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NUS National University of Singapore

On Intelligent Autonomous Robotics

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https://nusgs.nus.edu.sg/thesis-advisors/elegesz

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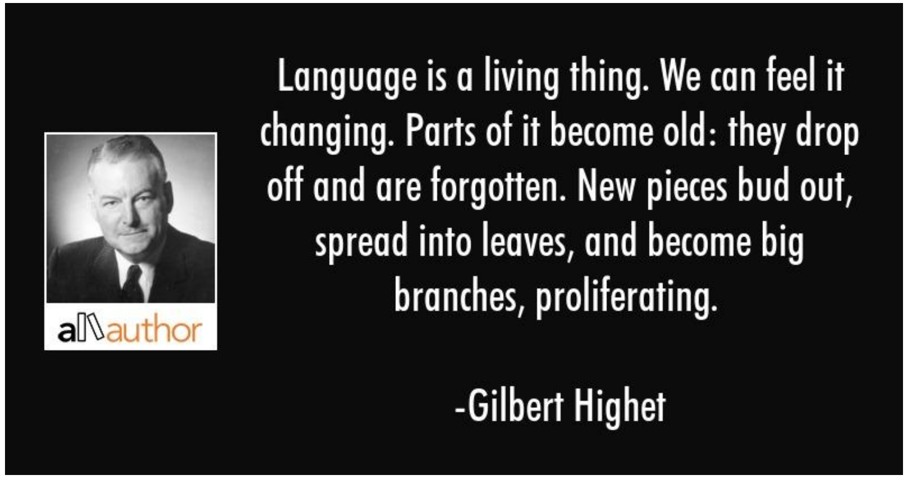
a. What is the Problem?

I. Language is a living thing!
II. Knowledge is a living thing.
III. Robot is a living thing!
IV. AI is a living thing.
V. ….



VI. To Learn to Live vs Life-Long Learning

1. Evolution of Robotics

Robotics is an interdisciplinary field that involves the design, construction, operation, and application of robots, as well as the development of their control systems, sensory feedback, and information processing.

Intelligent autonomous robotics refers to a specialized branch of robotics focused on the design, development, and study of robots that possess both intelligence and autonomy—meaning they can perceive their environment, process information, make decisions, and execute tasks with minimal or no human intervention.

a. What was a Robot?

Definition: A **robot** is a machine—especially one programmable by a computer—capable of carrying out a complex series of actions automatically.

A robot can be guided by an external control device, or the control may be embedded within. Robots may be constructed to evoke human form, but most robots are task-performing machines, designed with an emphasis on stark functionality, rather than expressive aesthetics.

https://en.wikipedia.org/wiki/Robot

a. What is a Robot?

Definition: A robot, nowadays, is an **intelligent system** which could not only carry out a series of complex tasks, but also can **make their own decisions** when under unknown conditions.

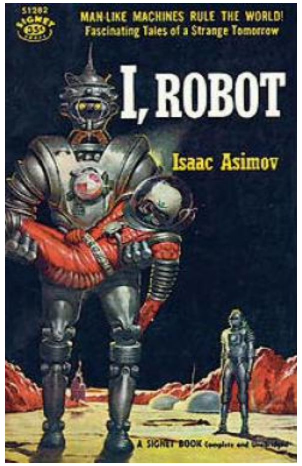
S.S. Ge, https://nusmods.com/courses/CEG5303/intelligent-autonomous-robotic-systems, 2023

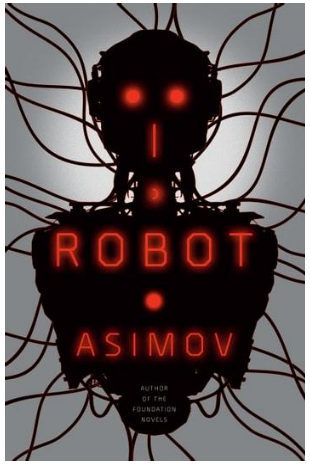
1. Evolution of Robotics

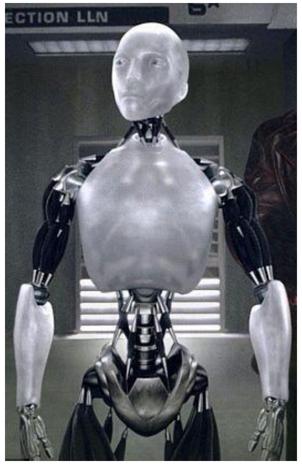
b. Historic Development of Robotics

Genesis Generation: Robotics from science fiction

Isaac Asimov coined the term “robotics” in 1942.





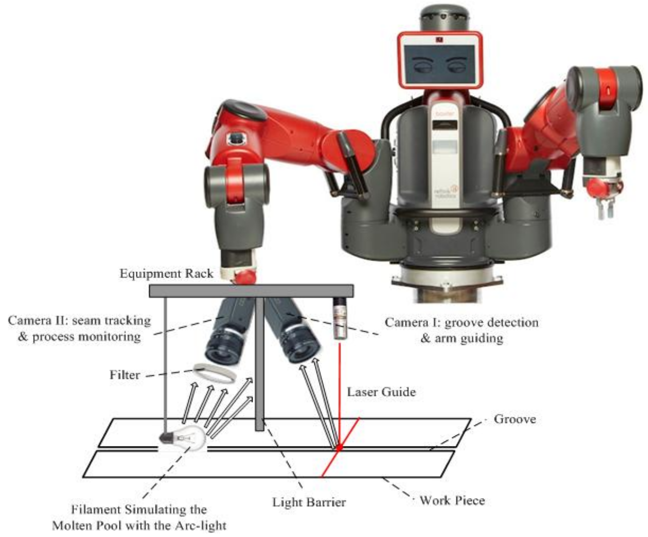


b. Historic Development of Robotics

1st Generation: Industrial Robotics: Robotic Arms/Manipulators (from 1970s)

50 Yrs old

"... a programmable, multifunction manipulator designed to move material, parts, tools, or specialized devices through variable programmed motions for the performance of a variety of tasks" Robot Institute of America (1980)

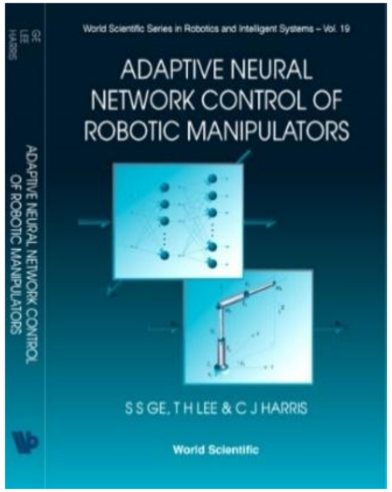


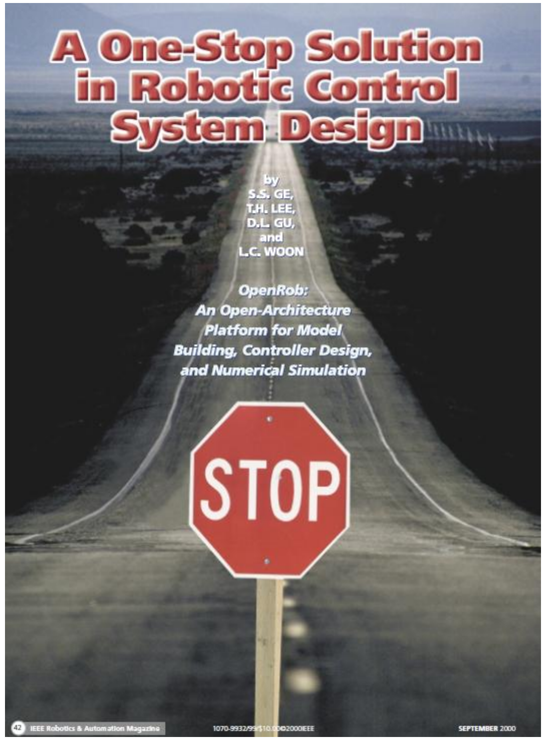
b. Historic Development of Robotics

1st Generation: Industrial Robotics (from 1970s)

Robotic arms for industrial automation

- Versatile, programmable
- The workhorse in the automation industry
- Release us from hard labor





The SMART system, Singapore

The SMART system is the first of its kind in the world for airfoil polishing.

National Technology Award, Singapore, 1999

http://www.kuka-robotics.com/china/zh/products/
http://www.abb.com/product/zh/9AAC100735.aspx

1. Evolution of Robotics

b. Historic Development of Robotics

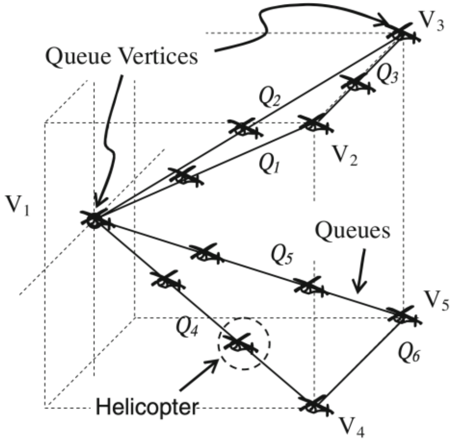
2nd Generation: Mobile Robotics (from 1990s)

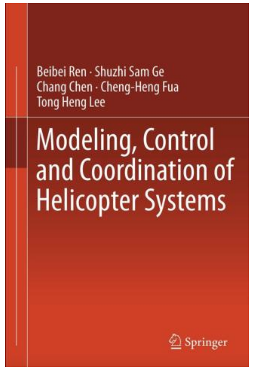
- On Land: Wheeled, Tracked, Legged, …
- In Air: Rotor Crafts, Helicopters, …
- Underwater: UUV, AUV, ROV, …

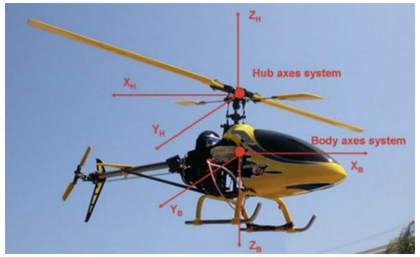
30 Yrs old

In mobile robotics this becomes 3 questions:

- Where am I ?
- Where am I going ?
- How do I get there ?





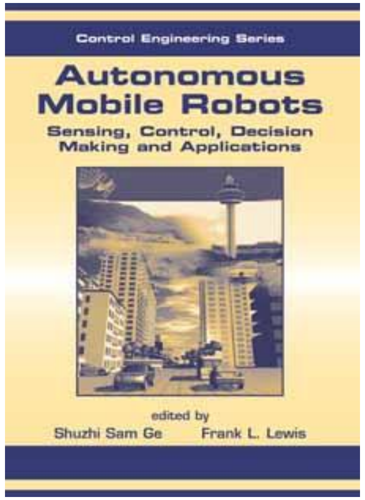


Ren B, Ge S S, Chen C, Fua C. Modeling, control and coordination of helicopter systems, Springer Science & Business Media, 2012.

1. Evolution of Robotics

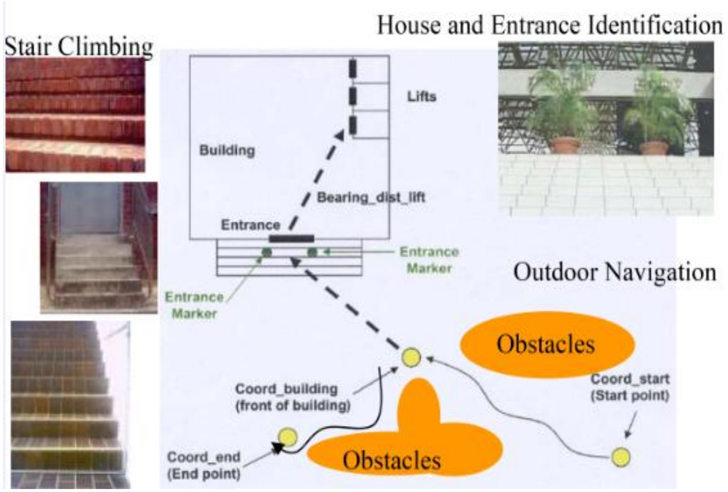
b. Historic Development of Robotics

2nd Generation: Mobile Robotics (from 1990s)



Autonomous Vehicle

- 3D Point Cloud Aided Precise Localization
- Hierarchical Topological Path Planning for Efficient Navigation
- Safety-Aware Motion Control Strategy



S.S. Ge and F.L. Lewis, Editors, Autonomous Mobile Robots: Sensing, Control, Decision-Making, and Applications, CRC Press, 2006.

1. Evolution of Robotics

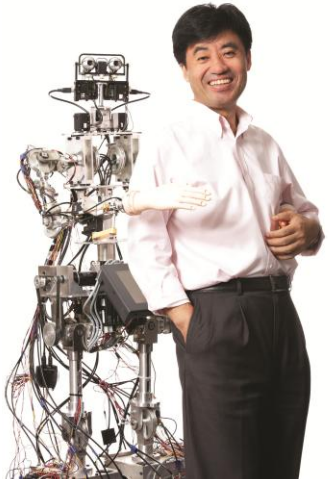
b. Historic Development of Robotics

3rd Generation: Social and Service Robotics (from 2000s)

Service Robots——a robot that performs useful tasks for humans or equipment **excluding industrial** automation application

Social Robots——a intelligent robot with **social attributes** as humans, being a part of our daily **lives in our society**.

20 Yrs old



Service Robotics

Social Robotics

Sophia , The world's first "robot citizen, Hanson Robotics

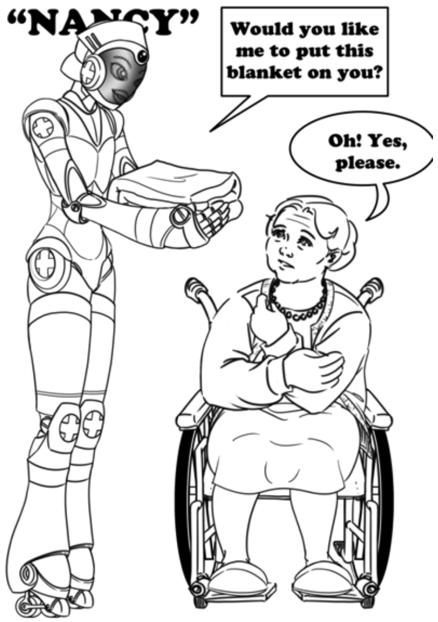
1. Evolution of Robotics

b. Historic Development of Robotics

3rd Generation: Social and Service Robotics (from 2000s)

The study of robots that are able to ***interact*** and ***communicate*** among ***themselves***, with ***humans***, and with the ***environment***, within the social and cultural structure attached to its role.

