAS

4) Future Research Directions in CPMAS

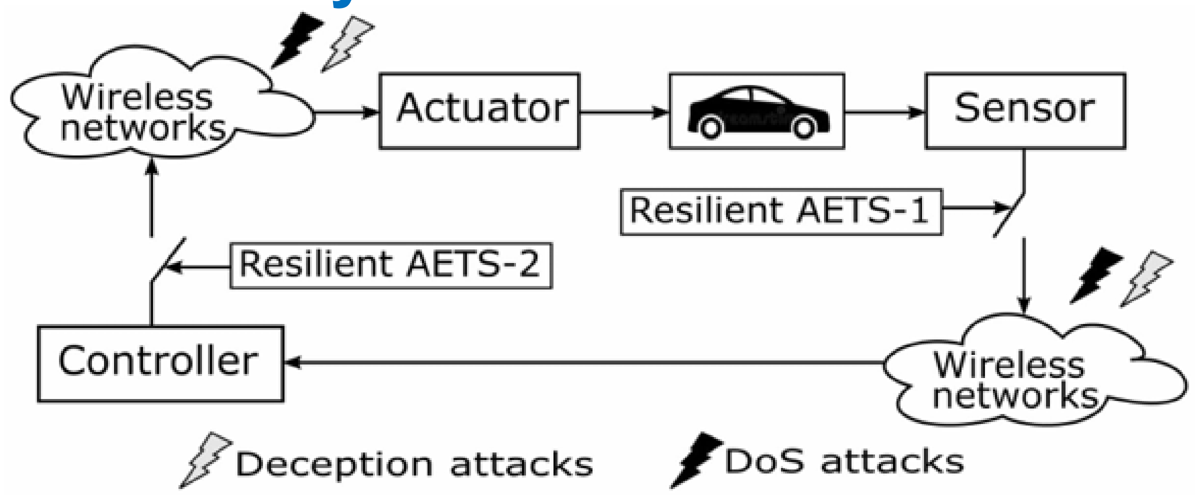
3. AI-Empowered Cooperative Control

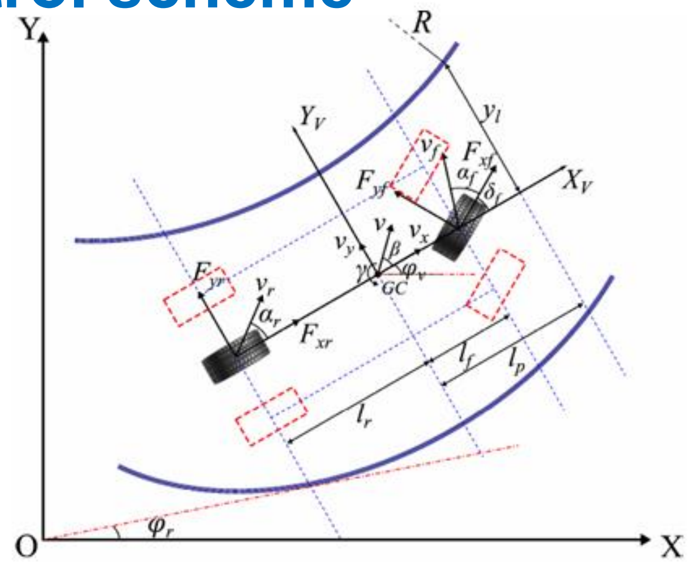
(1) Fuzzy control for MAS under hybrid cyber-attacks

Technical Hurdles
- Hybrid cyberattacks in both S-C and C-A channels are difficult to model
- Hybrid cyberattacks complicate event-triggered control design

Key Idea

Hybrid Attack Model and control scheme





S-C channel

$$y(t)=\begin{cases} b_s(t)F_s(t)+\big(1-bs(t)\big)y(t), & t\in I_{1,n} \\ \emptyset, & t\in I_{2,n} \end{cases}$$ DoS

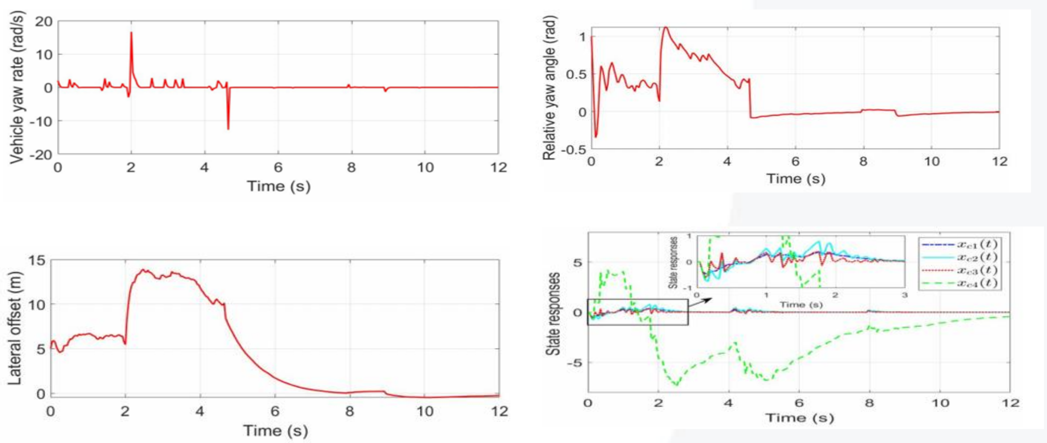
C-A channel

$$u(t)=\begin{cases} b_c(t)F_c(t)+\big(1-bc(t)\big)u_c(t), & t\in I_{1,n} \\ \emptyset, & t\in I_{2,n} \end{cases}$$ FDI

- Controller design

$$u(t)=\begin{cases} \sum_{j=1}^{2}\hbar_j(\eta_h(t_h^s h))\,\big(bc(t)C_j^c f_c(x_c(t_{g,n}^c h)\big) \\ +\big(1-bc(t)\big)C_j^c x_c(t_{g,n}^c h), & t\in L_{1,n}\cap Q_{k,n}^c \\ \emptyset, & t\in I_{2,n} \end{cases}$$

Experimental Results



Methods	The proposed AETS	ETS 1	ETS 2
Threshold σ_s and σ_c	0.05 , 0.2	0.05 , 0.05	0.2 , 0.2
TN from S-C	31	29	17
TN from C-A	78	140	56
Total TN	109	169	73
Transmission rate	36.3%	56.3%	24.3%

- **Accurate path tracking**
- **Good control performance,**
- **Improved network utilization**

