Cognitive Cyber-Physical Systems: Vision for the Next CPS Frontier

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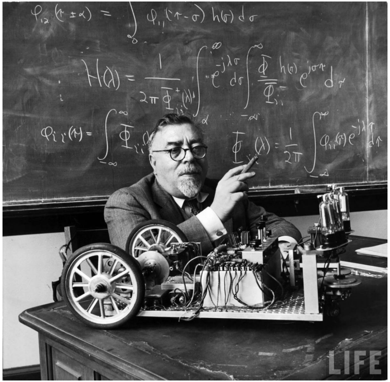
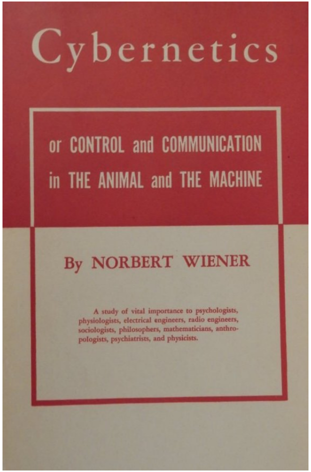
Outline

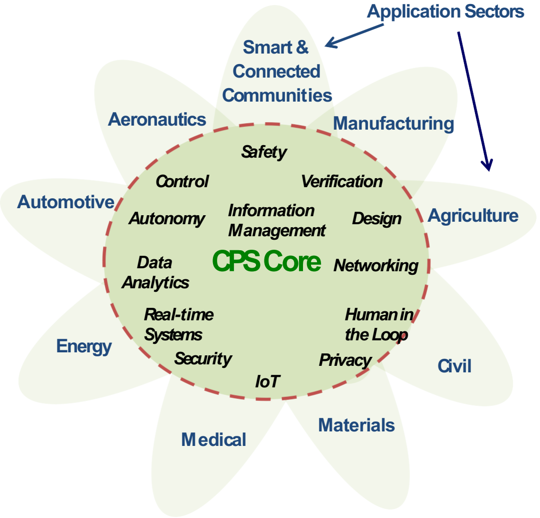
Wiener, Cybernetics, and Macy Conferences





How would the pioneers of cybernetics and AI envision the future of CPS?

Cyber-Physical Systems



Application Domains

Transportation

- Faster and safer vehicles (airplanes, cars, etc)
- Improved use of airspace and roadways
- Energy efficiency
- Manned and un-manned

Energy and Industrial Automation

- Homes and offices that are more energy efficient and cheaper to operate
- Distributed micro-generation for the grid

Healthcare and Biomedical

- Increased use of effective in-home care
- More capable devices for diagnosis
- New internal and external prosthetics

Critical Infrastructure

- More reliable power grid
- Highways that allow denser traffic with increased safety

Source: NSF

CPS Properties

- Pervasive computation, sensing, and control
- Networked at multiple scales
- Dynamically reorganizing/reconfiguring
- High degrees of automation
- Dependable operation with potential requirements for high assurance of reliability, safety, security and usability
- With or without human interaction/supervision
- Conventional and unconventional substrates/platforms
- Range from the very small to the large to the very large

Source: NSF

Aspirational and Emerging Applications: Examples

- Smart-X
  1. Smart manufacturing
  2. Smart grid
  3. Smart transportation
  4. Smart cities
  5. Smart health
- Autonomous systems
  1. Unmanned air vehicles
  2. Self-driving cars
  3. Autonomous robots

Human individual and group behavior is central in many of these applications:

Cyber-Physical-Human Systems (CPHS).

