Future Directions in Control in the Era of Machine Learning and Artificial Intelligence

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Outline

Control Systems : Strong Theoretical Foundations

- Stability theory
- Algebraic, analytical, and topological structures
- Linear multivariable control
- Robust control
- Nonlinear control
- Adaptive Control
- Stochastic control
- Optimal control
- Distributed control

Control Systems: Diverse Application Domains

- Aerospace
- Automotive
- Manufacturing
- Chemical processes
- Transportation
- Communications
- Energy and power
- Water and agriculture
- Biomedical

Aspirational and Emerging Applications: Examples

- Smart-X
  1. Smart manufacturing, Industry 4.0
  2. Smart grid
  3. Smart and connected health
  4. Smart transportation
  5. Smart cities
- Low carbon economy, e. g., energy efficiency
- Precision and population health and wellness
- Food-energy-water nexus

Examples of Smart Systems

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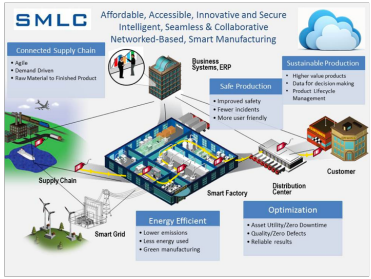

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SMART SOLUTIONS FOR SMART CITIES

Smart monitors and controls across all aspects of city life are set to transform the urban landscape

- Transport
- Infrastructure
- Environment
- Utilities
- Buildings
- Life

01 GREEN BUILDINGS
Rooftop gardens or vegetation on the side of buildings help insulate, absorb CO_2, and produce oxygen

02 BUILDING MANAGEMENT
Automation and optimisation of services such as heating, energy usage, lighting and ventilation

03 PERIMETER ACCESS CONTROL
Controlling access and monitoring of restricted areas with CO_2 or user detection and alarms

04 ROOFTOP WIND TURBINES
Wind turbines built on top of or features and mounted or integrated into the building design itself

05 AIR POLLUTION CONTROL
Controlling CO_2 emissions and features and monitoring car pollution

06 BUILDING-INTEGRATED PHOTOVOLTAICS
Solar panels integrated into the building facing to replace conventional materials

07 SMART GRID
Energy consumption monitoring and management

08 CHEMICAL LEAKAGE DETECTION
Detecting leakages and waste of factories in rivers

09 REAL-TIME UPDATES
Instant traffic updates sent to smartphones to help route-planning and avoid congestion

10 FIRE SAFETY
Fire detection and intelligent extinguishing tailored to each room

11 STRUCTURAL HEALTH
Monitoring vibrations/material conditions in buildings and infrastructure

12 ELECTRIC TRANSPORT
Electric vehicles and public transport, with charging stations across the city

13 SMART LIGHTING
Intelligent and weather-adaptive streetlights

14 TRAFFIC CONTROL/ SMART ROADS
Monitoring vehicles/pedestrian levels to optimise or divert traffic according to conditions