Ensure distributed autonomous control in insecure network environment

IEEE TCYB, 2023, 53(4): 2600-2609; IEEE TFS, 2022, 30(9): 3940-3951

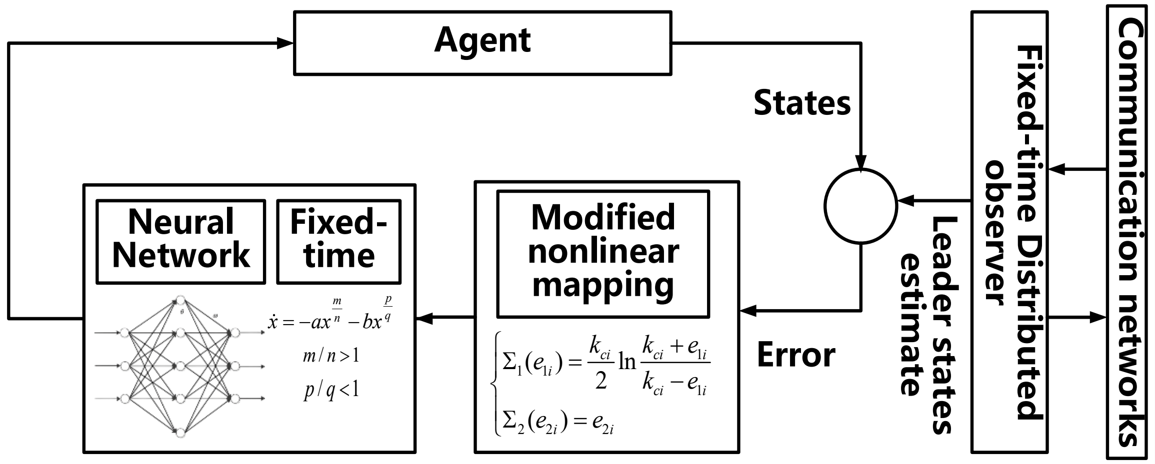
3. AI-Empowered Cooperative Control

(2) Fixed-time neural network control under physical constraints

Technical Hurdles
- Simultaneous handling of multiple constraints complicates controller design
- Existing methods cannot guarantee fixed-time performance

Distributed control framework

Constrained environment and unknown dynamics



Distributed observer-based framework for physical constraints and unknown dynamics

Fixed-time NN Control

- Neural network approximation

$$(f_i(x_i) - f_0(x_0) + (\boxed{g_i(x_i)} - 1)u_i + d_i)$$

Unknown sign

$$\le \sqrt{r+3}\,\|\bar{\Theta}_i\|$$

$$\le \frac{1}{2}\left(\frac{m_{\min}}{m_{\max}}(r+3) + \frac{m_{\max}}{m_{\min}}\|\bar{\Theta}_i\|^2\right)$$

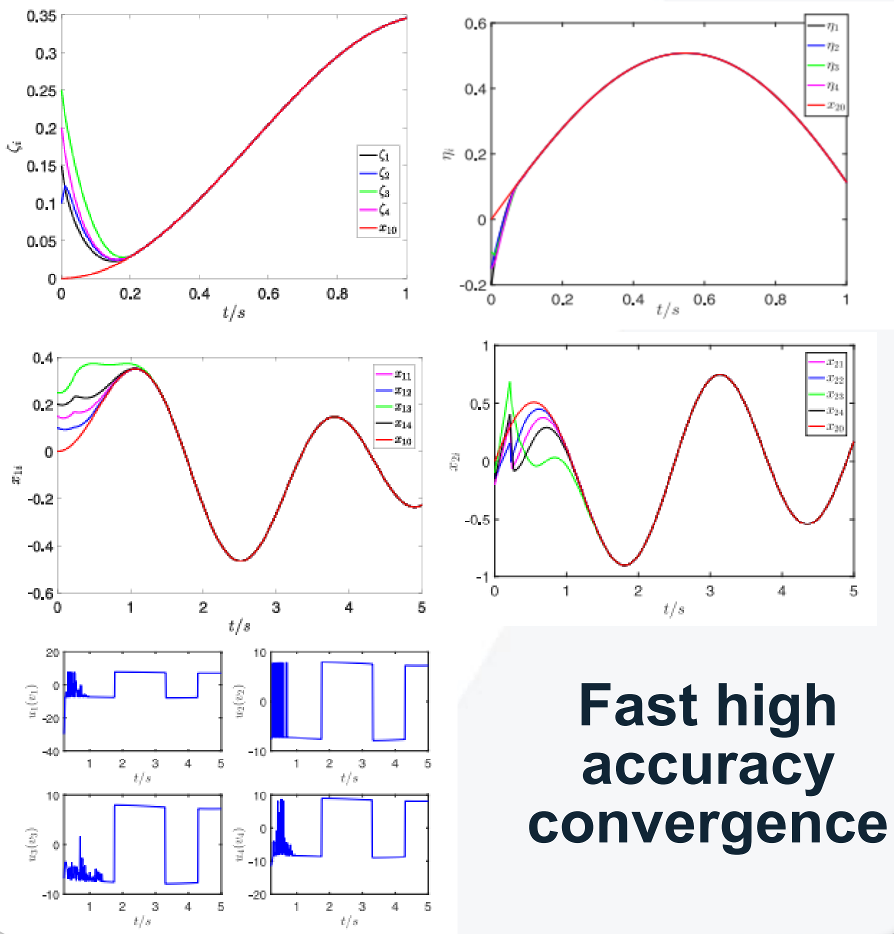
- Fixed-time control

$$u_i^* = -\left(\frac{m_{\min}}{2m_{\max}}\hat{\Pi}_i + \frac{m_{\max}}{2m_{\min}}(r+3) + \delta_i\right)\mathrm{sign}(\xi_2) - (k_2 + l_2(1+\xi_2^2) + \chi_1(\xi_1) + \chi_2(\xi))[\xi_2]^{1/q_3}$$

$$\boxed{v_i = \frac{u_i^*(v_i) - \Psi_i\,\mathrm{sign}(\xi_2)}{m_{\min}}}$$

Deadzone inverse

Experimental Results



Fast high accuracy convergence

Enable distributed autonomous control in constrained environment

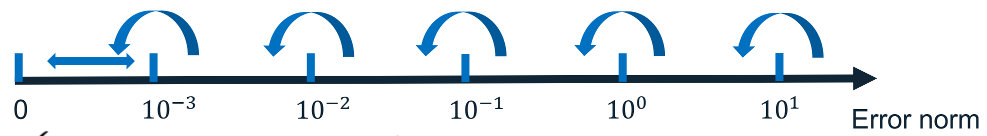
IEEE TCYB, 2021, 51(4): 1835-1848; IEEE TSMCA, 2021, 51(12):7903-7918

3. AI-Empowered Cooperative Control

(3) Uncertainty estimation based on neural networks

Technical Hurdles
- Static parameters induce chattering
- Saturated systems cause delay and oscillation