Shuzhi Sam Ge, Founding Editor-in-Chief
International Journal of Social Robotics, 2008
www.springer.com/12369



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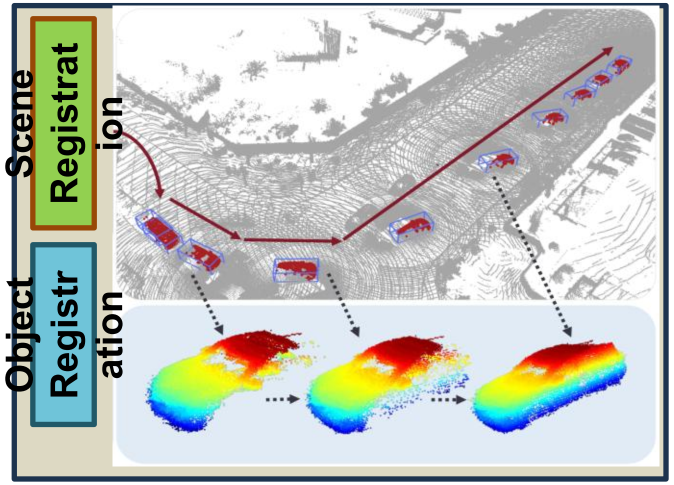
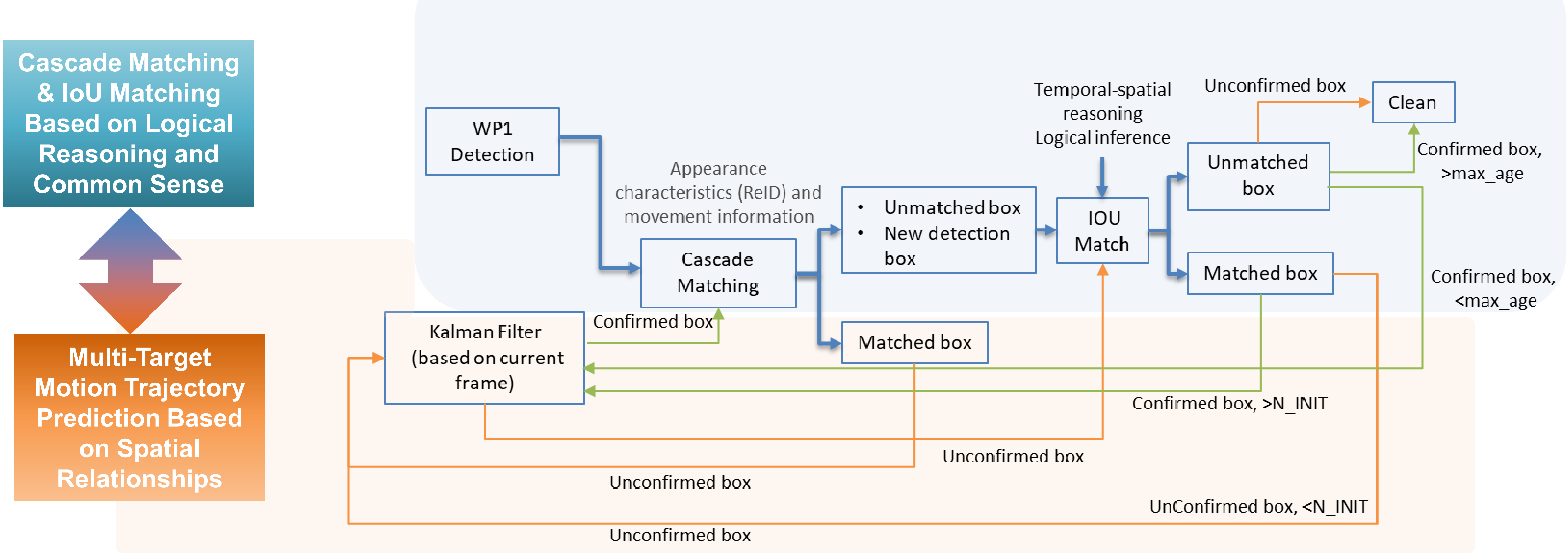
2. Autonomy and Intelligence

Autonomy:
The capacity to operate independently, without continuous human input, by planning actions, adjusting to changes (e.g., obstacles, shifting task requirements), and completing objectives on their own.

SLAM allows robots to build a map and localize themselves simultaneously, forming the backbone of autonomous navigation.



AI Model Stability and Robustness Analysis with Theoretical Guarantee



- Integration of Temporal dependencies, spatial reasoning, logical inference, object relationship and contextual interactions for better robustness and consistence of object trajectory tracking
- Transfer of pose estimation and 3D shape priors for more complete and accurate object representation
- Multi-modal fusion (LiDAR, radar, camera) to enhance detection reliability

New Potential Field Function for Dynamic Path Planning

The Goals Non-Reachable with Obstacles Nearby (**GNRON**) Problem is a well-known issue in the APF method, where the robot **fails to reach the goal** due to the combined effects of attractive and repulsive forces. This happens when obstacles are positioned close to the target, creating a **strong repulsive field** that prevents the robot from reaching its destination.

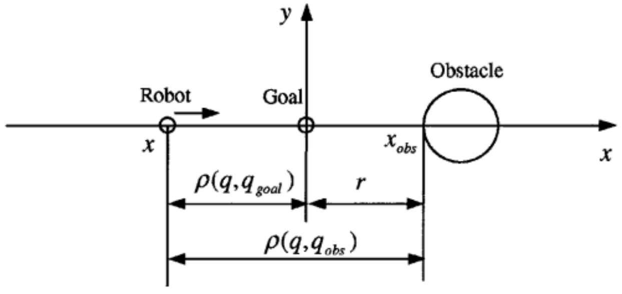


Fig. 1. Locations of the robot, goal, and obstacle in a 1-D case.

$$U_{rep}(q) = \begin{cases} \frac{1}{2}\eta\left(\frac{1}{\rho(q,q_{obs})} - \frac{1}{\rho_0}\right)^2, & if\, \rho(q,q_{obs}) \le \rho_0 \\ 0, & if\, \rho(q,q_{obs}) > \rho_0 \end{cases}$$

$$U_{rep}(q) = \begin{cases} \frac{1}{2}\eta\left(\frac{1}{\rho(q,q_{obs})} - \frac{1}{\rho_0}\right)^2 \rho^n(q,q_{goal}), & if\, \rho(q,q_{obs}) \le \rho_0 \\ 0, & if\, \rho(q,q_{obs}) > \rho_0 \end{cases}$$

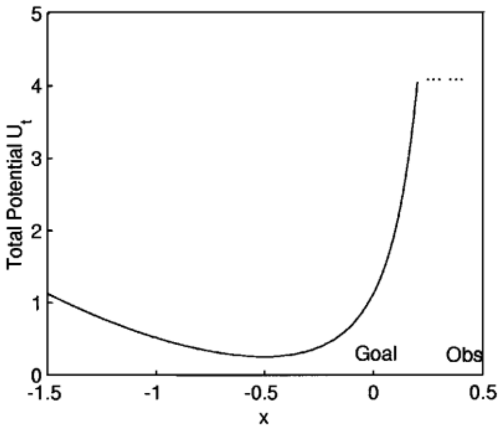
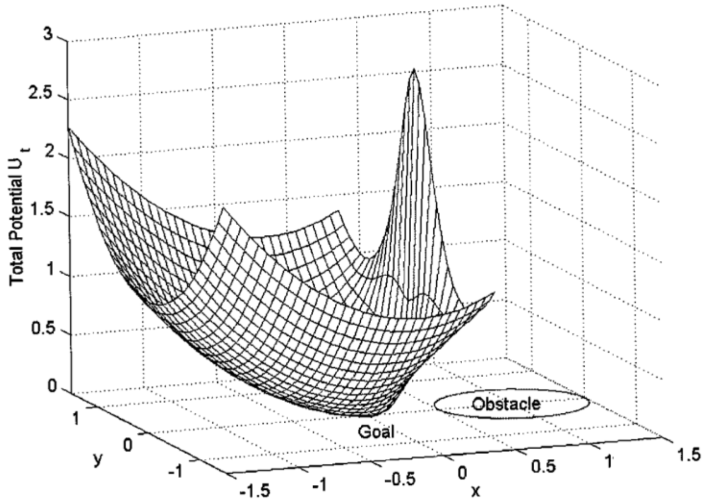


Fig. 2. Total potential function in a 1-D case.



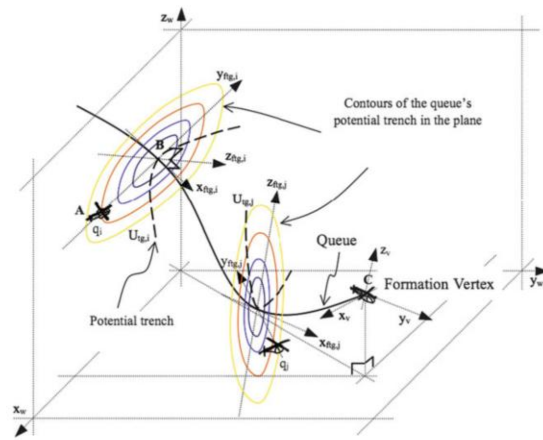
S. S. Ge and Y. J. Cui, "New Potential Functions for Mobile Robot Path Planning", IEEE Transactions on Robotics Automation, Vol. 16, No. 5, pp.615 -620, October 2000.

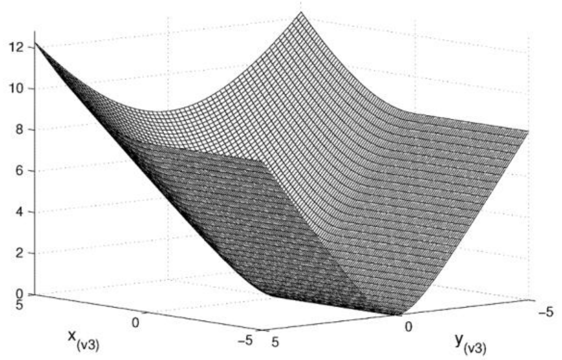
2. Autonomy and Intelligence

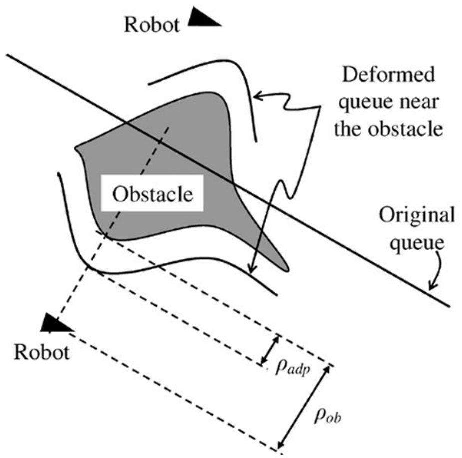
Autonomous: Planning for Multi-Agent Systems

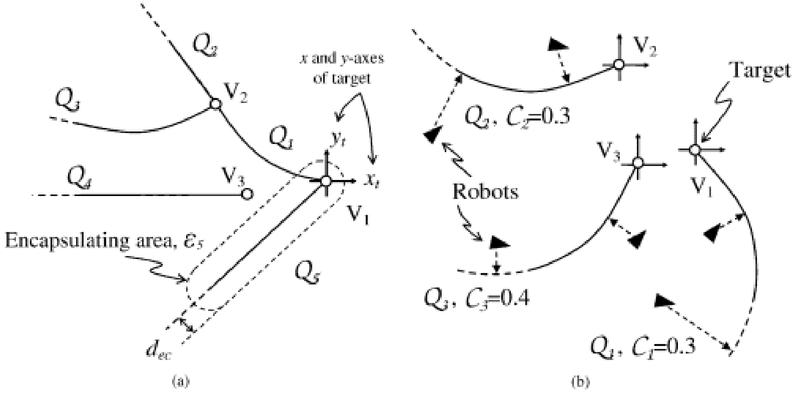
- Queues and Artificial Potential Trenches for Multirobot Formations

Goal: Ensuring stable and flexible robot formations in dynamic, obstacle-filled environme









Three-dimensional view of the potential trench function

S.S. Ge and Cheng-Heng Fua. "Queues and artificial potential trenches for multirobot formations." IEEE Transactions on Robotics 21.4 (2005): 646-656.

2. Autonomy and Intelligence

NUS National University of Singapore

Time Space Intelligence + Intelligent Control = Cybernetics!?

1. Deren Li (李德仁 院士) 论无所不在的时空智能, 2024中国测绘学会年会 (On Time Space Intelligence, Annual Conference of the Chinese Society for Geodesy, Photogrammetry and Cartography, 2024)

2. Space Time Intelligence System (STIS) software holds the promise of relaxing some of the technological constraints of spatial only GIS, making possible visualization approaches and analysis methods that are appropriate for temporally dynamic geospatial data.

3. Space Intelligence: Geographic Information System (GIS) software is constrained, to a greater or lesser extent, by a static world view that is not well-suited to the representation of time (Goodchild 2000).

4. Intelligence: The ability to use sensors (e.g., cameras, lidar) to gather environmental data, analyze it via algorithms (like machine learning or computer vision), and adapt to new or unforeseen situations.

https://link.springer.com/article/10.1007/s10109-005-0146-7

2. Autonomy and Intelligence

Message from the President

Control science and engineering are both fundamental and crucial in the successfully transforming science and technology into practical applications by closing the loop with the physical world to ensure safe, trustworthy and reliable operations.

With the fast advancement in Computing, Communication, and Control (C^3) technologies, many advanced machines are emerging to revolutionize our work, life, and leisure. Innovations such as autonomous vehicles, artificial intelligence.

http://acacontrol.org/about-aca/message-from-the-president/

ASIAN CONTROL ASSOCIATION
LEADING IN CONTROL, AUTOMATION AND SYSTEMS

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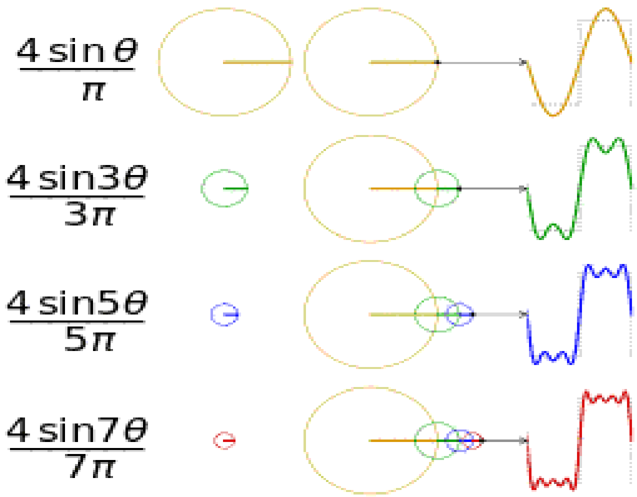
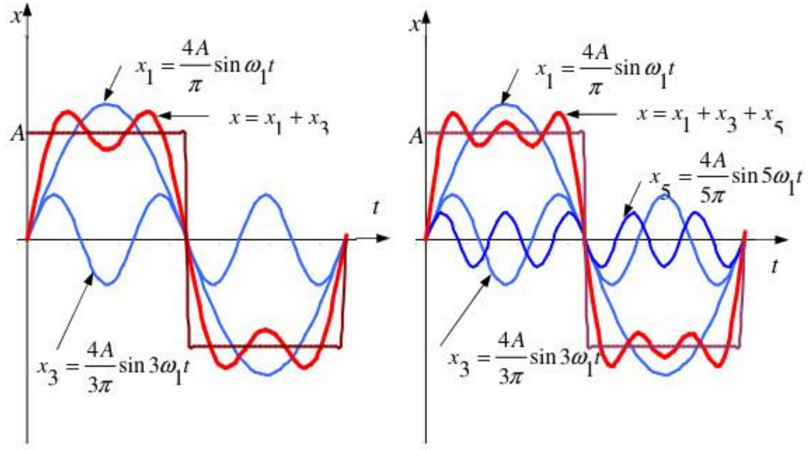
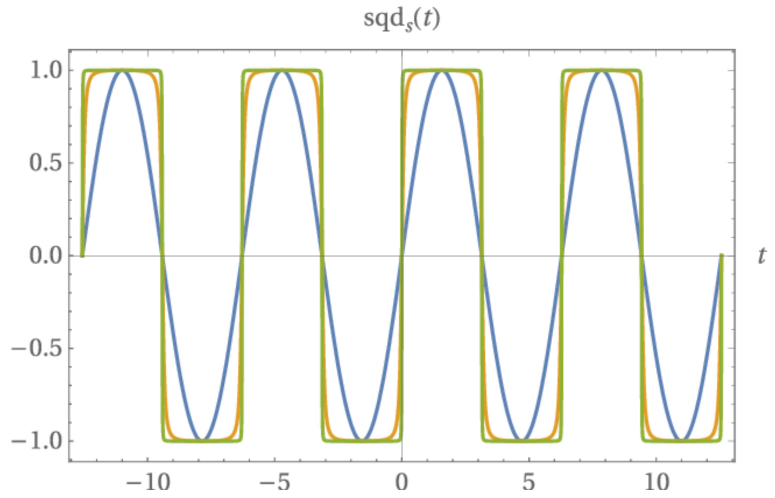
3.1 Adaptive Neural Network Control

Square Wave Approximation







True values and true functions are not available and we have to approximate, adapt and learn them!

3. Intelligent Control of Robots

3.1 Adaptive Neural Network Control

1. Before 90s：Offline training is much in use;
2. After 90s：Combining Adaptive and NN Approximative, online adaptive control was in fashion.