15 FAST LANES
Intelligent, adaptive fast and slow lanes for walking and cycling

16 LANDSLIDE AND AVALANCHE PREVENTION
Monitoring soil moisture, vibrations and earth density

17 WATER LEAKAGE DETECTION
Detecting liquid presence outside pipes and pressure variations along pipes

18 WI-FI
Citywide free wi-fi for public use, rebuilding wi-fi on the Tube/Metro

19 POTABLE WATER MONITORING
Monitoring the quality of tap water across the city

20 EARTHQUAKE EARLY DETECTION
Monitoring specific places susceptible to tremors

21 SMART PARKING
Monitoring availability of parking spaces across the city

22 VERTICAL-AXIS WIND TURBINES
Helical twisted wind turbine towers across the city for efficient use of space

23 WASTE MANAGEMENT
Monitoring rubbish levels in containers to optimise refuse collection routes

Visual Capitalist

Smart-X: Conceptual View

Sensors

Communications

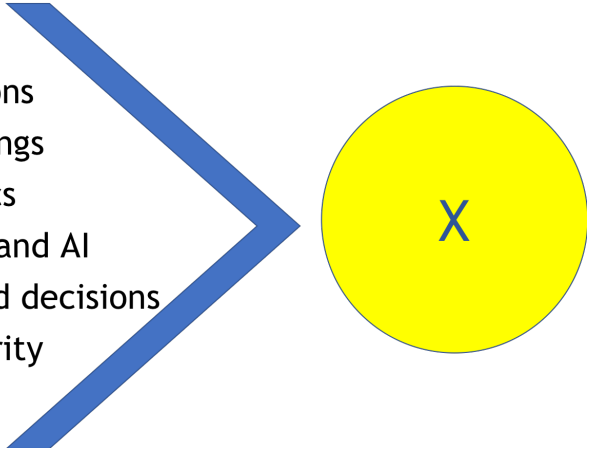
Internet-of-things

Data analytics

Machine learning and AI

Distributed control and decisions

Cyber(PS)security



Common Themes

- These "systems of systems" are large heterogeneous distributed networks of (IoT) connected devices, systems, and human/social agents
- They require high reliability and efficiency under uncertainty
- Physical and informational flows, hierarchies, and interactions
- Real time distributed decision and control
- Technology meets human behavior
- Essential role for socio-economic-political-legal public, private, non-profit organizations

Challenge: Design, operation, management and control of large, distributed, heterogeneous, complicated, interconnected socio-techno-economic systems

Vision: Control systems will play an important role but it will need to integrate with sensors, cyber-physical-human systems, internet-of-things, data science, and machine learning

Background and Past Work

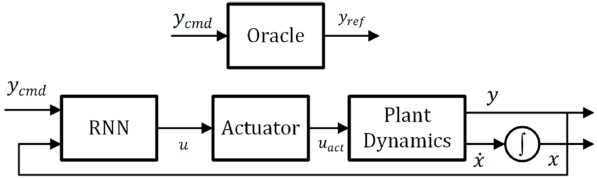
- Control theory: robust and $\mathcal{H}_\infty$ control, system identification, ...
- Applications of modeling and control to semiconductor manufacturing (plasma processing
- Modeling and logic control of reconfigurable manufacturing systems
- Seizure detection using support vector machines, modeling of neural systems
- Recent interest: renewable integration and smart electric grid
- Recent PhD student at the University of Florida: machine learning for flight control

Machine Learning Applications to Flight Control

- Long-term learning of adaptive controllers using sparse neural networks
- Robust deep recurrent neural network controllers
- Sparse, recurrent neural network adaptive controllers
- Key publications:

1. S. Nivison and P. P. Khargonekar, "Improving Long-Term Learning of Model Reference Adaptive Controllers for Flight Applications: A Sparse Neural Network Approach," Proc. 2017 AIAA Guidance, Navigation, and Control Conference, 2017.
2. S. Nivison and P. P. Khargonekar, "Development of a Robust Deep Recurrent Neural Network Controller for Flight Control Applications," Proc. American Control Conference, pp. 5336-5342, 2017.
3. S. Nivison and P. P. Khargonekar, "A Sparse Neural Network Approach to Model Reference Adaptive Control with Hypersonic Flight Applications," Proc. 2018 AIAA Guidance, Navigation, and Control Conference.
4. S. Nivison and P. P. Khargonekar, "Development of a Robust, Sparsely-Activated, and Deep Recurrent Neural Network Controller for Flight Application," Proc. IEEE Conference on Decision and Control, 2018.

Deep Learning based Flight Control



Deep Learning Training Architecture

Generalized Form of the Discrete Plant Dynamics

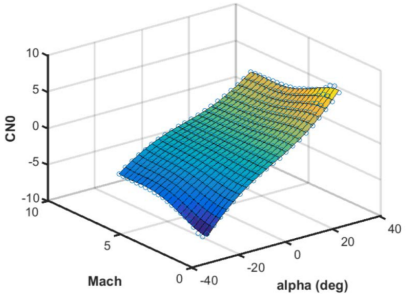
$$
\begin{aligned}
x_{t+1} &= f(x_t, (\lambda_u(u_t^{act} + \rho_u)) + d_u, \rho_\alpha, \rho_q) + \zeta_p \\
y_t &= f(x_t, (\lambda_u(u_t^{act} + \rho_u)) + d_u, \rho_\alpha, \rho_q) + \zeta_p
\end{aligned}
$$

x_t are the states of the plant
u_t^{act} is the actuator output
y_t is the output vector
ζ_p is the plant noise
λ_u is the control effectiveness
d_u is an input disturbance
$\rho_u, \rho_\alpha, \rho_q$ are uncertainty parameters