Fractional Sensitivity Parameters



$$\gamma_i = \begin{cases} \gamma_{i,1} & \|x_i - \widehat{x}_i\| \in [10^{c_v-1}, +\infty) \\ \gamma_{i,2} & \|x_i - \widehat{x}_i\| \in [10^{c_v-2}, 10^{c_v-1}) \\ \vdots & \vdots \\ \gamma_{i,j} & \|x_i - \widehat{x}_i\| \in [10^{c_v-j}, 10^{c_v-j+1}) \\ \vdots & \vdots \\ \gamma_{i,n_v} & \|x_i - \widehat{x}_i\| \in [0, 10^{c_v-n_v+1}) \end{cases}$$

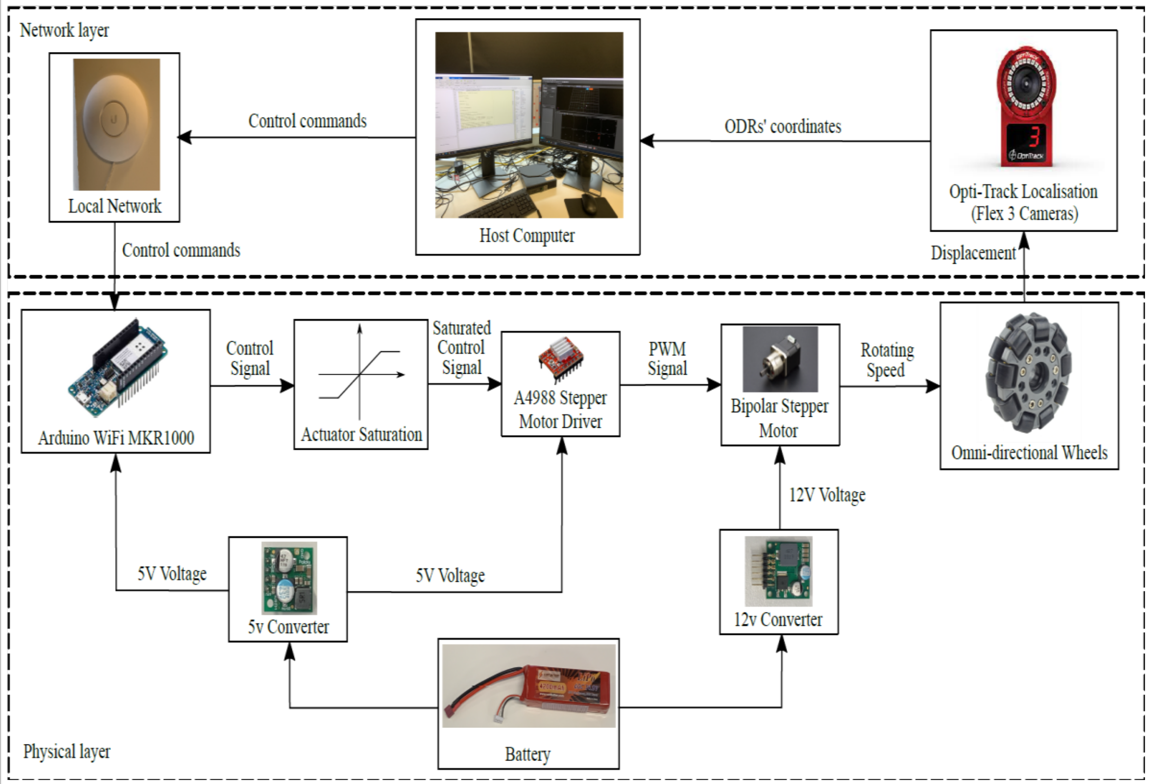
Balance estimation accuracy and system stability

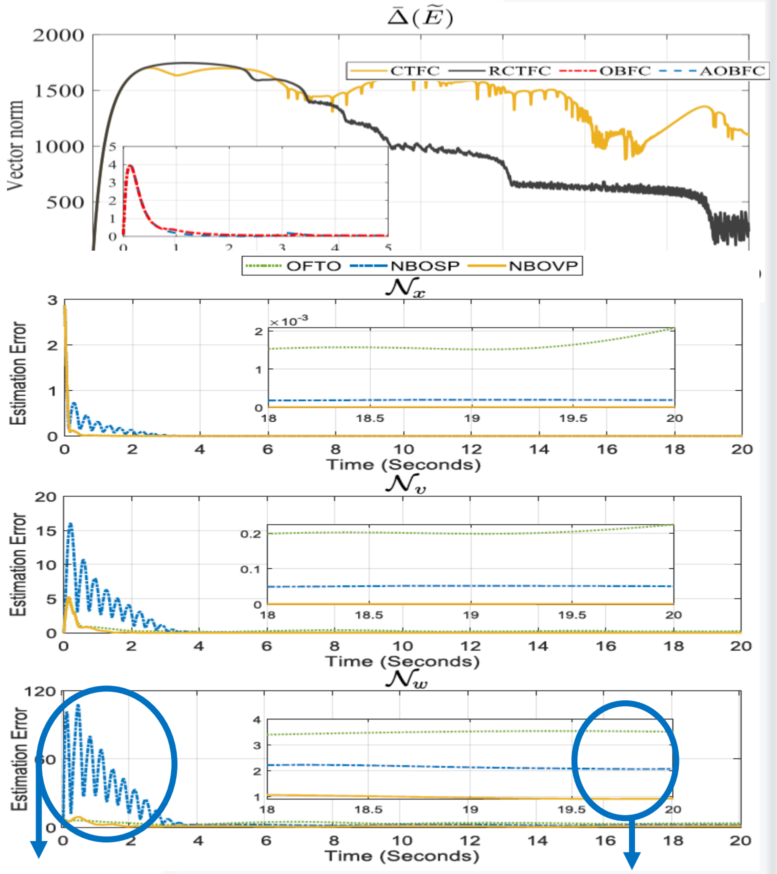
Neural-Based Observer

- Actual model $\dot{x}_i = g_i u_i + w_i$
- Fictitious system $\dot{\hat{x}}_i = g_i u_i - \tilde{x}_i + \widehat{W}_i^{\mathrm{T}} \varphi_i(Y_i)$
- Adaptive law $\dot{\widehat{W}}_i = \gamma_1 \varphi(Y_i) \tilde{x}_i^{\mathrm{T}} - \gamma_2 \|\tilde{x}_i\| \widehat{W}_i$