Consider dynamic equations of robots $D(q)\ddot{q} + C(q,\dot{q})\dot{q} + G(q) = \tau$

Then, NN control

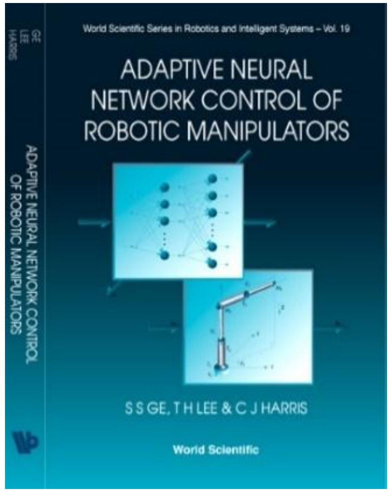
$$\tau = \hat{D}_{SNN}(q)\ddot{q}_r + \hat{C}_{DNN}(q,\dot{q})\dot{q}_r + \hat{G}_{SNN}(q) + K_P r + K_I \int_0^t r(\tau)d\tau + \tau_r$$

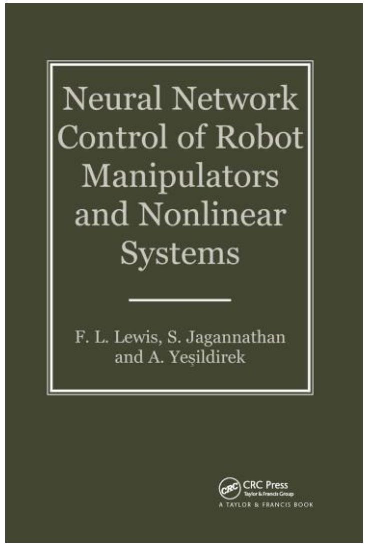
$$= \left[\{\hat{W}_D\}^T \cdot \{\Xi_D(q)\}\right]\ddot{q}_r + \left[\{\hat{W}_C\}^T \cdot \{\Xi_C(z)\}\right]\dot{q}_r + \left[\{\hat{W}_G\}^T \cdot \{\Xi_G(q)\}\right] + K_P r + K_I \int_0^t r d\tau + \tau_r$$

Adaptive Neural Network Control based on physics, system properties or topologies.

S. S. Ge, T. H. Lee, and C. J. Harris. *Adaptive neural network control of robotic manipulators*. Vol. 19. World Scientific, 1998

F. L. Lewis, S. Jagannathan and A Yesildirak, *Neural network control of robot manipulators and non-linear systems*, CRC, 1998.





3.1 Adaptive Neural Network Control

Theorem: if $K_P(t) > 0, K_I = K_I^T \geq 0$ and $k_{rii} \geq |E_i|$, then the closed-loop error system is an asymptotically stable, i.e. $r \to 0$ as $t \to \infty$ under the following parameter adaptation laws

$$\dot{\hat{W}}_{Dk} = \Gamma_{Dk} \cdot \{\xi_{Dk}(q)\}\ddot{q}_r r_k$$
$$\dot{\hat{W}}_{Ck} = \Gamma_{Ck} \cdot \{\xi_{Ck}(z)\}\dot{q}_r r_k$$
$$\dot{\hat{W}}_{Gk} = \Gamma_{Gk}\xi_{Gk}(q) r_k$$

where $\Gamma_{Dk}, \Gamma_{Ck}, \Gamma_{Gk}$ are symmetric positive definitive constant matrices, and $\hat{W}_{Dk}, \hat{W}_{Ck}, \hat{W}_{Gk}$ are elements of $\{\hat{W}_D\}, \{\hat{W}_C\}, \{\hat{W}_G\}$, respectively

- $e \in L_2^n \cap L_\infty^n$, is continuous, e and $\dot{e} \to 0$ as $t \to \infty$;
- all the signals in the closed-loop system are bounded.

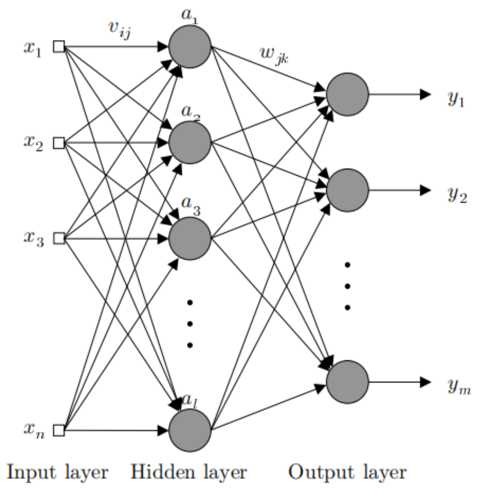
Proof: ***refer to the proof of Theorem 5.2 in***

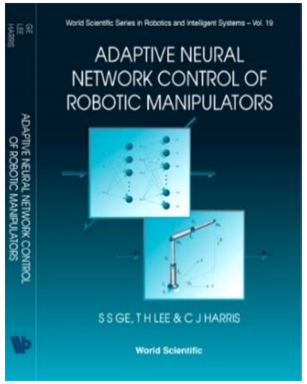
S. S. Ge, T. H. Lee, and C. J. Harris, *Adaptive neural network control of robotic manipulators,* World Scientific, 1998.

3.1 Adaptive Neural Network Control

a. Linearly/Nonlinearly Parametrized Neural Networks

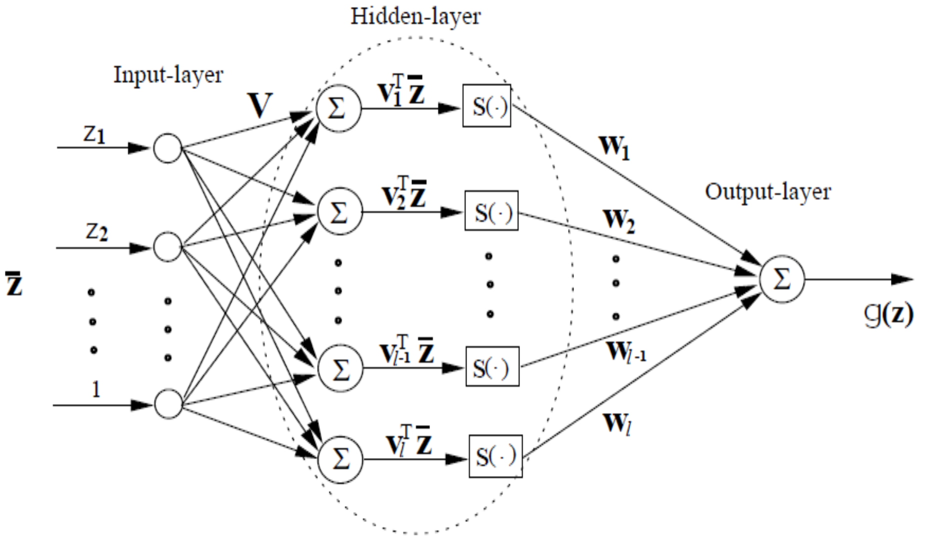
The adjustable parameters appear **linearly**.

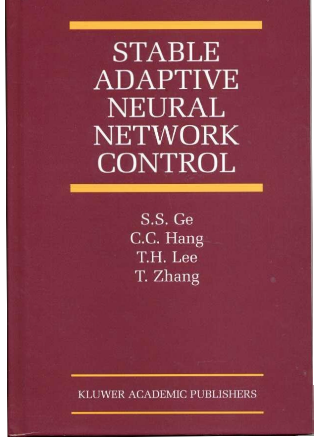




$$y(x) = W^T a = W^T a(V^T x)$$

The adjustable parameters appear **nonlinearly**.





$$g(z) = \sum_{j=1}^{\ell} \left[w_j s \left(\sum_{k=1}^{n} v_{jk} z_k + \theta_{vj} \right) \right] + \theta_w$$

S. S. Ge, T. H. Lee, and C. J. Harris. *Adaptive neural network control of robotic manipulators*. Vol. 19. World Scientific, 1998.

S. S. Ge, CC Hang, TH Lee and T. Zhang, Stable adaptive neural network control. Vol. 13. Springer Science & Business Media, 2013.

3.1 Adaptive Neural Network Control

Lemma 1.2: Consider the positive function given by

$$V(t) = \frac{1}{2}e^T(t)Q(t)e(t) + \frac{1}{2}\tilde{W}^T(t)\Gamma^{-1}(t)\tilde{W}(t) \quad (7)$$

where $e(t) = x(t) - x_d(t)$ and $\tilde{W}(t) = \hat{W}(t) - W^*$ with $x(t) \in R^n$, $x_d(t) \in \Omega_d \subset R^n$, $\hat{W}(t) \in R^m$, and constants $W^* \in R^m$, $Q(t) = Q^T(t) > 0$ and $\Gamma(t) = \Gamma^T(t) > 0$ are dimensionally compatible matrices. If the following inequality holds:

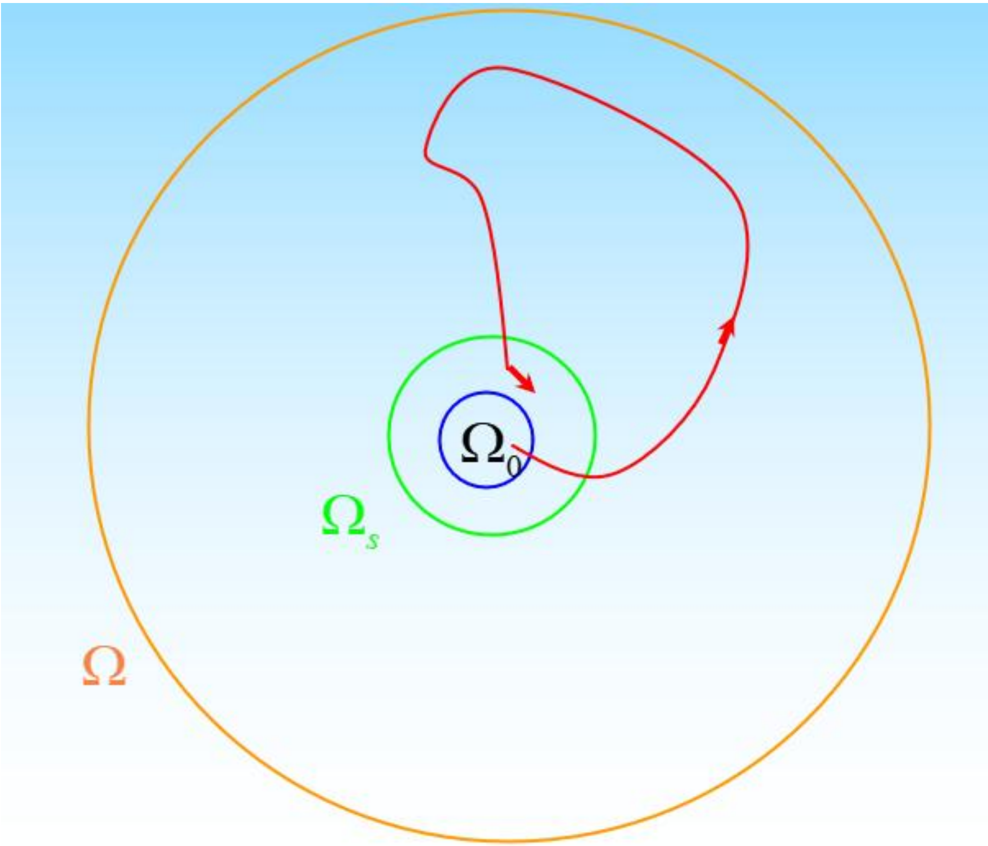
$$\dot{V}(t) \le -c_1 V(t) + c_2 \quad (8)$$

then, given any initial compact set defined by

$$\Omega_0 = \left\{x(0), x_d(0), \hat{W}(0) \mid x(0), \hat{W}(0) \text{ finite }, x_d(0) \in \Omega_d\right\} \quad (9)$$

we can conclude that

All the signals are stabe:Next page ☺



Compact Sets: Stability of NN Approximation and Control

Shuzhi Sam Ge, Cong Wang, "Adaptive neural control of uncertain MIMO nonlinear systems", IEEE Transactions on Neural Networks; 15(3), pp 674-692, 2004.

we can conclude that

i) the states and weights in the closed-loop system will remain in the compact set defined by

$$\Omega = \Big\{ x(t), \hat{W}(t) \Big| \|x(t)\| \le c_{e\max} + \max_{\tau\in[0,t]} \{\|x_d(\tau)\|\}, \; x_d(t) \in \Omega_d, \|\hat{W}\| \le c_{\tilde{W}\max} + \|W^*\| \Big\}$$

ii) the states and weights will eventually converge to the compact sets defined by

$$\Omega_s = \Big\{ x(t), \hat{W}(t) \Big| \lim_{t\to\infty} \|e(t)\| = \mu_e^*, \lim_{t\to\infty} \|\tilde{W}\| = \mu_{\tilde{W}}^* \Big\} \quad (10)$$

where constants

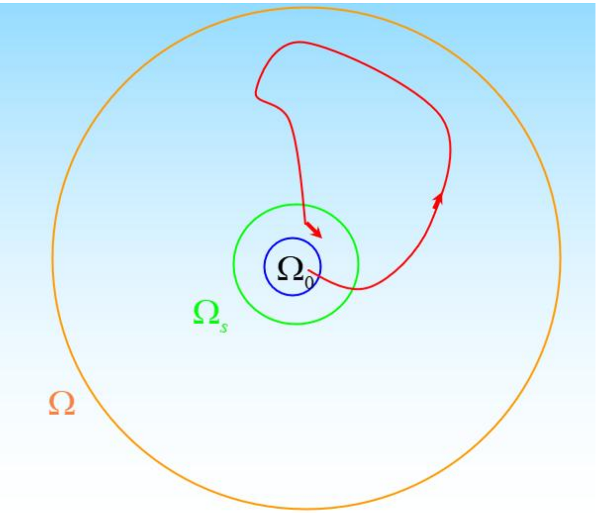
$$c_{e\max} = \sqrt{\frac{2V(0) + \frac{2c}{c}}{\lambda_{Q\min}}}$$

$$c_{\tilde{W}\max} = \sqrt{\frac{2V(0) + \frac{2c}{c}}{\lambda_{\Gamma\min}}}$$

$$\mu_e^* = \sqrt{\frac{2c_2}{c_1 \lambda_{Q\min}}}$$

$$\mu_{\tilde{W}}^* = \sqrt{\frac{2c_2}{c_1 \lambda_{\Gamma\min}}}$$

with $\lambda_{Q\min} = \min_{\tau\in[0,t]} \lambda_{\min}(Q($ … $\min_{\tau\in[0,t]} \lambda_{\min}(\Gamma^{-1}(\tau))$.



Remark 1.3: Lemma 1.2 gives an explicit theoretical explanation of approximation-based control techniques in the literature.

…

it follows the definition of SGUUB in the sense that bounded initial conditions guarantee the boundedness of all the signals in the closed-loop system provided the neural network is chosen to cover a compact set of sufficiently large size.

For clarity, it will not be repeated again and again in the paper, but is understood as such.

Compact Sets: Stability of NN Approximation and Control

Book Review by F. L. Lewis IEEE Fellow, USA

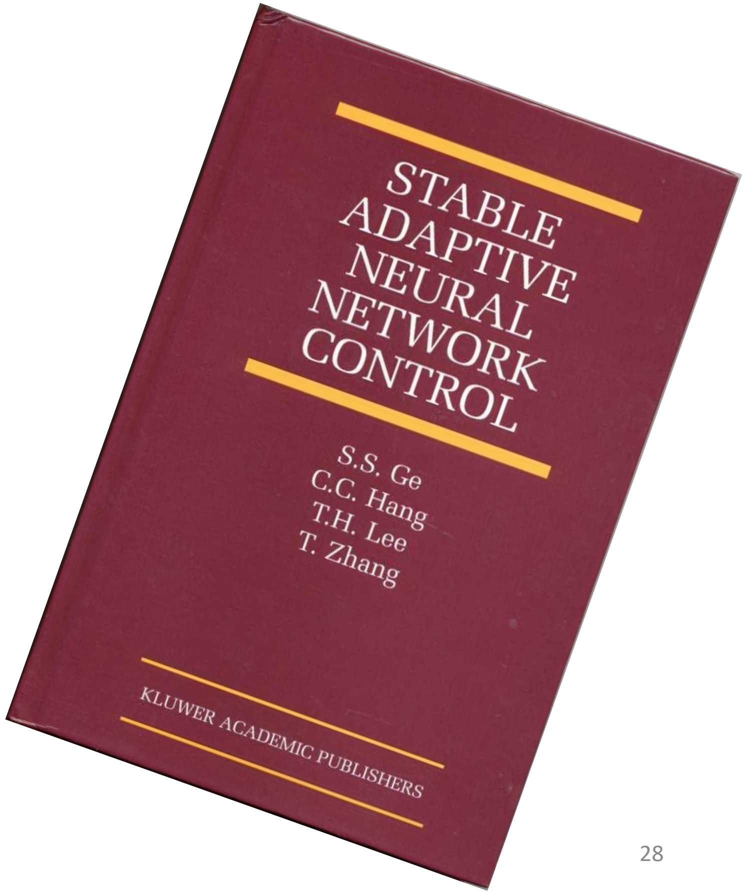
IEEE Transactions on Automatic Control, Vol. 47, No. 11, November 2002

$$\dot{x} = f(x,u)$$

1. A novel family of integral Lyapunov functions is used to avoid the control singularity problem in feedback linearization-based designs, and to design neural network controllers with global stability.

