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

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Outline

Emerging Smart-X and Control

Recent Past Work: Machine Learning for Flight Control

Ideas for Future Exploration
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

- DOE
- SMLC
- NIH
- DOT
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:

Deep Learning based Flight Control

Generalized Form of the Discrete Plant Dynamics

\[ x_{t+1} = f(x_t, (\lambda_u(u_{t}^{act} + \rho_u)) + d_u, \rho_\alpha, \rho_q) + \zeta_p \]
\[ y_t = f(x_t, (\lambda_u(u_{t}^{act} + \rho_u)) + d_u, \rho_\alpha, \rho_q) + \zeta_p \]

- \( x_t \) are the states of the plant
- \( u_{t}^{act} \) is the actuator output
- \( y_t \) is the output vector
- \( \zeta_p \) is the plant noise
- \( \lambda_u \) 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:

\[
\begin{align*}
\dot{V}_T &= \frac{1}{m}(T \cos(\alpha) - D) - g \sin(\theta - \alpha) \\
\dot{\alpha} &= \frac{1}{mV_T}(-T \sin(\alpha) - L) + q \frac{g}{V_T} \cos(\theta - \alpha) \\
\dot{\Theta} &= q \\
\dot{q} &= \frac{M}{I_{YY}} \\
\dot{h} &= V_T \sin(\theta - \alpha)
\end{align*}
\]

\[x = [V_T, \alpha, \Theta, q, h]\]

Force and Moment Equations:

\[
\begin{align*}
A &\approx \frac{1}{2} \rho V_T^2 S C_A \\
L &= N \cos(\alpha) - A \sin(\alpha) \\
N &\approx \frac{1}{2} \rho V_T^2 S C_N \\
D &= N \sin(\alpha) + A \cos(\alpha) \\
M &\approx \frac{1}{2} \rho V_T^2 S_{ref} C_m
\end{align*}
\]

Aerodynamic Coefficients (Longitudinal):

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

Stacked Recurrent Neural Network (S-RNN)

$u_t = s_t V + c$

$\theta_i$ matrix of parameters for each GRU module

$\theta_i = [U^u, W^u, U^r, W^r, U^h, W^h, b_1, b_2, b_3]$  
$\theta$ total parameters of the controller

$\theta = [\theta_1, \theta_2, ..., \theta_L, V, c]$  
$L$ total layers of GRU modules

Controller Input Vector:

$c_t = [e_t, \alpha, q, \bar{q}]$  
$e = y_{set} - y_{cmd}$  
$e_t = \int_0^{t_f} e \, dt$
Controller Performance

Flight Condition:

<table>
<thead>
<tr>
<th>Mach</th>
<th>α (deg)</th>
<th>q (deg/sec)</th>
<th>Altitude (km)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.7</td>
<td>0</td>
<td>0</td>
<td>14</td>
</tr>
</tbody>
</table>

Augmented polynomial short period model:

\[ \dot{\alpha} = \alpha - \alpha_{cmd} \]
\[ \dot{\alpha} = f(\alpha, q, \delta, \rho_\alpha, \rho_q, \rho_u, \lambda_u) \]
\[ \dot{q} = f(\alpha, q, \delta, \rho_\alpha, \rho_q, \rho_u, \lambda_u) \]

Performance Metrics:

\[ ATE = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T_f} |e_t| \]
\[ ACR = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{T_f} |\dot{u}_t| \]
\[ CTE = \sum_{j=1}^{M} ATE \]
\[ CCR = \sum_{j=1}^{M} ACR \]

Initial Conditions:

<table>
<thead>
<tr>
<th></th>
<th>MIN</th>
<th>MAX</th>
</tr>
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<tbody>
<tr>
<td>(\alpha_0) (deg)</td>
<td>-30</td>
<td>30</td>
</tr>
<tr>
<td>(q_0) (deg/sec)</td>
<td>-100</td>
<td>100</td>
</tr>
<tr>
<td>(R_\alpha)</td>
<td>-0.5</td>
<td>0.1</td>
</tr>
<tr>
<td>(R_q)</td>
<td>-7</td>
<td>5</td>
</tr>
<tr>
<td>(R_u)</td>
<td>-5</td>
<td>5</td>
</tr>
<tr>
<td>(\Lambda_u)</td>
<td>0.25</td>
<td>3.0</td>
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TABLE II

Summary of Results

<table>
<thead>
<tr>
<th></th>
<th>CTE</th>
<th>CCR</th>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>3-Layer RNN/GRU</td>
<td>339.15</td>
<td>100.16</td>
<td>1.0438</td>
</tr>
<tr>
<td>2-Layer RNN</td>
<td>359.28</td>
<td>313.64</td>
<td>2.4970</td>
</tr>
<tr>
<td>GS</td>
<td>1000.21</td>
<td>1180.04</td>
<td>-</td>
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DLC Performance: 66% reduction in CTE, 91.5% reduction in CCR
Controller Performance

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**Gain Scheduled Controller**

**Deep Learning Controller**
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?
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 episodic 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