Achieve a faster & more stable tuning process

Experimental Results





Less chattering

Higher precision

Improve uncertainty estimation performance and accuracy

IEEE TNNLS, 2021, 34(8): 4286-4295; Nonlinear Dynamics, 2022, 108(4): 3693-3709

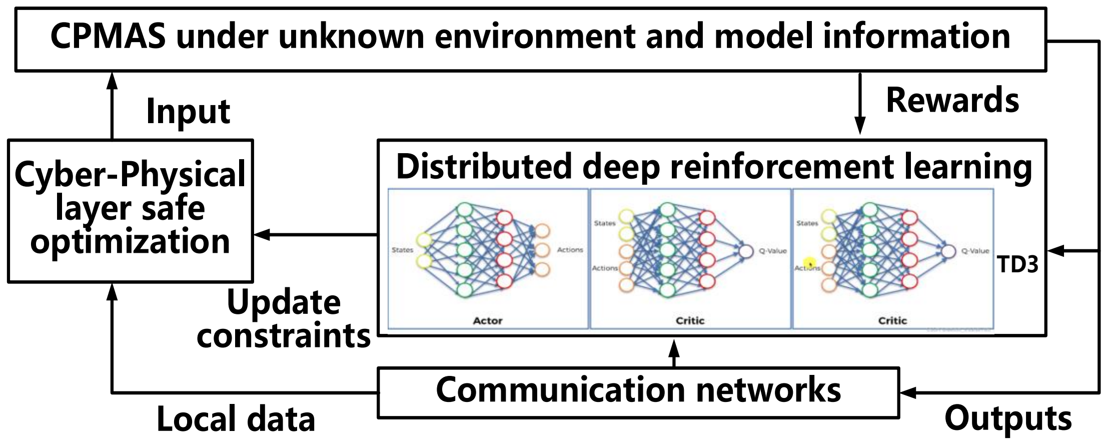
3. AI-Empowered Cooperative Control

(4) Distributed safe reinforcement learning and control optimization

Technical Hurdles
- Unknown environment and model limit traditional methods
- Distributed systems hinder safe coordination and optimization

Distributed Deep RL Framework

Unknown environment and model



Distributed policy learning for unknown model and environment variations

Safe Optimization Strategy

- Distributed control optimization

$$u_i^\star = \arg\min_{u_i} |u_i - u_i^{\mathrm{ref}}|^2$$

$$\text{s.t.} -\dot{\hat{h}}_{ij} \le \frac{a_i}{a_i + a_j}\gamma_h h_{ij}^3, \forall j \in \mathcal{O}_i \cap \mathcal{M}$$

$$-\dot{\hat{h}}_{ik} \le \gamma_h h_{ik}^3, \forall k \in \mathcal{O}_i \setminus \mathcal{M}$$

- Reward function for DDRL

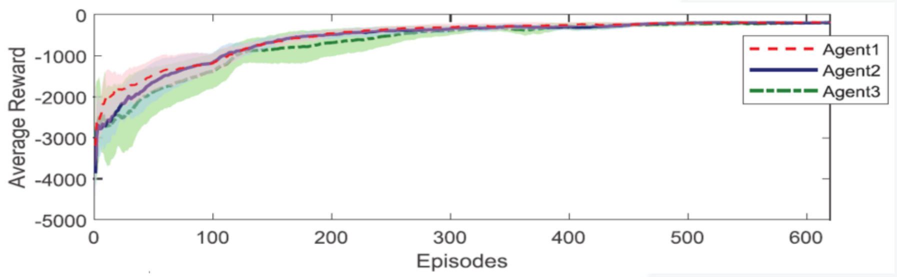
$$R = -\sum_{j\in\mathcal{O}_i\cap\mathcal{M}} \left|\dot{h}_{ij} - \widehat{h_{ij}} - \boxed{\widehat{h_{ji}}}\right|^2 - \sum_{k\in\mathcal{O}_i\setminus\mathcal{M}} \left|\dot{h}_{ik} - \boxed{\widehat{h_{ik}}}\right|^2 - \boxed{P_c}$$