2. This book is well and thoughtfully laid out, and represents the culmination of years of rigorous and insightful research.

3. Industry engineers will find advanced nonparametric adaptive controllers of several sorts that are directly designed to confront problems of plant structure and uncertainty that normally fall outside the capabilities of traditional adaptive controllers.



3.2 Innovative Lyapunov Functions based Control

A large class of robotic systems can be described in the strict feedback nonlinear system:

$$\dot{x}_i = f_i(\bar{x}_i) + g_i(\bar{x}_i)x_{i+1},\ i = 1,2,\dots,n-1$$
$$\dot{x}_n = f_n(\bar{x}_n) + g_n(\bar{x}_n)u$$

where $f_1, \dots, f_n, g_1, \dots, g_n$ are smooth functions, $x_1, \dots, x_n$ are the states, u and y are the input and output respectively.

Virtual control coefficients:

- $g_{\mathrm{i}} = 1$: Jiang & Hill, Polycarpou & Ioannou, et al.
- g_{i} are unknown constants with known signs: Krstic, Kanellakopoulos & Kokotovic
- g_{i} are functions of state with known signs and upper bound: Yesildirek & Lewis, Ge & Zhang
- g_{i} are unknown with unknown signs: Ye & Jiang, Ding, Soh & Zhang, Ge & Wang

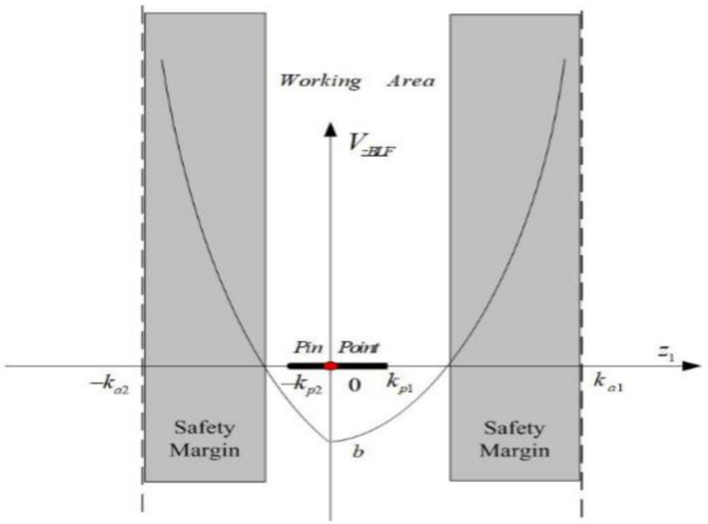
3.2 Innovative Lyapunov Functions based Control

Strict feedback nonlinear systems

$$\dot{x}_i = f_i(\bar{x}_i) + g_i(\bar{x}_i)x_{i+1}, i = 1,2,\cdots,n-1$$

$$\dot{x}_n = f_n(\bar{x}_n) + g_n(\bar{x}_n)u$$

$$y = x_1$$



Quadratic Lyapunov Function

$$V_1 = \frac{1}{2}z_1^2$$

↓

Integral Lyapunov Function

$$V_s = \int_o^s \frac{\sigma}{g_n(\varphi, \sigma + \varpi)} d\sigma$$

↓

Barrier Lyapunov Function

$$V_1 = \frac{1}{2}log\frac{k_{b1}^2}{k_{b1}^2 - z_1^2}$$

↓

Zone BLF

$$V_1 = \frac{1}{2}\ln\frac{k_{a_1}^r e^{-2b_1}}{k_{a_1}^r - z_1^r}$$

3.2 Innovative Lyapunov Functions based Control

a. Integral Lyapunov function

$$V_{z1} = \int_0^{z_1} \sigma\beta_1(\sigma + y_d)d\sigma,$$

with $z_1 = x_1 - y_\text{d}$, and $\beta_1(x_1) = \frac{\mathbf{g}_1(x_1)}{g_1(x_1)}$.

can solve the **controller singularity problem** elegantly as follows:

$$u_1 = \frac{1}{\mathbf{g}_1(x_1)}\left[-k_1(t)z_1 - \hat{W}_1^\text{T} S_1\left(\hat{V}_1^\text{T}\mathbf{Z}_1\right)\right]$$

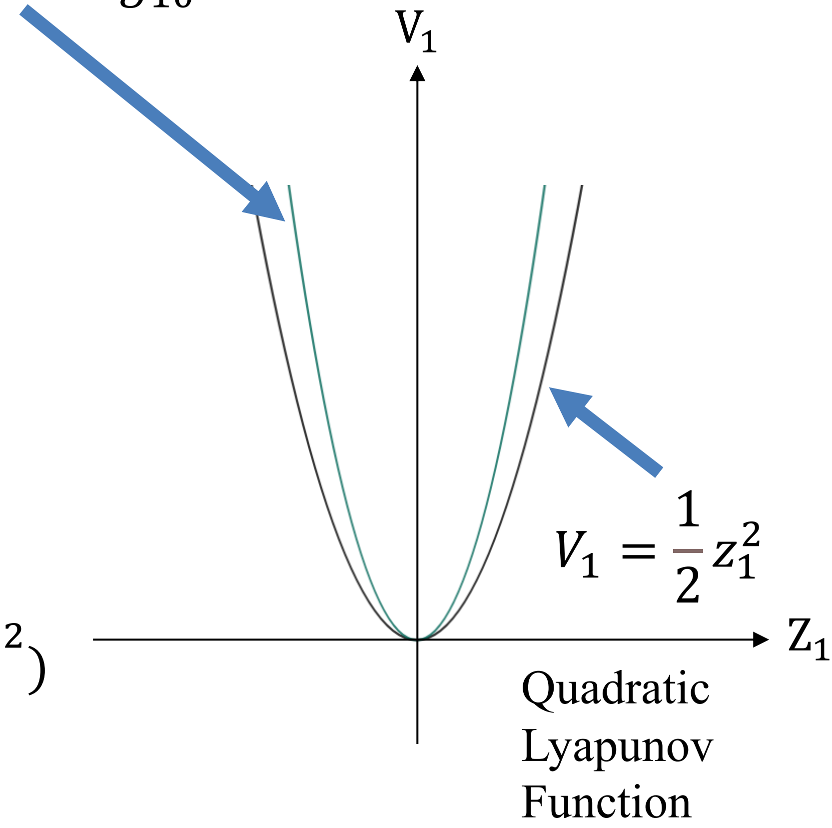
and the NN weights are updated by

$$\dot{\hat{W}}_1 = \Gamma_{w1}\left[\left(\hat{S}_1 - \hat{S}_1'\hat{V}_1^\text{T}\mathbf{Z}_1\right)z_1 - \sigma_{w1}\hat{W}_1\right],$$
$$\dot{\hat{V}}_1 = \Gamma_{v1}\left[\mathbf{Z}_1\hat{W}_1^\text{T}\hat{S}_1' z_1 - \sigma_{v1}\hat{V}_1\right]$$

and gain $k_1(t) = \frac{1}{\varepsilon_1}\left(1 + \int_0^1 \theta\mathbf{g}_1(\theta z_1 + y_\text{d})d\theta + \left\|\mathbf{Z}_1\hat{W}_1^\text{T}\hat{S}_1'\right\|_\text{F}^2 + \left\|\hat{S}_1'\hat{V}_1^\text{T}\mathbf{Z}_1\right\|^2\right)$

As $1 \le \beta_1(\theta z_1 + y_\text{d}) \le \mathbf{g}_1(\theta z_1 + y_\text{d})/g_{10}$, we have

$$\frac{z_1^2}{2} \le V_{z1} \le \frac{z_1^2}{g_{10}}\int_0^1 \theta\mathbf{g}_1(\theta z_1 + y_\text{d})d\theta$$

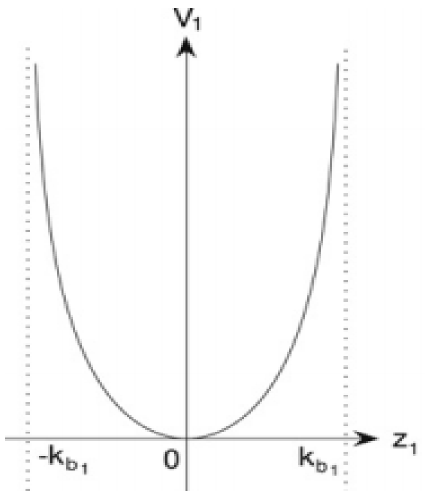


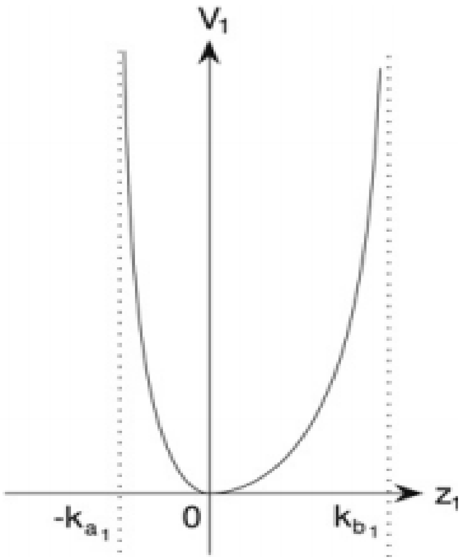
3.2 Innovative Lyapunov Functions based Control

b. Barrier Lyapunov Functions

Asymmetric BLF

Symmetric BLF





$$V_1 = \frac{1}{2}\log\frac{k_{b_1}}{k_{b_1}^2 - z_1^2}$$

$$V_1 = \frac{1}{p}q(z_1)\log\frac{k_{b_1}^p}{k_{b_1}^p - z_1^p} + \frac{1}{p}\big(1 - q(z_1)\big)\log\frac{k_{a_1}^p}{k_{a_1}^p - z_1^p}$$

where even integer $p \geq n$, the function $q(\cdot)$={1, if $*> 0$; 0, if$*\leq 0$}

3.2 Innovative Lyapunov Functions based Control

b. Barrier Lyapunov Functions

For the n-th order system with known functions, consider the following Lyapunov function candidates,

$$V_1 = \frac{1}{2}\log\frac{k_{b_1}^2}{k_{b_1}^2 - z_1^2}, \quad V_i = V_{i-1} + \frac{1}{2}z_i^2, \quad i = 2, \ldots, n$$

and the following standard control laws

$$\alpha_1 = \frac{1}{g_1}\left(-f_1 - \left(k_{b_1}^2 - z_1^2\right)\kappa_1 z_1 + \dot{y}_d\right), \quad \alpha_2 = \frac{1}{g_2}\left(-f_2 + \dot{\alpha}_1 - \kappa_2 z_2 - \frac{g_1 z_1}{k_{b_1}^2 - z_1^2}\right)$$

$$\alpha_i = \frac{1}{g_i}\left(-f_i + \dot{\alpha}_{i-1} - \kappa_i z_i - g_{i-1} z_{i-1}\right), i = 3, \ldots, n, \quad u = \alpha_n$$

where $\kappa_1, \ldots, \kappa_n$ are positive constants.

3.2 Innovative Lyapunov Functions based Control

It can be obtained that

$$\dot{V}_n = -\sum_{j=1}^{n} \kappa_j z_j^2 \le 0$$

(i) The error signal z_1 is ensured to satisfy $|z_1| < k_{b_1}$, provided that $|z_1(0)| < k_{b_1}$.

(ii) The signals $z_i(t), i = 1,2, \dots, n$, remain in the compact set defined by

$$\Omega_z = \left\{ \bar{z}_n \in \mathbb{R}^n : |z_1| \le D_{z_1}, \|z_{2:n}\| \le \sqrt{2V_n(0)} \right\}$$

$$D_{z_1} = k_{b_1} \sqrt{1 - \mathrm{e}^{-2V_n(0)}}$$

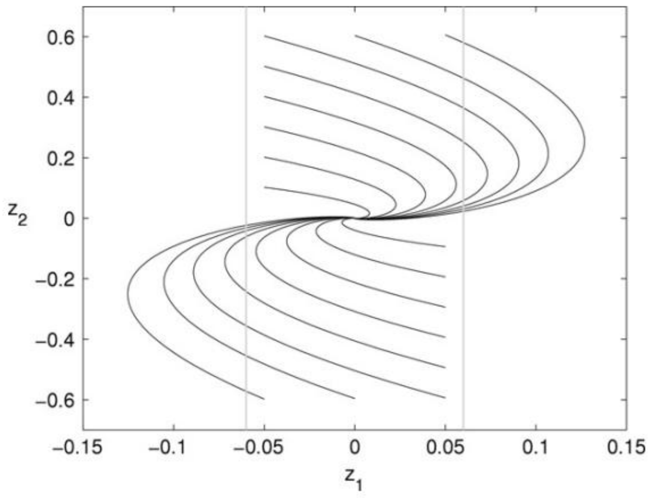
(iii) All closed loop signals are bounded.

(iv) The output tracking error $z_1(t)$ converges to zero asymptotically, i.e., $y(t) \to y_d(t)$ as $t \to \infty$.

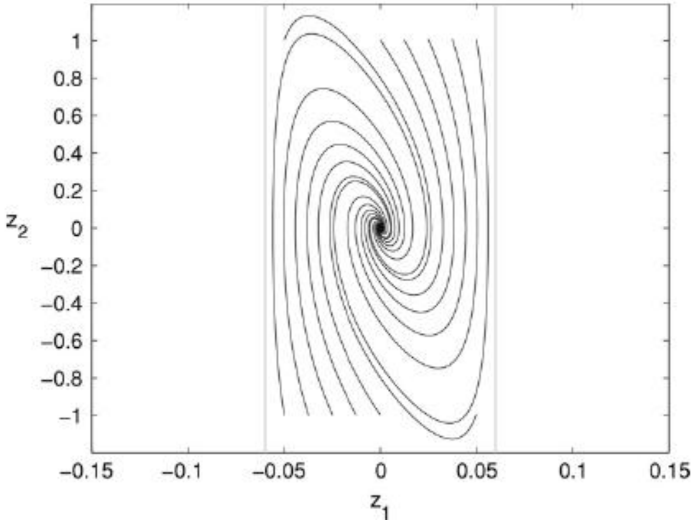
3.2 Innovative Lyapunov Functions based Control

For the second order system:

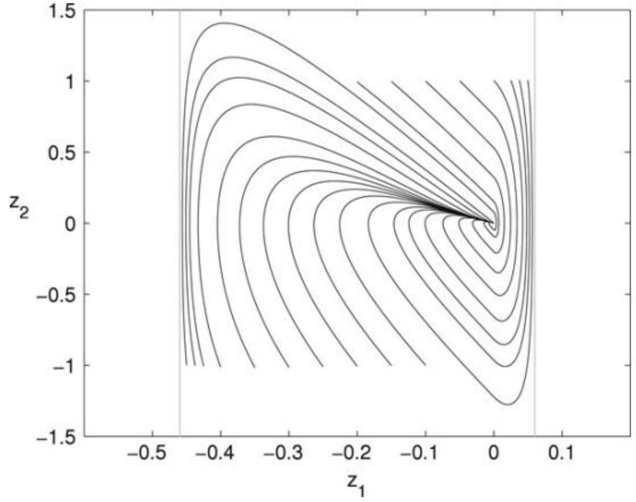
$$\dot{x}_1 = \theta_1 x_1^2 + x_2$$
$$\dot{x}_2 = \theta_2 x_1 x_2 + \theta_3 x_1 + (1 + x_1^2)u$$