Dynamic Model of the Aircraft

Longitudinal Rigid Body Dynamics:

$$
\begin{aligned}
\dot{V}_T &= \frac{1}{m}(T cos(\alpha) - D) - g sin(\theta - \alpha) \\
\dot{\alpha} &= \frac{1}{mV_T}(-T sin(\alpha) - L) + q + \frac{g}{V_T} cos(\theta - \alpha) \\
\dot{\Theta} &= q \\
\dot{q} &= \frac{M}{I_{YY}} \qquad x = [V_T,\, \alpha,\, \Theta,\, q,\, h] \\
\dot{h} &= V_T sin(\theta - \alpha) \qquad y = [\alpha,\, q,\, A_z,\, \bar{q}]
\end{aligned}
$$



Force and Moment Equations:

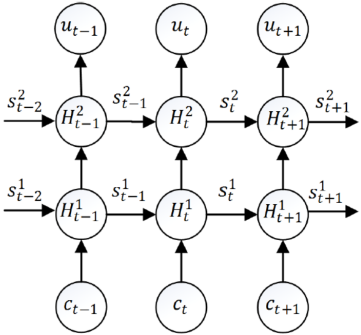
$$
\begin{aligned}
A &\approx \frac{1}{2}\rho V_T^2 S C_A \qquad & L &= N cos(\alpha) - A sin(\alpha) \\
N &\approx \frac{1}{2}\rho V_T^2 S C_N \qquad & D &= N sin(\alpha) + A cos(\alpha) \\
M &\approx \frac{1}{2}\rho V_T^2 S c_{ref} C_m
\end{aligned}
$$

Aerodynamic Coefficients (Longitudinal):

$$
\begin{aligned}
C_A &= C_{A_{ALT}}(h,\, M) + C_{A_{AB}}(\alpha,\, M) \\
&\quad + \sum_{i=1}^{4} C_{A_{\delta_i}}(\alpha,\, M,\, \delta_i) \\
C_N &= C_{N_0}(\alpha,\, M) + \sum_{i=1}^{4} C_{N_{\delta_i}}(\alpha,\, M,\, \delta_i) \\
C_m &= C_{m_0}(\alpha,\, M) + \sum_{i=1}^{4} C_{m_{\delta_i}}(\alpha,\, M,\, \delta_i) \\
&\quad + C_{m_q}(\alpha,\, M,\, q) + q\rho_q + \alpha\rho_\alpha
\end{aligned}
$$

Recurrent Neural Network

Stacked Recurrent Neural Network (S-RNN)



Algorithm 1 Gated Recurrent Units (GRU)

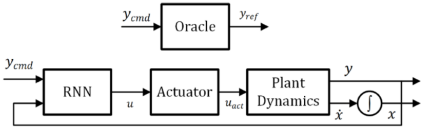
1: $z = \sigma(c_t U^u + s_{t-1} W^u + b_1)$
2: $r = \sigma(c_t U^r + s_{t-1} W^r + b_2)$
3: $h = tanh(c_t U^h + (s_{t-1} * r) W^h + b_3)$
4: $s_t = (1 - z) * h + z * s_{t-1}$
5: $*$ represents element-wise multiplication

$$u_t = s_t V + c$$

Θ_i matrix of parameters for each GRU module
$\Theta_i = [U^u, W^u, U^r, W^r, U^h, W^h, b_1, b_2, b_3]$
Θ total parameters of the controller
$\Theta = [\Theta_1, \Theta_2, \ldots, \Theta_L, V, c]$
L total layers of GRU modules

Controller Input Vector:

$c_t = [e_i, \alpha, q, \bar{q}]$
$e = y_{sel} - y_{cmd}$
$$e_i = \int_0^{t_f} e \, dt$$



Controller Performance

Flight Condition:

Mach	α (deg)	q (deg/sec)	Altitude (km)
1.7	0	0	14

Augmented polynomial short period model:

$$
\begin{aligned}
\dot{e}_I &= \alpha - \alpha_{cmd} \\
\dot{\alpha} &= f(\alpha, q, \delta_e, \rho_\alpha, \rho_q, \rho_u, \lambda_u) \\
\dot{q} &= f(\alpha, q, \delta_e, \rho_\alpha, \rho_q, \rho_u, \lambda_u)
\end{aligned}
$$

Initial Conditions:

	MIN	MAX
α_0(deg)	-30	30
q_0(deg/sec)	-100	100
R_α	-0.5	0.1
R_q	-7	5
R_u	-5	5
Λ_u	0.25	3.0

Performance Metrics:

$$ATE = \frac{1}{N}\Sigma_{i=1}^{N}\Sigma_{t=1}^{t_f}|e_t|$$

$$ACR = \frac{1}{N}\Sigma_{i=1}^{N}\Sigma_{t=1}^{t_f}|\dot{u}_t|$$

$$CTE = \Sigma_{j=1}^{M} ATE$$

$$CCR = \Sigma_{j=1}^{M} ACR$$

TABLE II

CUMULATIVE ERROR (CTE), CONTROL RATE (CCR), AND FINAL COST

	CTE	CCR	Cost
3-Layer RNN/GRU	339.15	100.16	1.0438
2-Layer RNN	359.28	313.64	2.4970
GS	1000.21	1180.04	-

DLC Performance: 66% reduction in CTE, 91.5% reduction in CCR

Controller Performance

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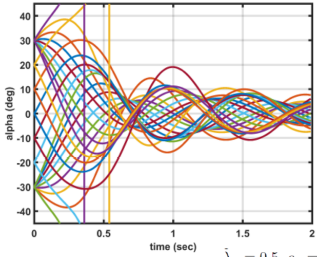
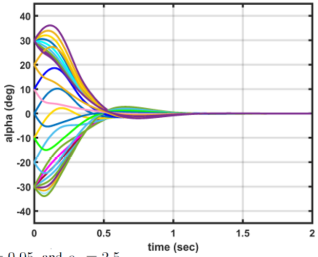
Gain Scheduled Controller



Deep Learning Controller



$\bar{\lambda}_u = 0.5$, $\rho_u = 0$, $\rho_\alpha = 0.05$, and $\rho_q = 2.5$

Directions at the Confluence of Machine Learning and Control

- Leverage the new dimensionality reduction techniques to deal with high-dimensional data from sensors
- Exploit "learning to learn" paradigm for controlling "new systems" from control of known systems
- Address large uncertainties in the environment (and models)
- Learning to overcome modeling barrier ubiquitous in control
- Explore creative approaches to combine machine learning techniques with model based control
- Leverage what humans do well with autonomous systems to create more capable systems
- How to deal with not having large datasets?

New NSF EAGER Grant

- Title: EAGER: Real-time: Reinforcement, Meta, and Episodic Learning for Control under Uncertainty
- Co-PI: Professor Pierre Baldi
- Start Date: September 2018

"A key focus will be on novel control architectures inspired by neuroscience and reinforcement learning. Besides architectural innovations, the project will explore questions of stability, performance, and uncertainty by integrating ideas from rapid (one-shot) learning, meta-learning, and episodic control into control algorithms."

Episodic Memory and Control

- What is or should be the role of one-shot learning and/or epsiodic memories in RL and control?
- Does it have potential relevance to "small data" learning and control?
- Use of episodic memory for estimation of state-action value pair in RL.
- Chaining of episodes and options in hierarchical RL.
- Sparse distributed representations for episodic memory

Meta Learning and Control

- Two level learning: within a task and across tasks
- Use of external or internal memory
- LSTM is an example of internal memory
- Neural Turing Machines
- Memory augmented neural networks

Neuroscience Inspired Control

- New discoveries on how brain works
- Example: Predictive brain theory [Clark (2013), Friston (2010)]
- Example: Brain employs a mixture of model-based and model-free RL
- Example: Detailed models of sensori-motor control systems [Wolpert et al. (2011)]

Concluding Remarks

- A large opportunity to advance the field of systems & control
- Leverage tremendous progress and investments in ML and AI
- Address important societal problems and capture technological opportunities
- Important role for collaboration, team science, and convergence