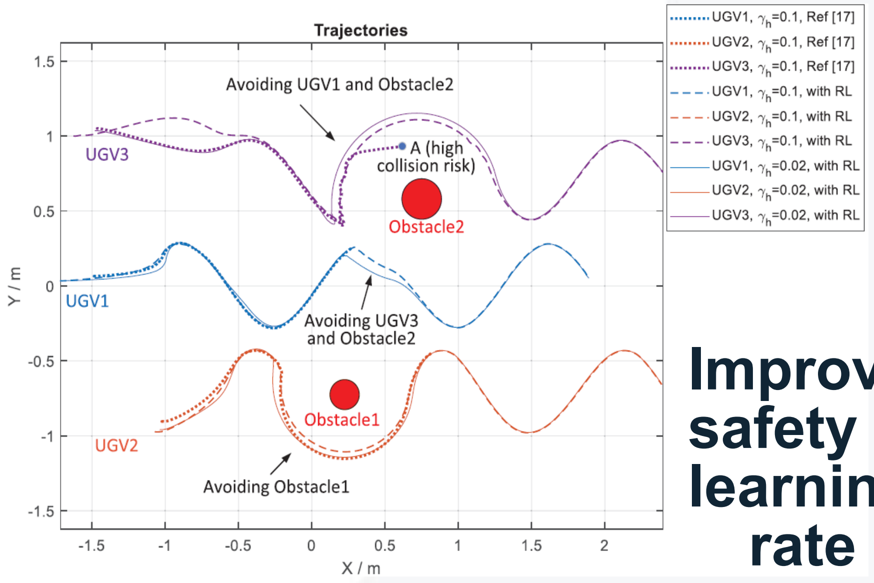
Local data

Env changes

Safety penalty

Experimental Results





Improve safety & learning rate

Empower distributed autonomous optimization in complex environment

IEEE TNNLS, 2025, 36(2): 2777-2788; IEEE TSMCS, 2024, 54(8):4876-4886

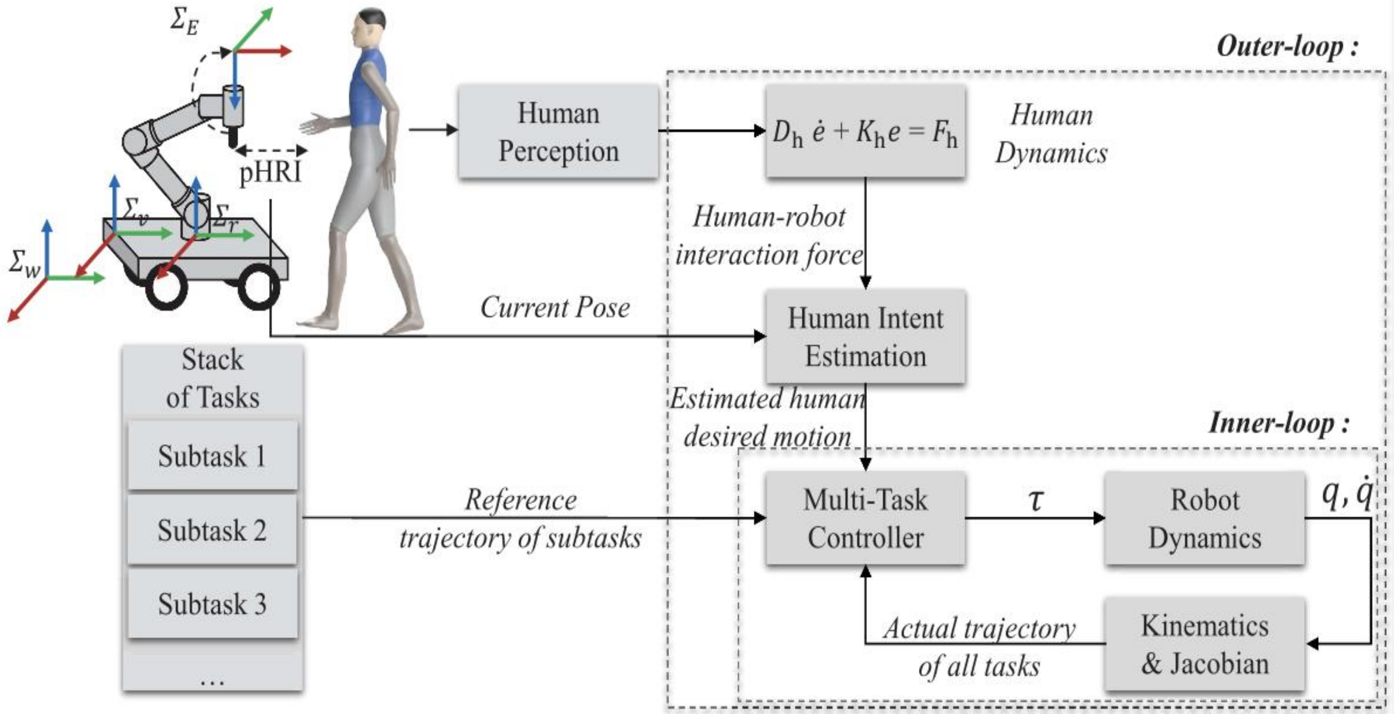
3. AI-Empowered Approaches

(5) Fuzzy-based control for human-machine collaboration

Technical Hurdles

- Hierarchical fuzzy control integrates human intention estimation and multi-task coordination
- Unmeasurable intention, task interference, and uncertain robot dynamics

FLS-based Multitask Control Framework



An outer loop estimates human intent with fuzzy logic, while an inner loop uses adaptive fuzzy control and null-space projection for prioritized multitask execution.

Fuzzy-Based Control Strategy

- Outer-loop: Human Intention Estimation

$$[x_{hd}^T, \dot{x}_{hd}^T, k_h^T, d_h^T]^T = W_d^T h_{d(u_d,c_d,\sigma_d)} + \epsilon_d$$

- Inner-loop: Task-Space Mapping

$$\dot{x}_i = J_i(q)\dot{q}$$

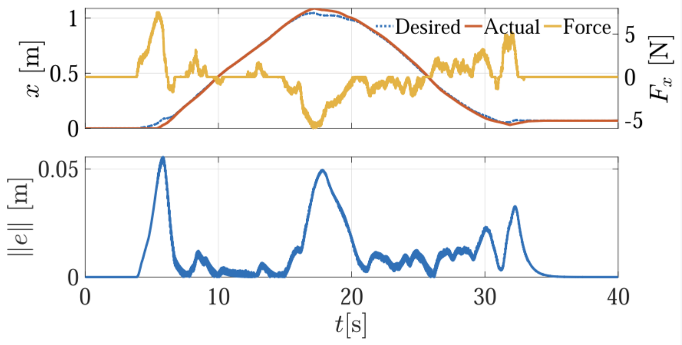
- Inner-loop: Adaptive Fuzzy Control Law

$$F_{ctrl} = K_v r + \hat{W}_\Psi^T h_\Psi + K_r sgn(r) + F_v$$

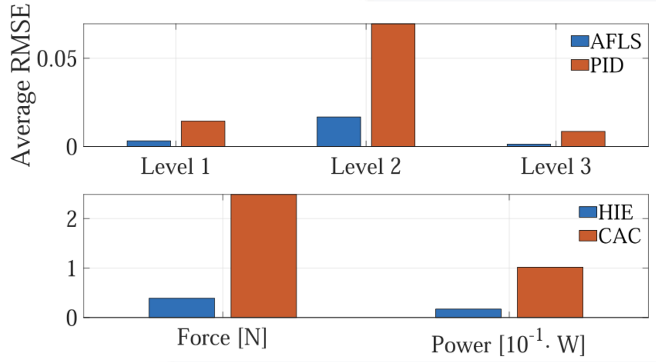
- Inner-loop: FLS Weight Tuning

$$\dot{\hat{w}}_{\Psi i} = \beta_{\Psi i}(h_\Psi r_i - \delta_{\Psi i}\|r\|\hat{w}_{\Psi i})$$