Quadratic Lyapunov Function



Symmetric Barrier Lyapunov Function



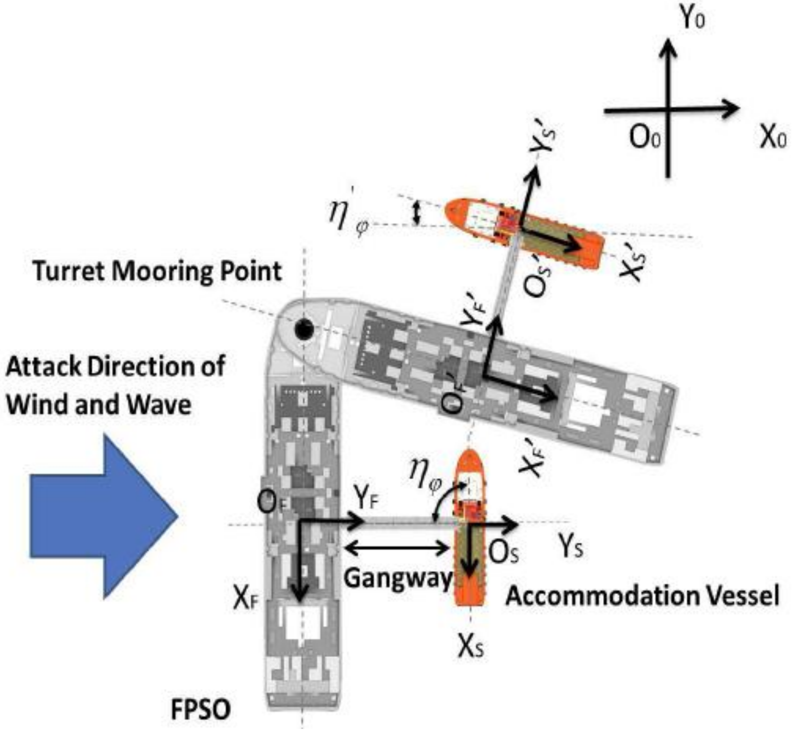
Asymmetric Barrier Lyapunov Function

Tee K P, Ge S S, Tay E H. Barrier Lyapunov functions for the control of output-constrained nonlinear systems[J]. Automatica, 2009, 45(4): 918-927.

c. Zone Barrier Lyapunov Function

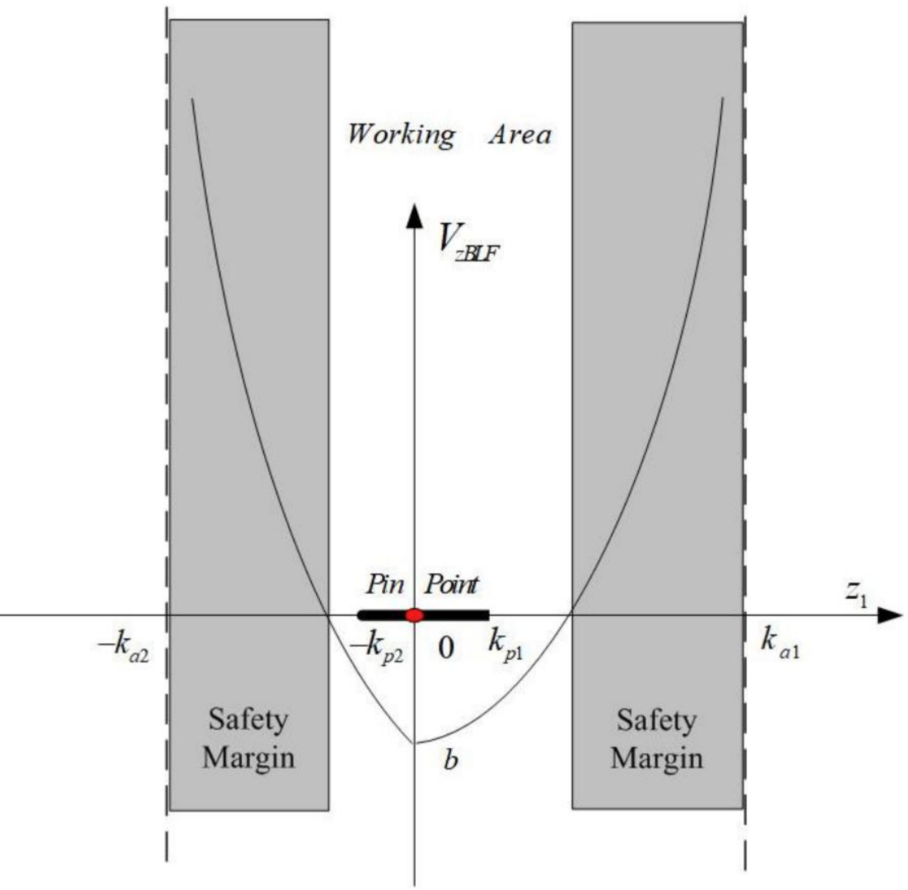
Output constraint control has conservative feasibility conditions since not all the states' motions are concerned in the real system.

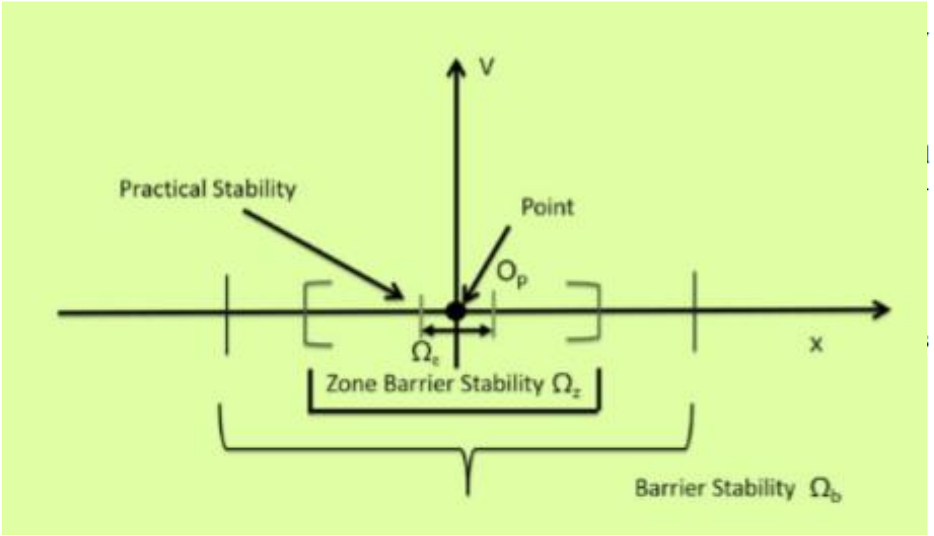
Air-to-air refueling



Side-by-side offloading operation

c. Zone Barrier Lyapunov Function





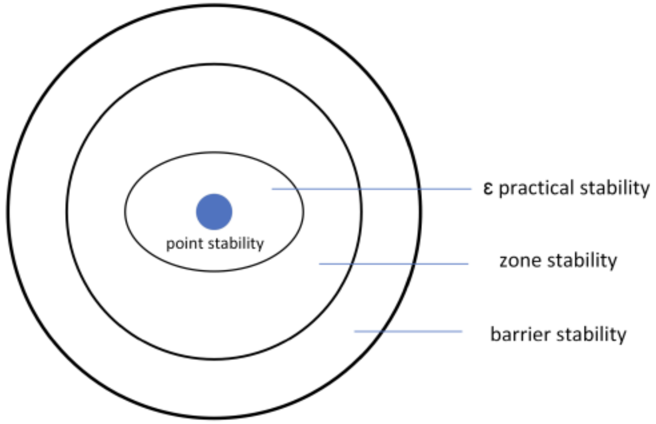


Fig. 1. Stability relationship.

The objective is to set the free position boundaries and design a controller to ensure the state operates within the constrained task space.

Liang, Xiaoling, Shuzhi Sam Ge, and Bernard Voon Ee How. "Nonlinear Control Design Based on Zone Barrier Lyapunov Function." International Conference on Mechatronics, Control and Robotics (ICMCR), IEEE, 2023.

3.2 Innovative Lyapunov Functions based Control

c. Zone Barrier Lyapunov Function

Theorem 1 (Liang, 2023): Consider the nonlinear system (4.4) with the virtual control (4.5)-(4.7), and the control input (4.8) under Assumptions 4.1 and 4.2. If the initial condition satisfies $-ka2 < z1(0) < ka1$, the following properties hold:

(i) The output state remains within the constrained area, and

(ii) The states are bounded in the closed-loop system.

The zBLF-based backstepping method has the following advantages

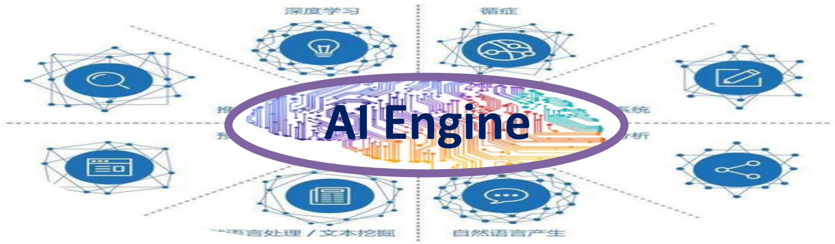
- For convergence performance, sufficient conditions have been proposed through practical control.
- The output state is free to move within a safety domain but does not exceed a set boundary while achieving a reduction in actuator energy consumption.

Liang, Xiaoling, Shuzhi Sam Ge, and Bernard Voon Ee How. "Nonlinear Control Design Based on Zone Barrier Lyapunov Function." International Conference on Mechatronics, Control and Robotics (ICMCR), IEEE, 2023.

3.2 Innovative Lyapunov Functions based Control

d . Learning-Based Optimized Backstepping Control

With the continuous advancement of information technologies centered on computing, communication, control, and intelligence



Auto-mobiles

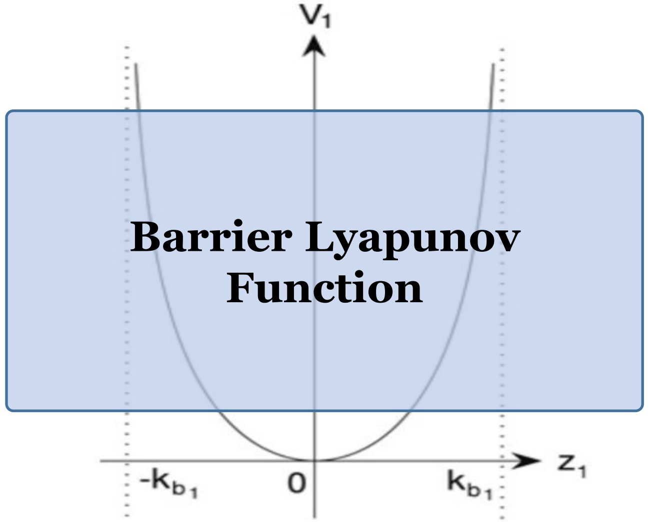
（百度Apollo）

Ensure safety and performance for safety-critical systems

3.2 Innovative Lyapunov Functions based Control

d . Learning-Based Optimized Backstepping Control

- Appropriately arranges the Barrier Lyapunov Function items into the optimized backstepping
- Constrain the state-variables in the designed region during the whole learning process



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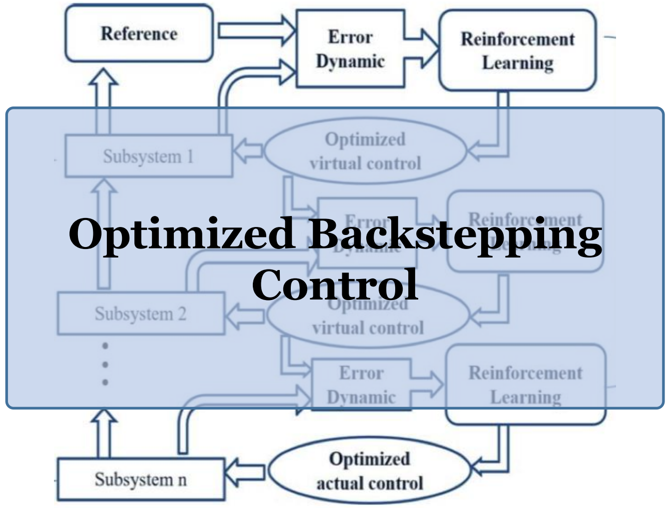
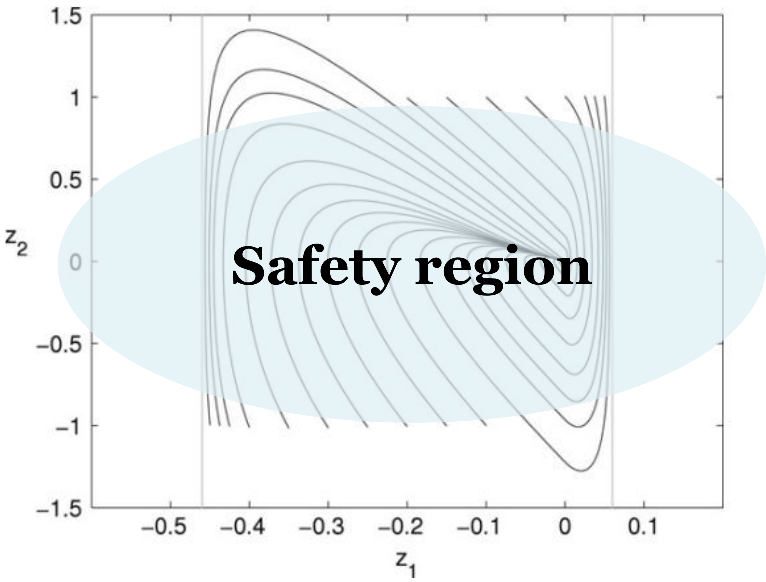


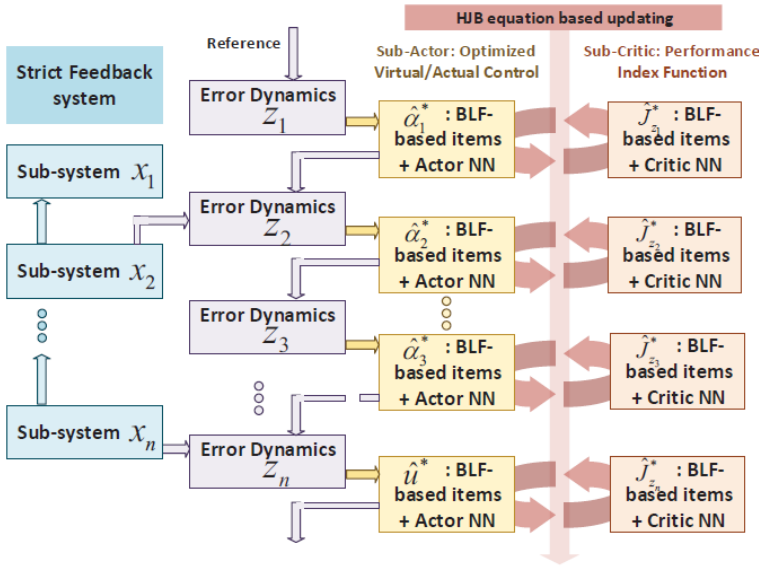


Guaranteed safety and solvable performance control for safety-critical system

Zhang Y, Ge S S, Liang X, et al. "Barrier Lyapunov Function-Based Safe Reinforcement Learning for Autonomous Vehicles With Optimized Backstepping," in IEEE Transactions on Neural Networks and Learning Systems, vol. 35, no. 2, pp. 2066-2080, Feb. 2024, doi: 10.1109/TNNLS.2022.3186528.

Step 1-n:

The optimal performance index and the optimal control are both unknown, in which two independent NNs are used to approximate the uncertain terms in them. With this design, the solutions (estimations) is then founded via the subsequent procedure of policy evaluation and policy improvement under the Actor-Critic framework.



	Optimal system control	Optimal performance index
➢ **Step 1:**	$\hat{\alpha}_1^* = \frac{1}{g_1(\bar{x}_1)}\left(-\kappa_1 z_1 - f_1(\bar{x}_1) + \dot{y}_d - \hat{h}_{a_1}\right)$	$\hat{J}_{z_1}^* = \frac{2\kappa_{1c}}{g_1(\bar{x}_1)^2}\left(\kappa_1 z_1 + f_1(\bar{x}_1) - \dot{y}_d + \hat{h}_{c_1}\right)$
➢ **Step i** (i=2,..,n-1):	$\hat{\alpha}_i^* = \frac{1}{g_i(\bar{x}_i)}\left(-\kappa_i z_i - f_i(\bar{x}_i) + \dot{\hat{\alpha}}_{i-1}^* + \alpha_{i,aux} - \hat{h}_{a_i}\right)$	$\hat{J}_{z_i}^* = \frac{2\kappa_{ic}}{g_i(\bar{x}_i)^2}\left(\kappa_i z_i + f_i(\bar{x}_i) - \dot{\hat{\alpha}}_{i-1}^* - \alpha_{i,aux} + \hat{h}_{c_i}\right)$
➢ **Step n:**	$\hat{u}^* = \frac{1}{g_n(\bar{x}_n)}\left(-\kappa_n z_n - f_n(\bar{x}_n) + \dot{\hat{\alpha}}_{n-1}^* + \alpha_{n,aux} - \hat{h}_{a_n}\right)$	$\hat{J}_{z_n}^* = \frac{2\kappa_{nc}}{g_n(\bar{x}_n)^2}\left(\kappa_n z_n + f_n(\bar{x}_n) - \dot{\hat{\alpha}}_{n-1}^* - \alpha_{n,aux} + \hat{h}_{c_n}\right)$

d. BLF - Safe Reinforcement Learning (SRL)

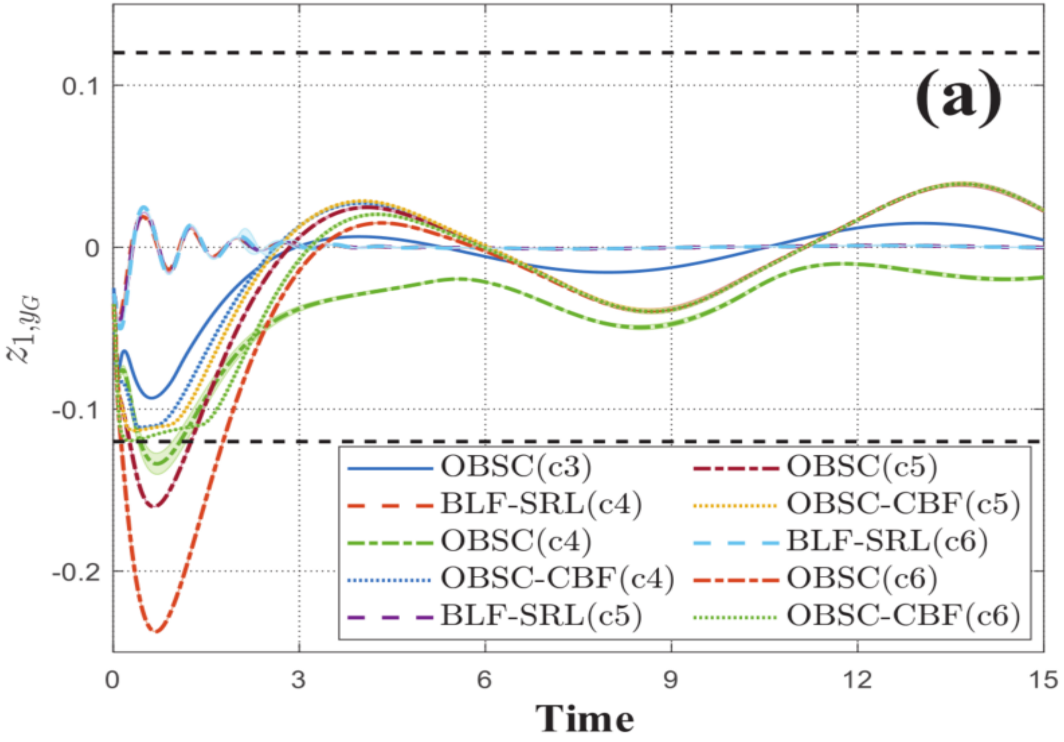
◆ Comparison Simulation

With the proposed BLF-SRL, the safety-related state-variables trajectories are under control during the whole learning period and enable the state-variables away from the safety boundary rather than an auxiliary control when approaching the safety boundary.

BLF-SRL →

OBSC+CBF →

OBSC →



Different from the proposed BLF-SRL, the auxiliary safe controller is used to compensate the original control inputs to realize safe control when the state-variables are going to be outside the safe region. If the state-variables are insider of safe region, the control will retained by its original computed control inputs.

3.3 Multi Agents Colaborative Control

a. Time Synchronized Control

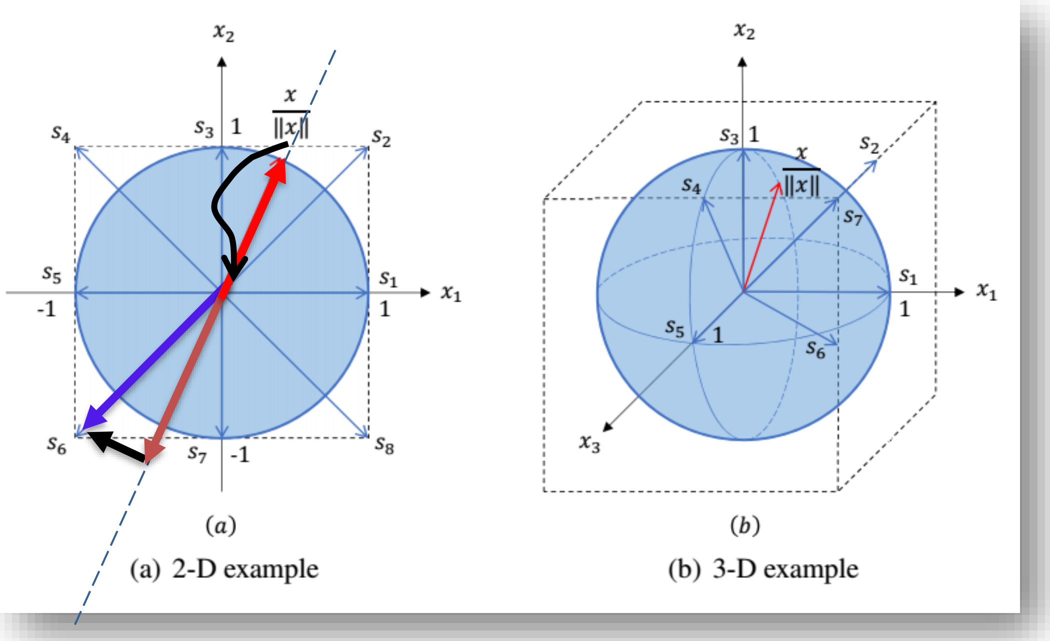
The magic touch

- Classical sign function

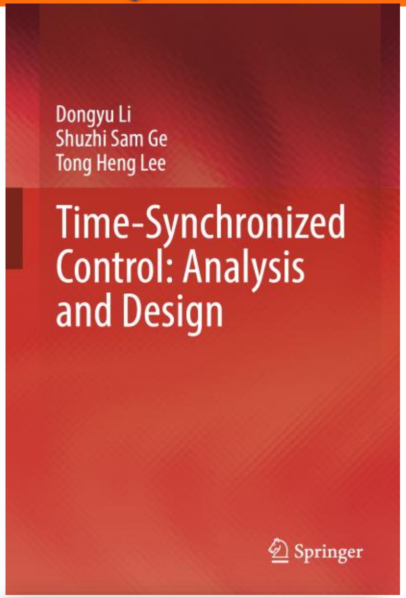
$$\operatorname{sign}_c(x_i) = \begin{cases} +1, & x_i > 0 \\ -1, & x_i < 0 \end{cases}$$

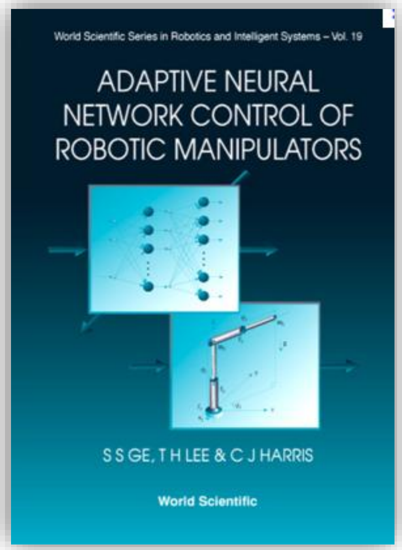
- Unit Vector function

$$\operatorname{sign}_n(x) = \frac{x}{\|x\|},$$



(a) 2-D example (b) 3-D example



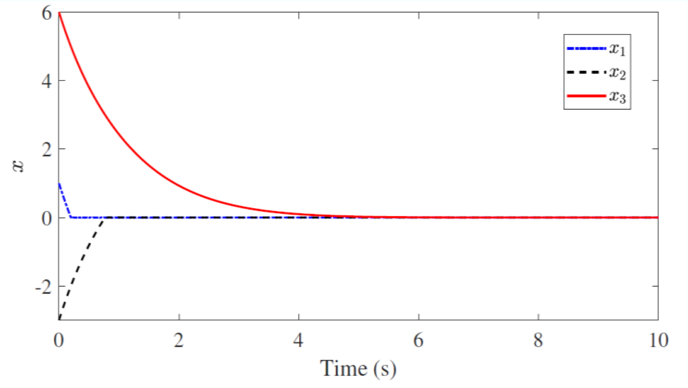


3.3 Multi Agents Colaborative Control

a. Time Synchronized Control

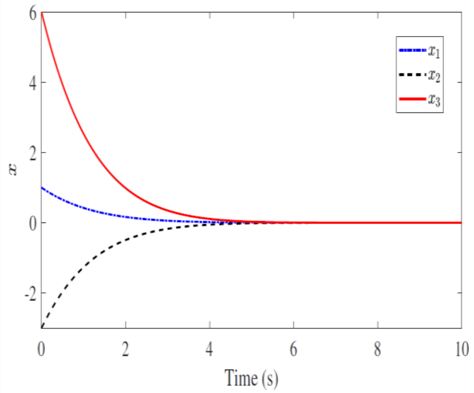
Finite/fixed/predefined-time control:

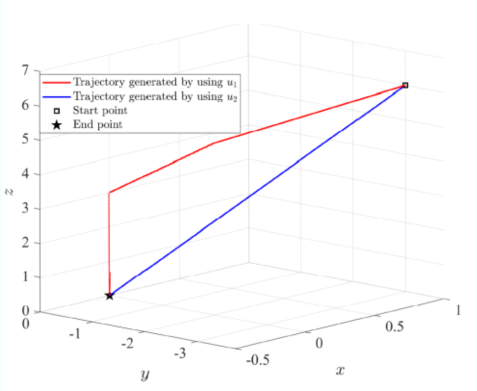
- **Adjustable settling time**
- **High precision, robustness, no overshoot**



Time-synchronized control:

- **Simultaneous Convergence in time space**
- **Ratio persistence in state space**
- **Adjustable settling time**
- **High precision, robustness, no overshoot**





Li D, Ge S S, Lee T H. Time-Synchronized Control: Analysis and Design[M]. New York: Springer, 2022.

3.3 Multi Agents Colaborative Control

a. Time-synchronized control for multi-agent systems:

Definition 5: (Time-Synchronized Consensus). A group of networked agent systems achieve time-synchronized consensus if and only if all the agents reach consensus synchronously, i.e., we have

$$\lim_{t \to T} \sum_{i,j \in \mathcal{V}_c, i \neq j} \|x_i(t) - x_j(t)\| = 0, \tag{18}$$

with a positive time instant T, while for any time instants t_1 and t_2 satisfying $0 \leq t_1 < t_2 < T$ and any $i \in \mathcal{V}_c$, we have

$$\|x_{i,k}(t) - \chi_k\| \neq 0, \ \forall t_1 \leq t \leq t_2, \tag{19}$$

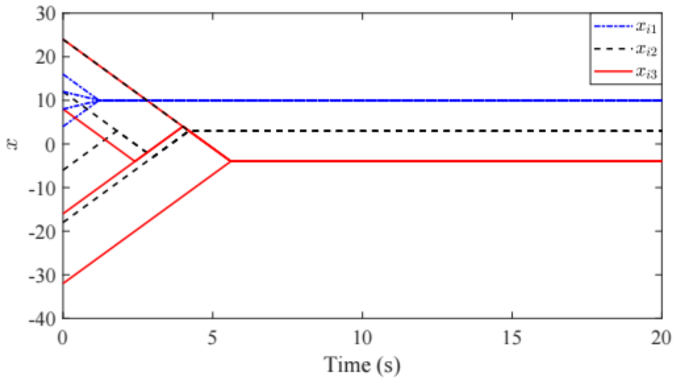


Fig. 8. Performance of the control law (29).

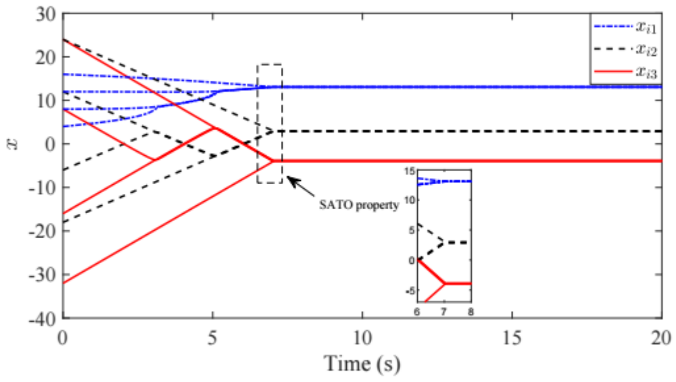


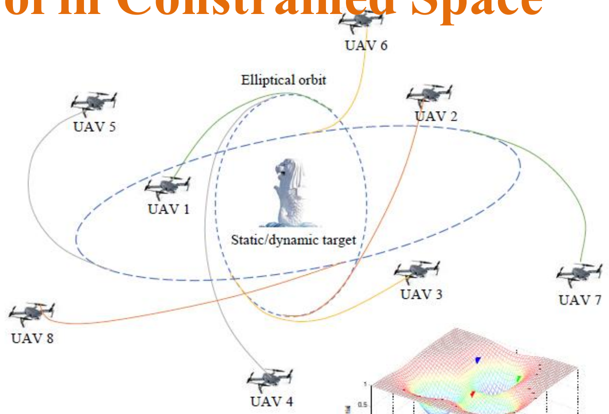
Fig. 9. Performance of the control law (30).

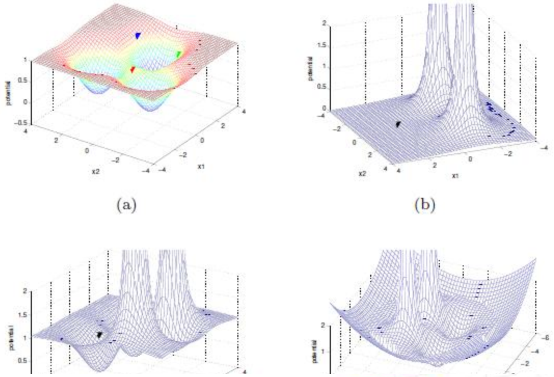
D. Li, S. S. Ge, T. H. Lee, Simultaneous-Arrival-to-Origin Convergence: Sliding-Mode Control through the Norm-Normalized Sign Function, *IEEE Transactions on Automatic Control*, 2021.