Experimental Results



Effective trajectory tracking



Prevail over the PID controller on multitask tracking

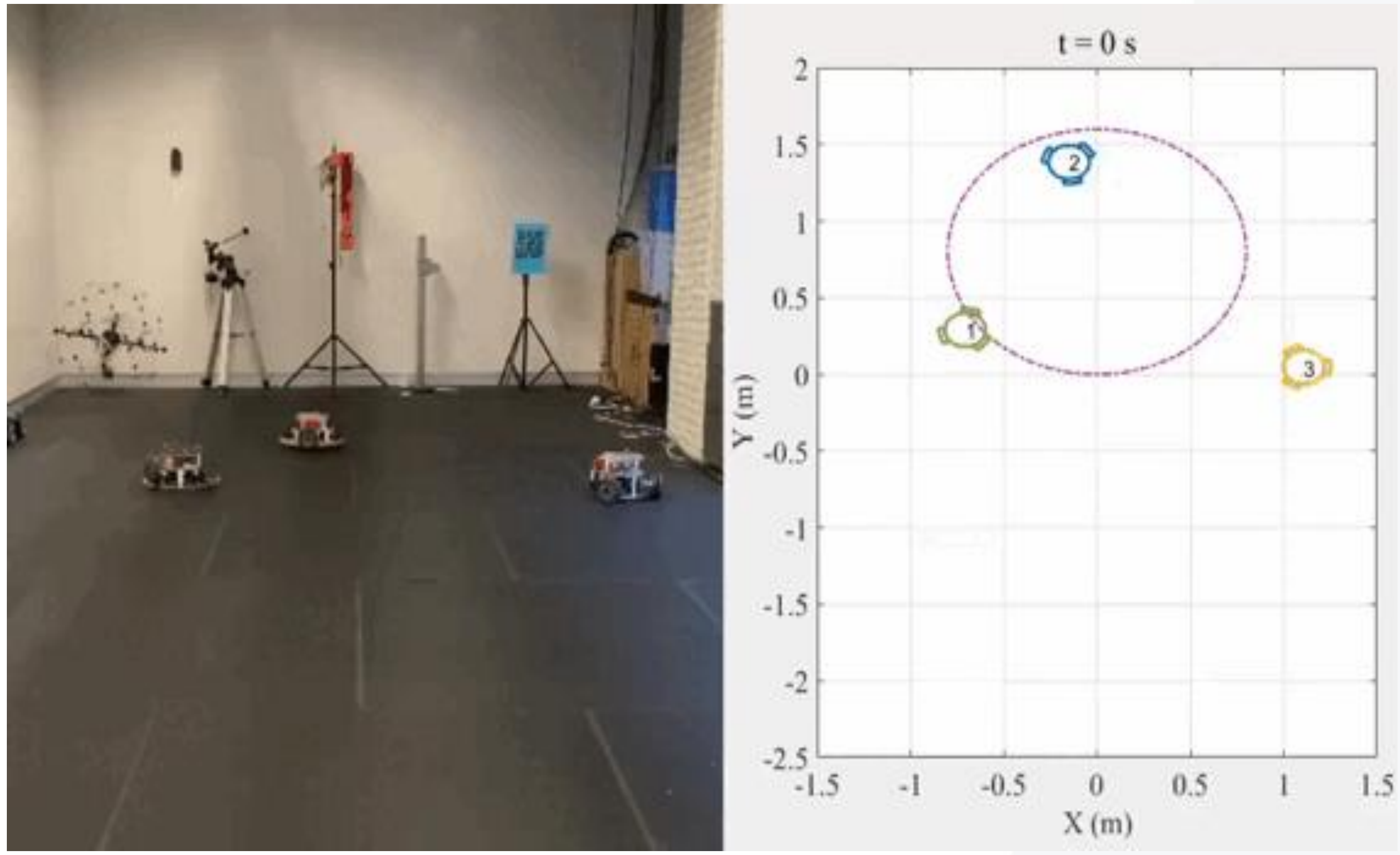
Enable adaptive human-robot collaboration with unified intention estimation and multi-task control

IEEE TFS, 2024, 32(10): 5802–5814

3. AI-Empowered Approaches

- **Verifications — applied to drone swarms and multi-robot systems**

Done swarm passing through a bounded window



Formation control in the networked multi-robot system

Autonomous optimization Overcome → **Chall.3 Both layers: low autonomy**

Outline

1) Introduction and Challenges of CPMAS

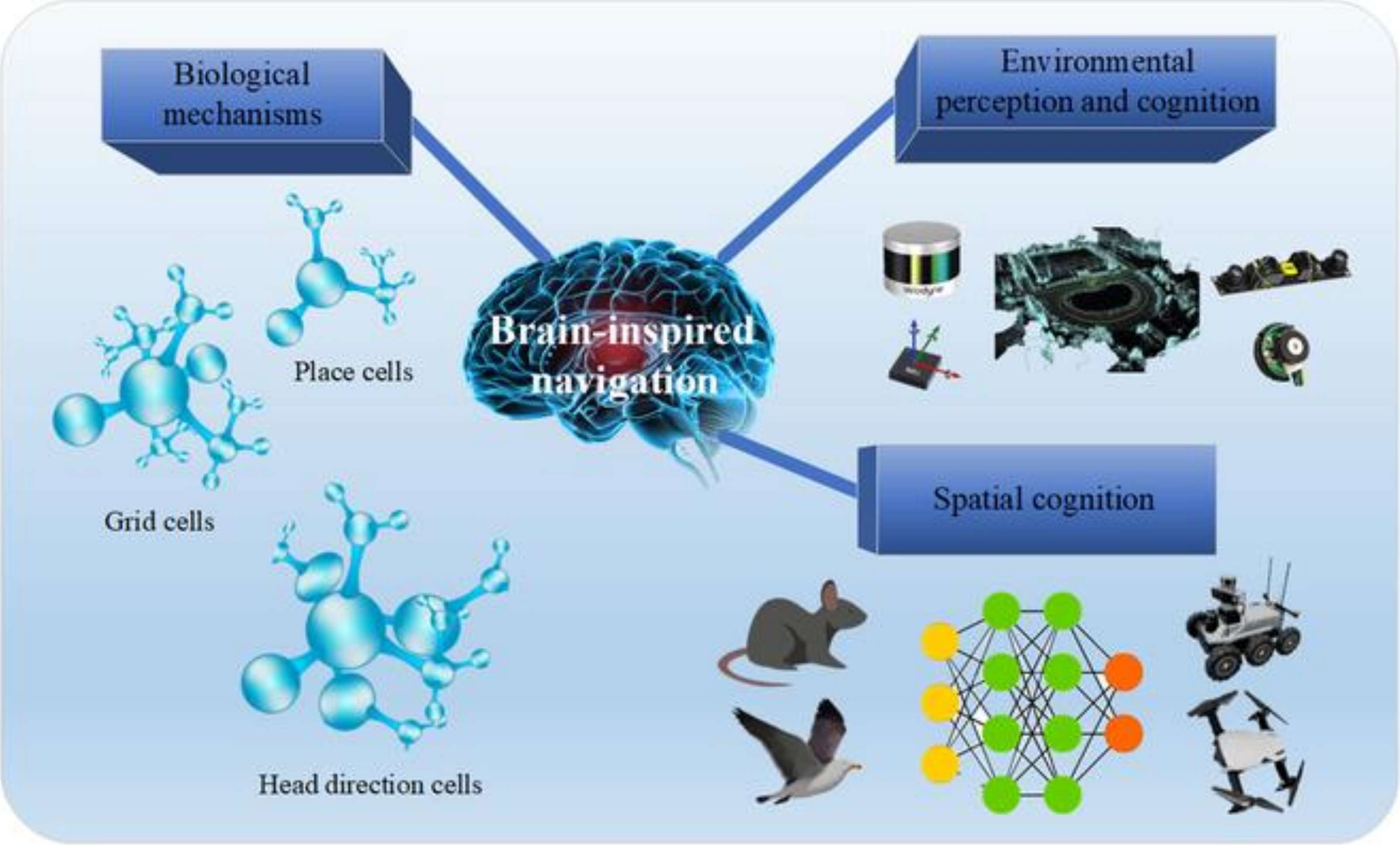
2) Model-Based Control in CPMAS

3) AI-Empowered Approaches for CPMAS

4) Future Research Directions in CPMAS

4 What's next ?

(1) Brain-inspired human-cyber-physical collaborative intelligence



Brain-inspired navigation

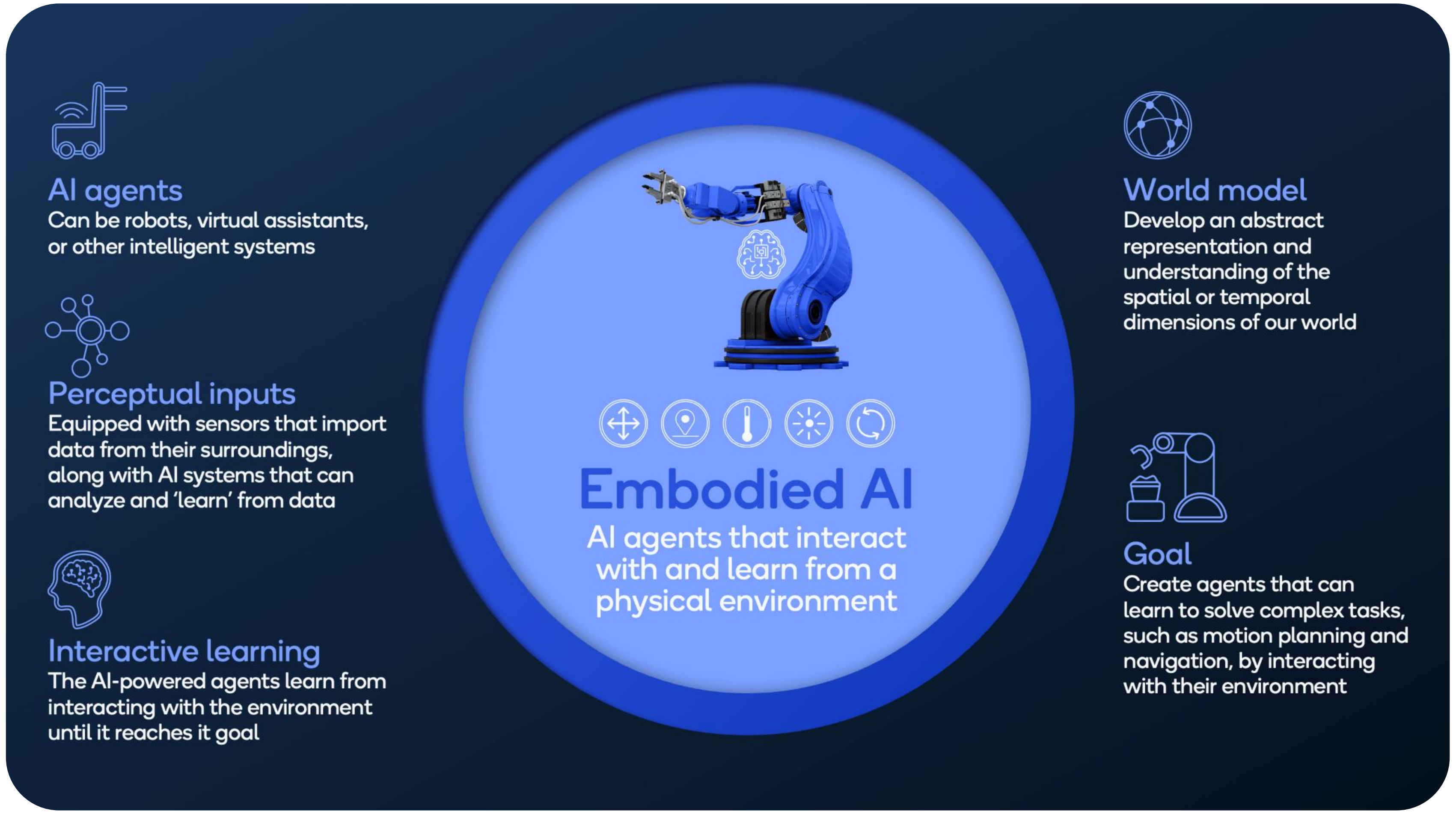
Source from: https://spj.science.org/doi/10.34133/cbsystems.0128

Human-cyber-physical collaborative Combat

THE UNIVERSITY of ADELAIDE

4 What's next ?

(2) Multimodal embodied perception and co-decision among agents



Embodied AI

Large language models enabled space exploration

Source from: https://www.qualcomm.com/news/onq/2023/09/embodied-ai-how-do-ai-powered-robots-perceive-the-world