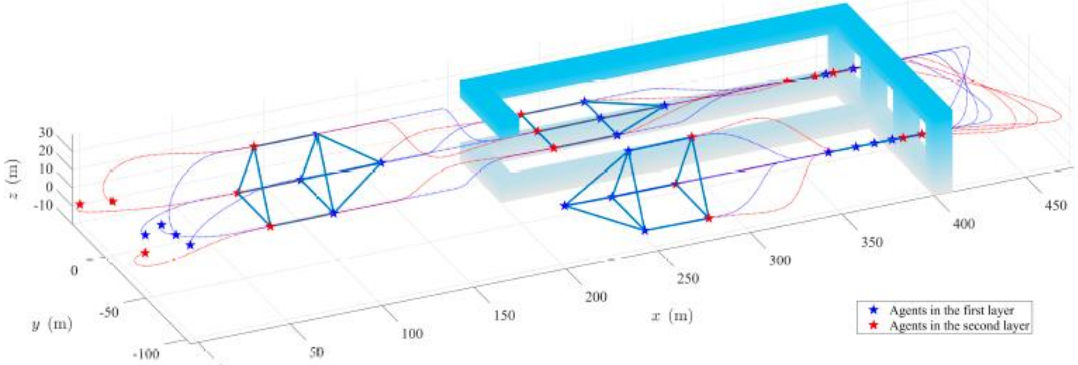
3.3 Multi Agents Colaborative Control

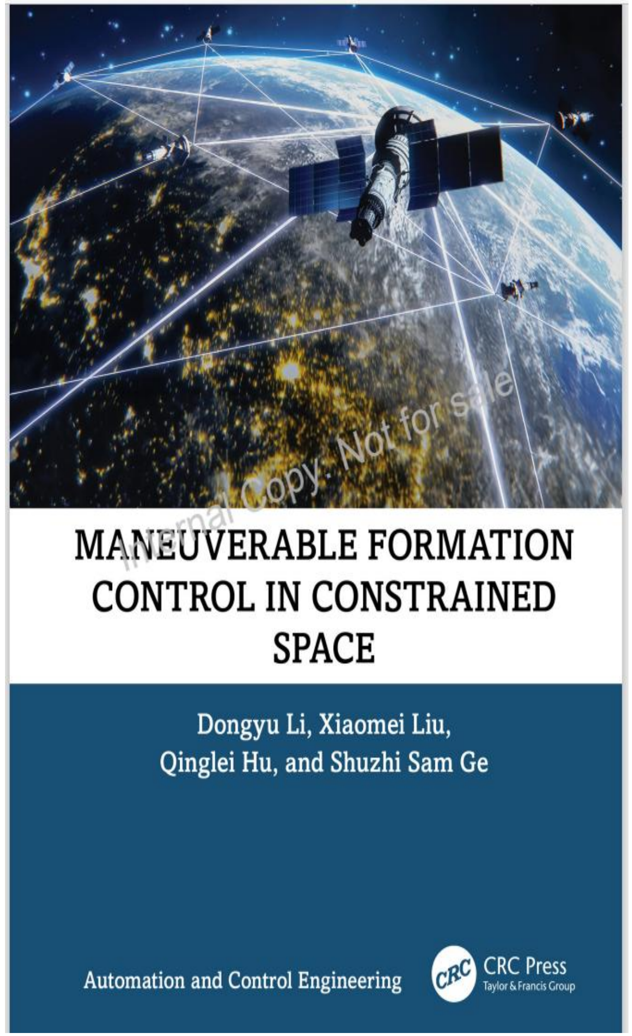
a. Maneuvrable Formation Control in Constrained Space

- **Multi-layer formation control**
- **Cooperative circumnavigation**
- **Formation tracking in constrained space**
- **TSC in constrained space**





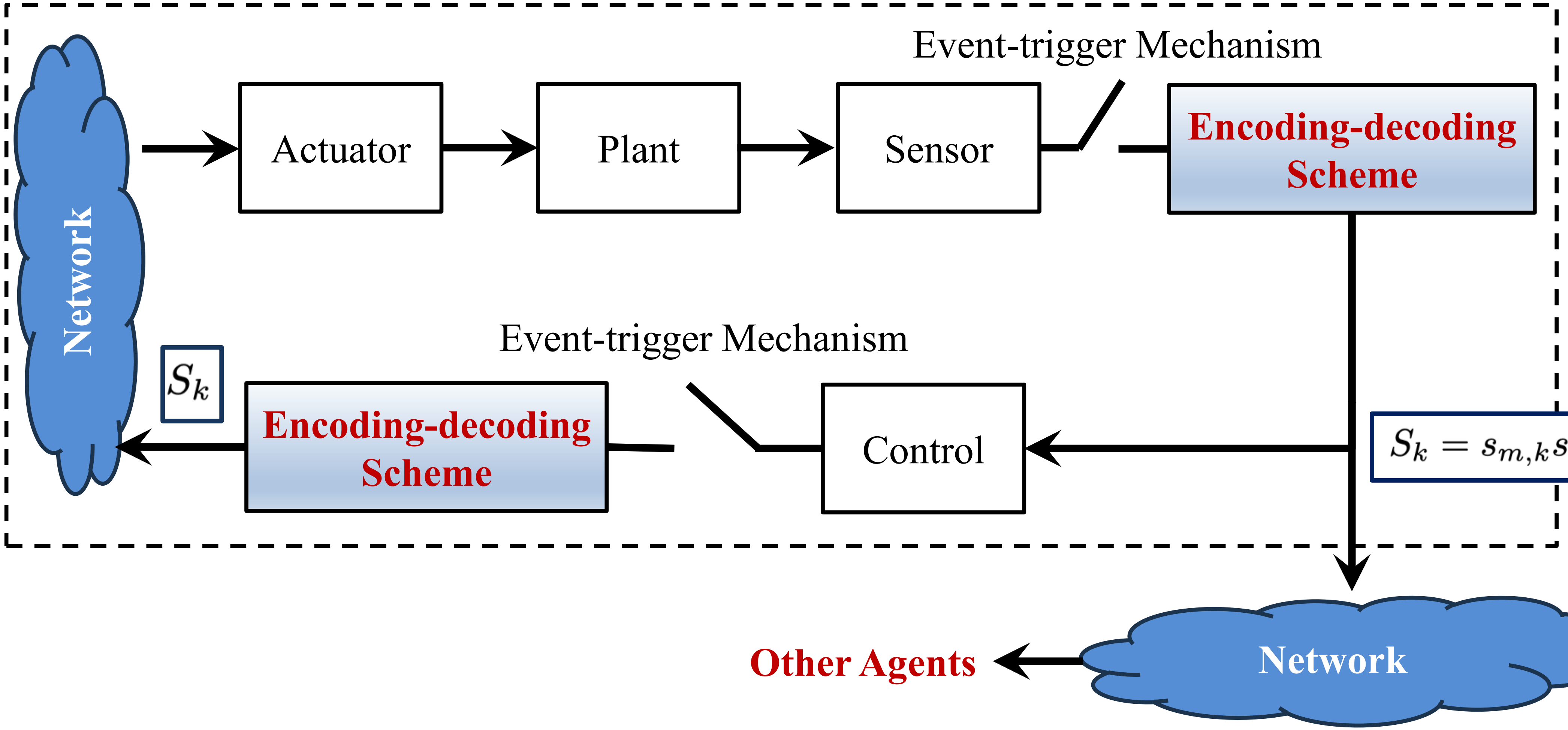


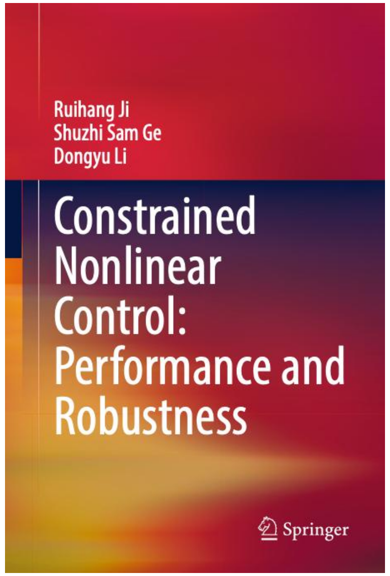


D. Li, X. Liu, Q. Hu and S.S. Ge, Maneuverable Formation Control in Constrained Space， CRC Press, 2024

3.3 Multi Agents Colaborative Control

b. Coded Event-triggered Control





Ruihang Ji, Shuzhi Sam Ge and Dongyu Li. Constrained Nonlinear Control: Performance and Robustness. Springer, 2025.

3.3 Multi Agents Colaborative Control

b. Coded Event-triggered Control

1-bit Control

- On-Off protocol
- Fixed single rules
- Easily deciphered

Coded Control

- Multi-bit encoding algorithm
- Fixed but multi-rule protocol
- Secure communication

Rate-coded Control

- Related to signal and its changing rate
- Mixed rules protocol
- More secure communication

Dynamic-coded Control

- Dynamic encoding algorithm
- Difficult to decipher
- Self-adjustable strategy

Ruihang Ji, Shuzhi Sam Ge, and Kai Zhao. Coded event-triggered control for nonlinear systems. Automatica, 2024, 167: 111753.

Ruihang Ji, and Shuzhi Sam Ge. Rate-coded secure control for multi-agent systems. *IEEE Transactions on Automatic Control* (2024).

Ruihang Ji, and Shuzhi Sam Ge. Secure Asymptotic Consensus Control for MASs. *IEEE Transactions on Automatic Control* (2025).

3.3 Multi Agents Colaborative Control

b. Coded Event-triggered Control

Event-triggered/Self-triggered Control

- Reduced Resource Usage (Computational and Communication Savings)
- Improved Efficiency with Performance Guarantee

$$t^i_{k_i+1} = inf\left\{t > t^i_{k_i} \middle| |e_{i,q}(t)| \geq a_i|y_i(t)| + b_i\right\}$$

(Rate-) Coded Event-triggered Control

- Reduce **communication bit** consumption for each transmission
- Enhance **communication security** as sensitive information has been encoded
- Reduced Resource Usage (Computational and Communication Savings)
- Improved Efficiency with Performance Guarantee

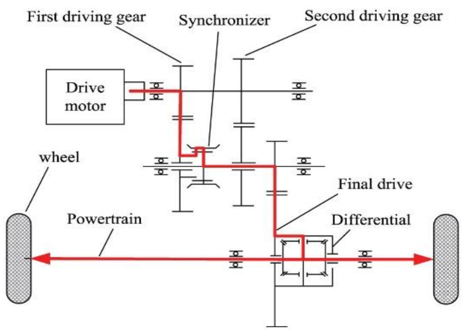
$$t^{k+1}_{i,q} = inf\left\{t > t^i_{k_i} \middle| |e_{i,q}(t)| \geq \omega_{i,q}p^{\beta_{i,q}}\right\}$$

$$R_{iq} = \delta_{iq}\frac{|x_{iq}(t) - x_{iq}(t_{iq,k_i})|}{t - t_{iq,k_i}} = \frac{\delta_{iq}|e_{iq}(t)|}{t - t_{iq,k_i}}$$

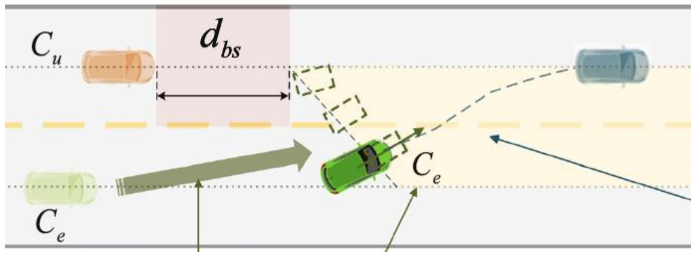
Ruihang Ji, Shuzhi Sam Ge, and Kai Zhao. Coded event-triggered control for nonlinear systems. Automatica, 2024, 167: 111753.
Ruihang Ji, and Shuzhi Sam Ge. "Rate-coded secure control for multi-agent systems." *IEEE Transactions on Automatic Control* (2024).

3.3 Multi Agents Colaborative Control

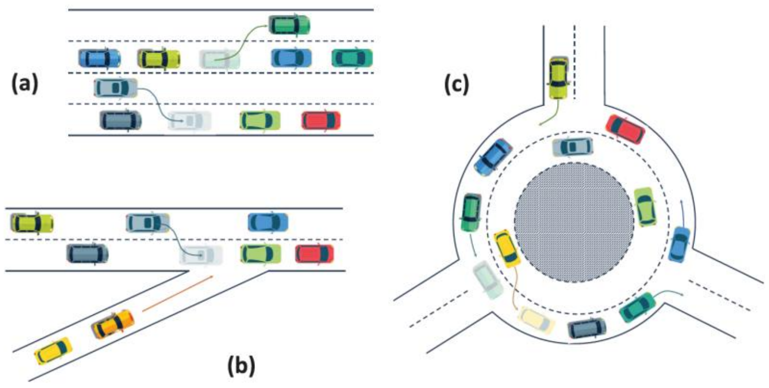
c. Time-synchronized Optimized Control



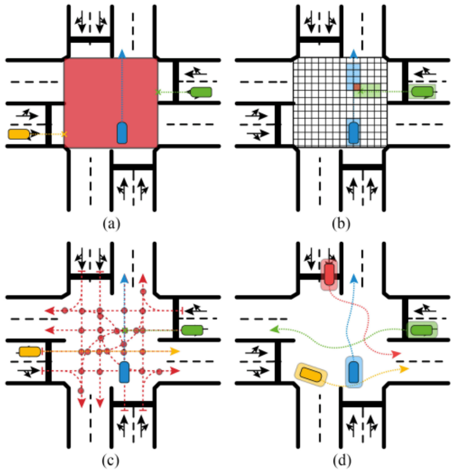
1. The synchronization control for shift control of inverse automated manual transmission to rejects jerk



2. Synchronized control governor for autonomous vehicle motion control



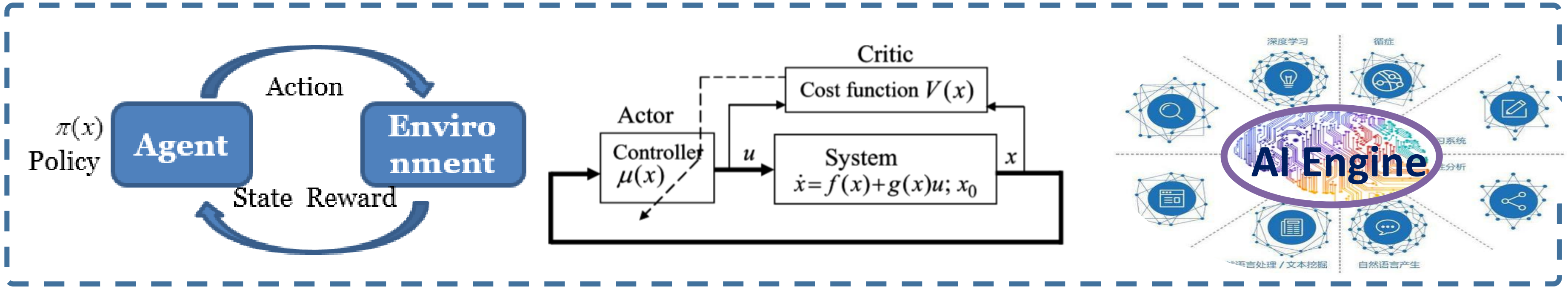
3. Vehicle Platoon Control: Synchronously motion and cooperatively work



4. Adaptive reference-free trajectory planning of autonomous vehicles under multi-scenario driving

3.3 Multi Agents Colaborative Control

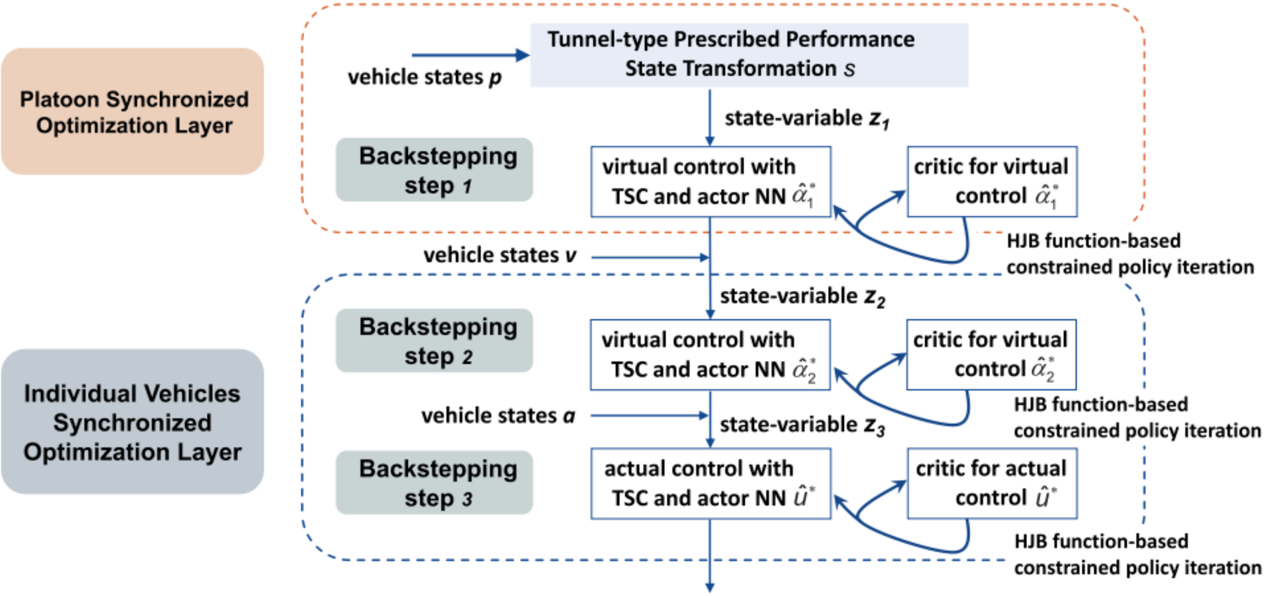
c. Time-synchronized Optimized Control with safety guarantee while learning



Goal:

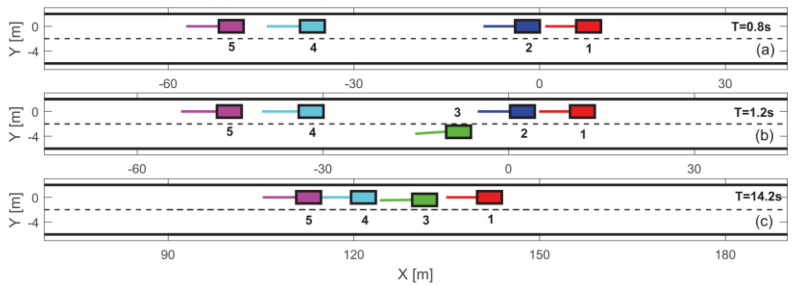
i. Ensure safe performance during the learning process

ii. Reduce the variance of control performance under stochastic uncertainty

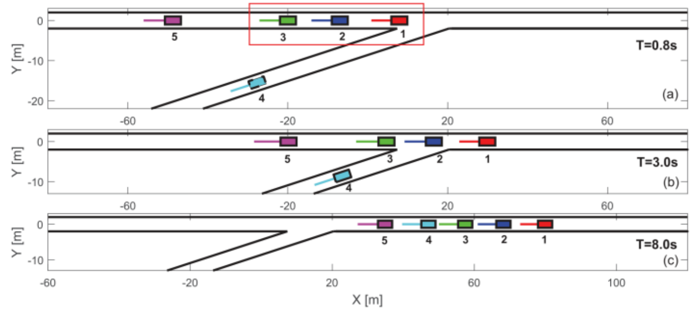


Y. Zhang, X. Liang, D. Li, S. Sam Ge and T. Heng Lee, "Bi-Layered Synchronized Optimization Control With Prescribed Performance for Vehicle Platoon," in IEEE Transactions on Intelligent Transportation Systems, vol. 25, no. 11, pp. 16473-16489, Nov. 2024, doi: 10.1109/TITS.2024.3432149.

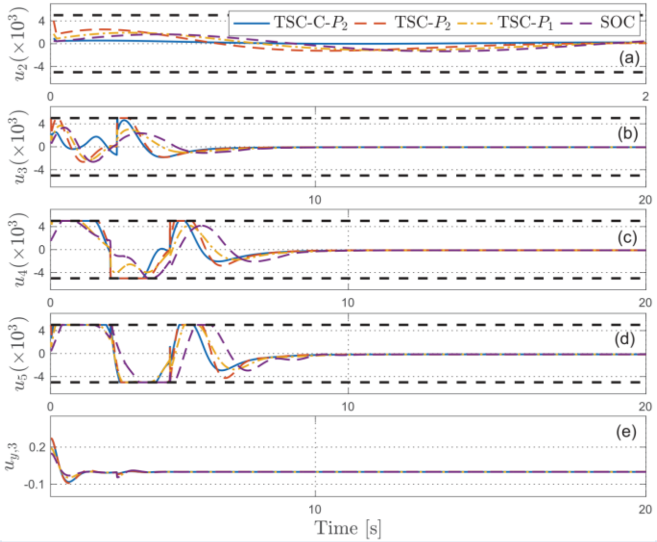
c. TSOC performance with safe reinforcement learning (SRL)

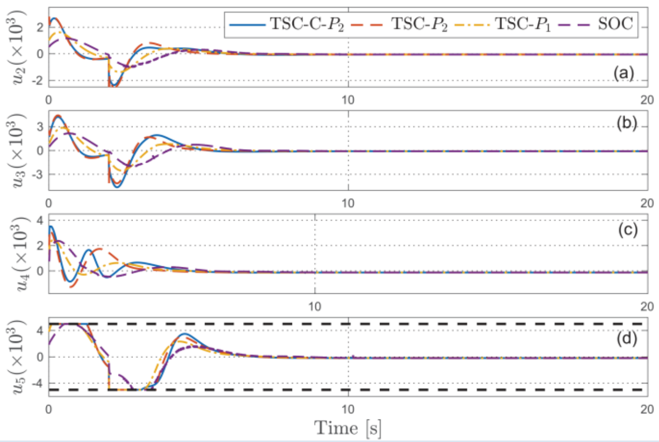


multi-stage lane-merging scenario



multi-stage on-ramp merging scenario





The overall platoon control can be adjusted timely after the vehicle joins or leaves the platoon; control inputs are especially smaller in the first about 2s with SOC

The control inputs with the TSC method increase significantly because of the sudden change of states caused by the merging maneuver, and the platoon is dynamically changing, the SOC method leads to a reduced frequency of occurrences where the control input limits are attained.

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4.1 Development of Stable, Robust and Secure (SRS) Intelligent Systems for Autonomous Vehicles

- **PI:** Prof Shuzhi Sam Ge
- **Co-PIs:** Yong Liu, Liangli Zhen, Rong Su, Mike Zheng Shou, Lin Zhao, Huazhu Fu, Rick Siow Mong Goh and Ong Yew Soon

Agency for Science, Technology and Research SINGAPORE

NUS National University of Singapore

NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

https://aisingapore.org/s20m-research-funding-to-address-challenges-related-to-the-increasing-use-of-ai-in-emerging-applications/

4.1 Grand Challenge Award in Robust AI, AI Singapore

4.1 Grand Challenge Award in Robust AI, AI Singapore

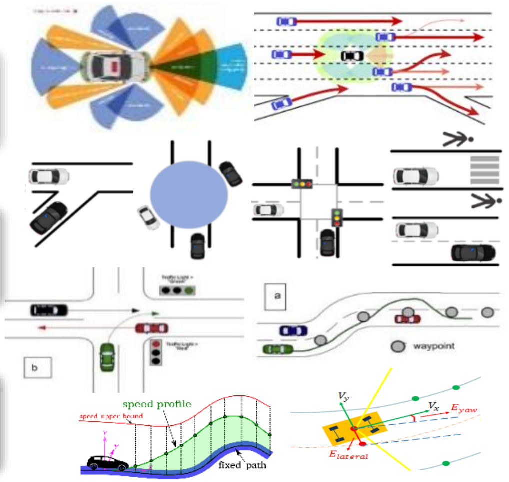
a. Autonomous Vehicles and Motivation

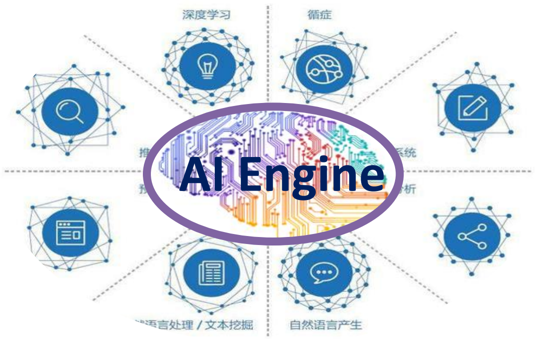
With the great development of Control, Communication, and Computing (C^3), high-performance autonomous vehicle systems are under heavy investment and critical research!

Model based, Learning-based， optimization and adaptive technologies, among other, are being used to solved complex and demanding requirements,

With the continuous advancement of information technologies centered on computing, communication, control, and intelligence

Perception → Decision → Planning





4.2 Modular Reconfigurable Mobile Robots (MR)^2

Tao Pey Yuen (SIMTech), Mohan Rajesh Elara (SUTD) , Shuzhi Sam GE (NUS),
Albertus Hendrawan Adiwahono (I2R), Lim Tao Ming (ARTC)

NUS National University of Singapore
Singapore Institute of Manufacturing Technology A*STAR SIMTech
Advanced Remanufacturing and Technology Centre A*STAR ARTC
Institute for Infocomm Research A*STAR I²R
SINGAPORE UNIVERSITY OF TECHNOLOGY AND DESIGN

4.2 Modular Reconfigurable Mobile Robots

A modular reconfigurable mobile robot system enabling quick assembly, terrain adaptability, heavy payload support, and fast repair through reusable hardware and software blocks.

Modules

Actuation
Dynamic Morphology
Payload Engagement

→

Software Building Blocks

Design Library
Physical Functional Building Blocks

→

Task Optimized Mobile Robots

Quick Assembly
Synthesis

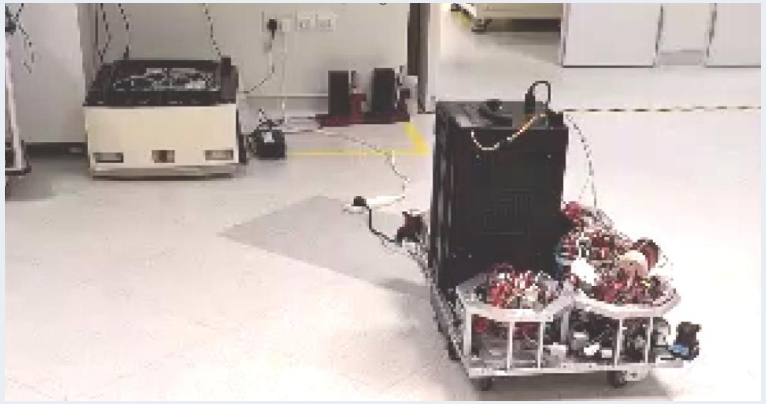
4.2 Modular Reconfigurable Mobile Robots

Quick Customization

- Reduce development costs
- Improve return on investment for end-users
- Enable automation for niche applications

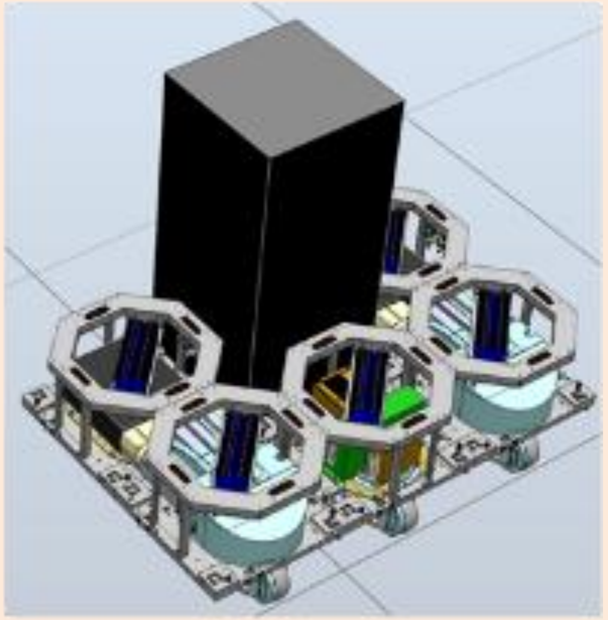
Reconfigurability and Flexibility

- Reconfigure for current production needs
- Share resources for optimized usage



Expedient Repair and Upgradability

- Quick repair via module replacement
- Incremental upgrade via module addition



4.3 Horizon Enripe Program: INPACE

INPACE: INdo-PACific-European Hub for Digital Partnerships:

Shuzhi Sam Ge, Singapore Lead and Asian Co-lead，

INPACE: INdo-PACific-European Hub for Digital Partnerships:

Trusted Digital Technologies for Sustainable Well-Being, EU$2.5million Horizon Europe Program,

Program Director, Dr Svetlana Klessova, COST- European Cooperation in Science and Technology, 1 January 2024-30 June 2027.

General Chairs：
Shuzhi Sam Ge, Singapore; Eva Pejsova, Belgium; Sebastian Engell, Germany; Franck Le Gall, France

INPACE: EU-Indo-Pacific Digital Partnership Conference 2025, 28 -29 Oct 2025

https://inpacehub.eu/eu-indo-pacific-digital-partnership-conference-2025

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5. Conclusion and Acknowledgements

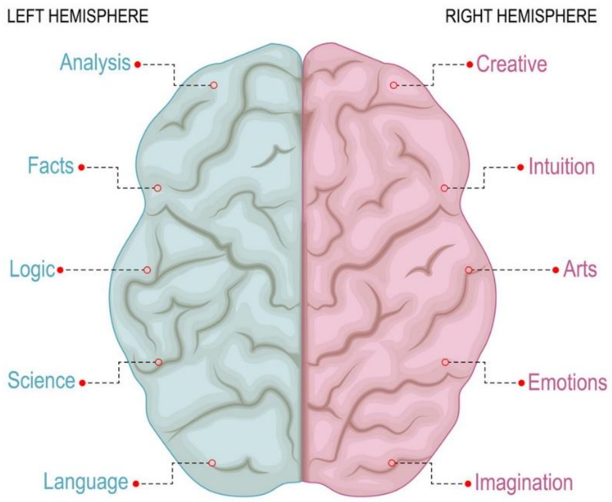
AI drives in Modelling, Control and Decision

Simplified understanding: Left brain = language/logic, Right brain = creativity

Complex thinking (logic, problem-solving) uses networks across both sides of the brain, working together. It is more about teamwork than strict left/right division!

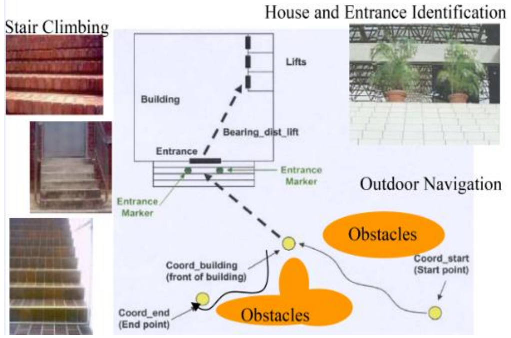
For example: - Left brain might handle the "rules" (e.g., math formulas).- Right brain might help with seeing the "big picture" (e.g., solving a puzzle by recognizing patterns).

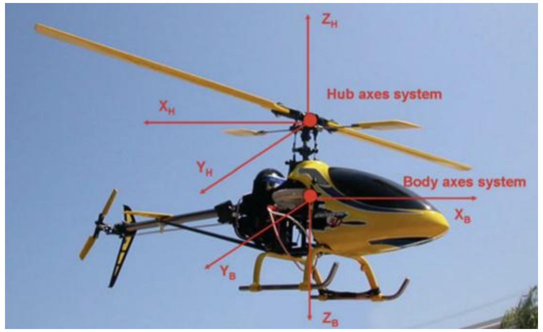
- Language Centre: LLM
- Visual Centre： occipital lobe, processing what we see LVM
- Cerebellum： Motion Control
- Auditory centre: temporal lobe, dealing with sounds and speech comprehension

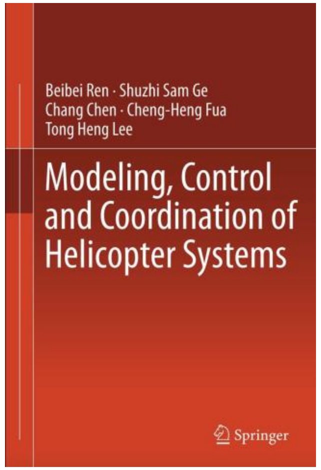


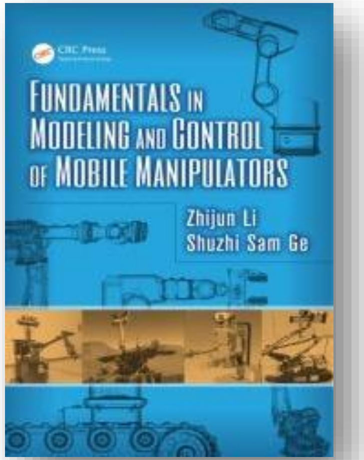
5. Conclusion and Acknowledgements

AI: Control Systems









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5. Conclusion and Acknowledgements

Enjoy Multi-Million Dollar Collaborations across Tertiary Institutions (NUS, NTU, SUTD, A*Star) and Industry

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IEEE Fellow
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(Autonomous Vehicles)

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Mohan Rajesh Elara
Associate Professor, SUTD
(Co-Lead PI)

Albertus Hendrawan Adiwahono
Principal Scientist, A*STAR
(I^2R Team PI)

Lim Tao Ming
Research Engineer, A*STAR
(ARTC Team PI)

5. Conclusion and Acknowledgements

We are still recruiting energetic and research translation Research Fellows and PhD students

Post Doctoral Researcher Fellow

Ruihang Ji,Yuxiang Zhang, Xiaoling Liang, Min Yuan, Pengyu Zhang, Jiafeng Li, Qizhi He,

Jingtao Sun, Haining Sun, …

PhD Students

Aoqian Zhang, Dong Huang, Dan Bao,Yunze Leng, Zeyuan Yang, Chuang Yang, Yueyi Chen,

Zhiwei Hao, Qing Yi, Xiangxiang Wang…

Master Students

Jiwei Tang, Wenkai Yang, Ruiqi Shi, Ankush Mishra， many more…

5. Conclusion and Acknowledgements

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