4 What’s next ?

(3) Explainable and trustworthy autonomy architecture

Companion robots for emotional support

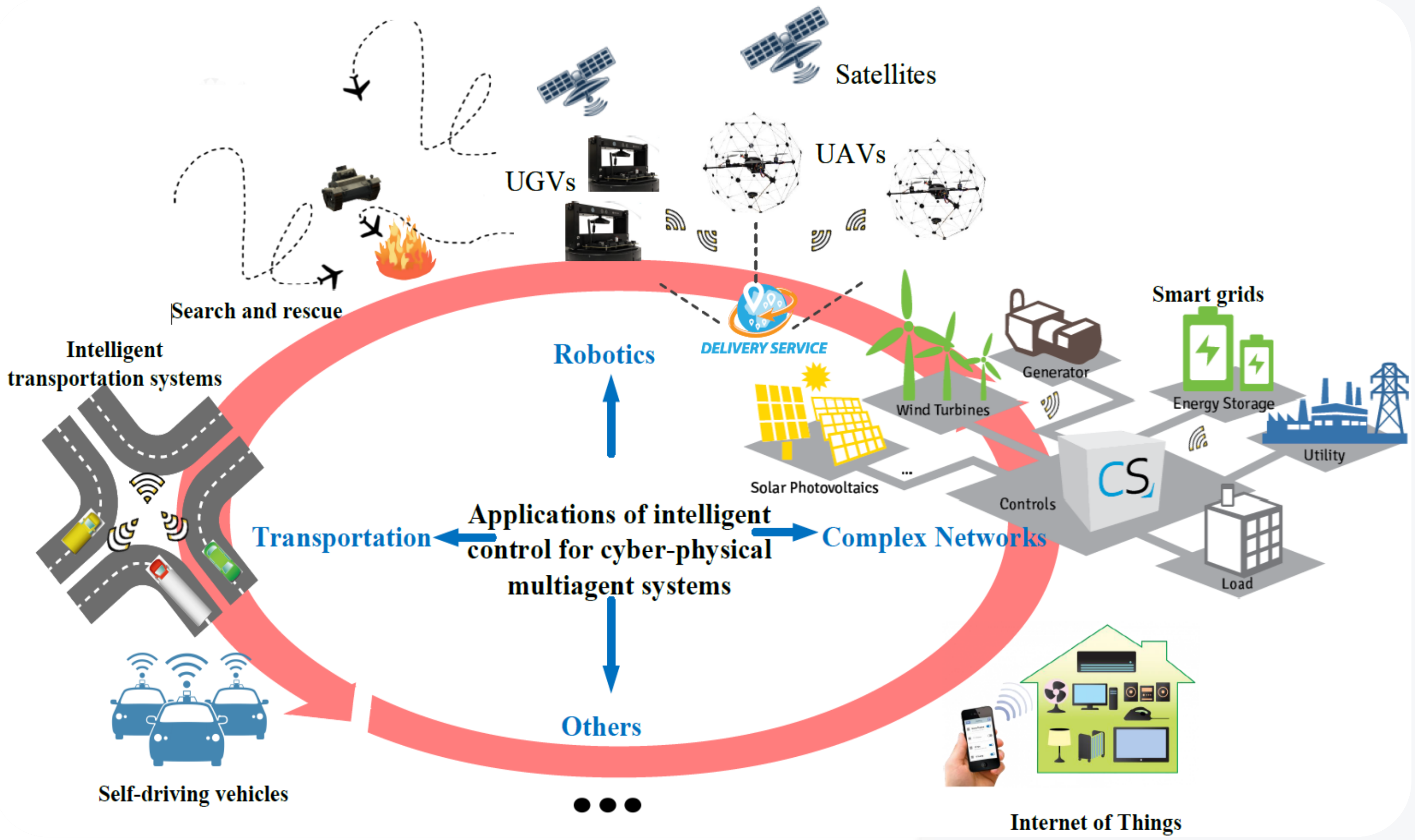
Trust intelligent healthcare systems

Source from: https://www.forbes.com/sites/williamhaseltine/2023/10/06/the-needles-edge-autonomous-robotic-surgery-and-its-implications-for-medicine/

4 What's next ?

4.4 Large-scale heterogenous CPMAS control and cross-field applications

Large-scale CPMAS in smart cities



Cross-field application

THE UNIVERSITY of ADELAIDE

Acknowledgement

Bing Yan

Xin Yuan

Md Tagor Hossain

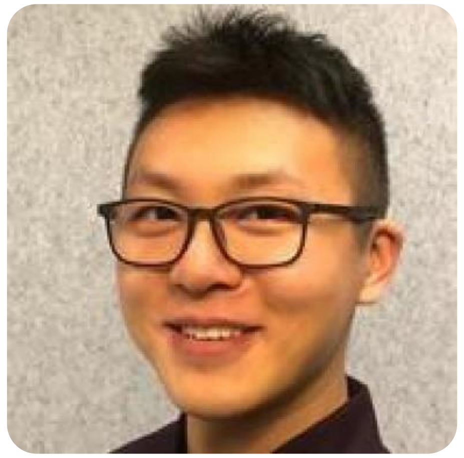
Kamal Mammadov

Yize Yang

Daotong Zhang

Acknowledgement

Zhi Lian



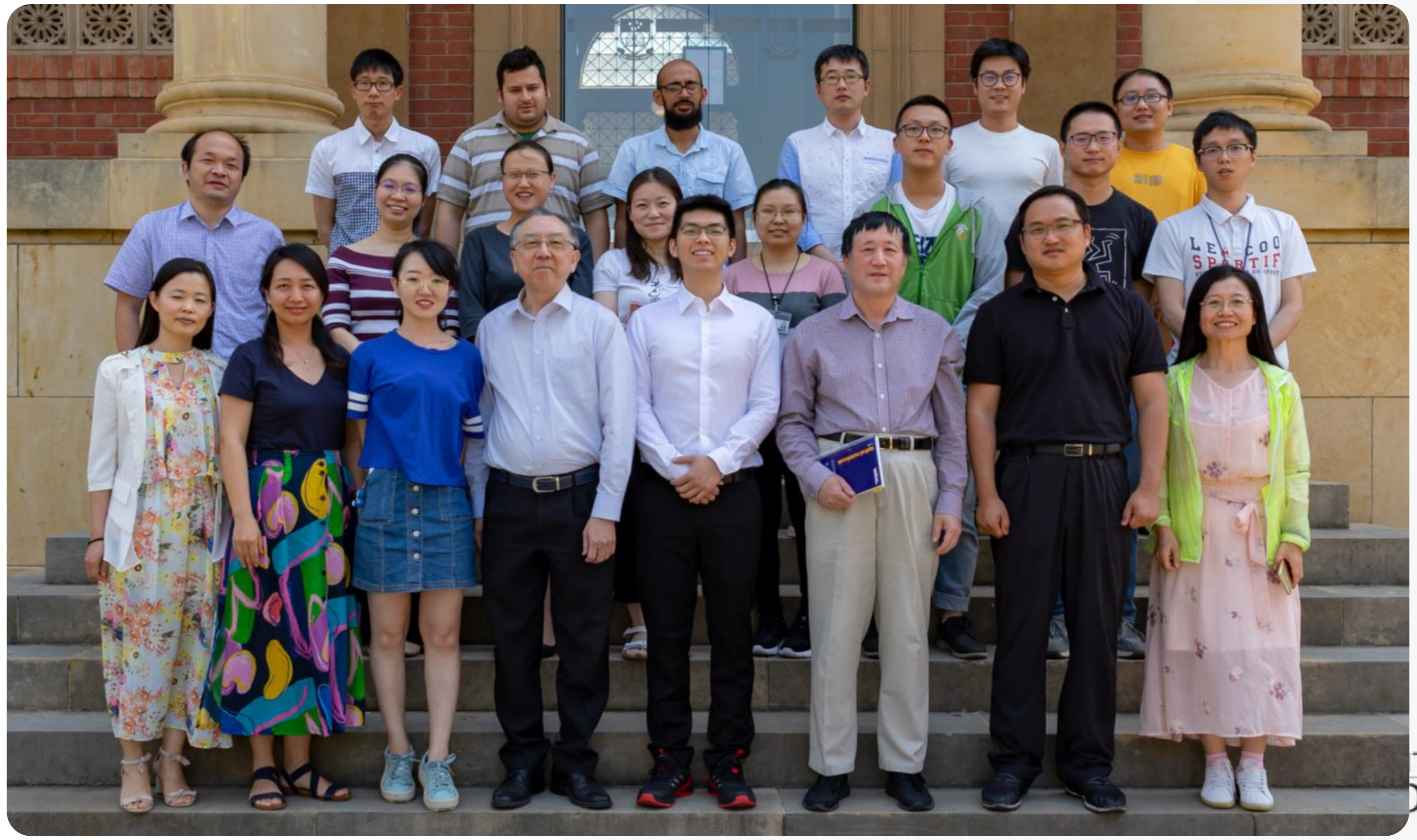
Yang Fei

Saeed Aslam

Yuan Sun

Syed Imranul Islam

Isira Naotunna



Thank you so much for your listening!

THE UNIVERSITY *of* ADELAIDE