Smart-X: Conceptual View

Sensors

Communications

Internet-of-things

Automation

Data analytics

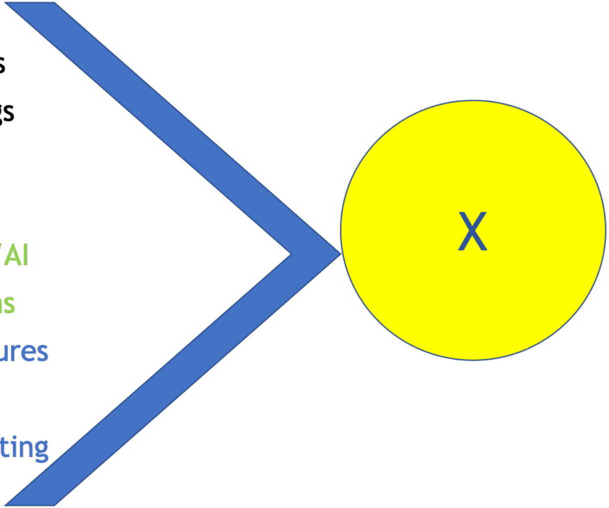
Machine learning/AI

Control/Decisions

Software Architectures

Cybersecurity

Cloud/Edge Computing



Smart Manufacturing: Industrie 4.0

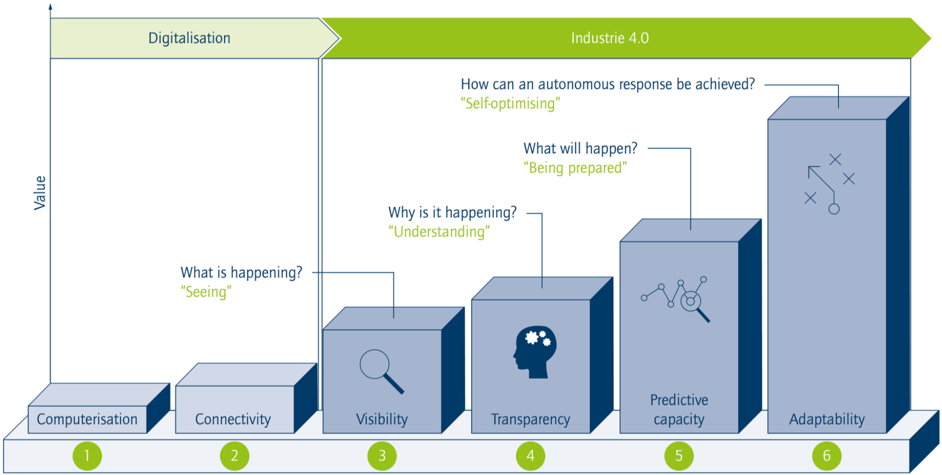


Figure 5: Stages in the Industrie 4.0 development path (source: FIR e. V. at RWTH Aachen University)

BMW Self-Steering Supply Chain

"…the Connected Supply Chain anticipates a huge shift towards a cyber-physical production system, with logistics not only the heart of production, but also the mobile mind guiding parts and vehicles to where they need to be, based on real demand and transport conditions, as well as the arms and legs supporting the picking and moving of material."

BMW's 'connected' logistics: Shaping a self-steering supply chain

Smart-X Future

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

Vision: CPS will play a central role but will need to integrate with ML/AI and enable human flourishing.

Cognitive Cyber-Physical Systems

Marr's 3 Levels of Analysis and Cognitive Science

Goal/Function (Computational)

Algorithm and Architecture

Implementation

Symbolic vs. Neural Connectionist Approaches

- Historical and ongoing debate on the nature of human cognition and the structure of the brain.
- Key topic in cognitive science: neuroscience, ML/AI, psychology, liguistics.
- Three major components:
  - Computational logic systems
  - Connectionist neural network models
  - Models and tools for uncertainty
- Pragmatic approach: combine connectionist, logic and probabilistic approaches to achieve desired system goals and objectives.

Besold et al. (2017)

Computational Intelligence: Pattern Recognition or Model Building

Two fundamentally different perspectives on learning from data:

1. Statistical pattern recognition from data for prediction and control.
2. Use prior knowledge and data to build causal models to understand, predict and control.

It is possible to combine these two approaches.

Causality a critical issue.

Cognition - Definitions and Characteristics

- "All processes by which the sensory input is transformed, reduced, elaborated, stored, recovered, and used." — Neisser, Cognitive Psychology, 1967.
- Important role of in-built capacity in the brain from genetics and evolution, e. g., symmetry, intuitive physics.
- Key Cognitive Functions
  1. Perception
  2. Attention
  3. Memory
  4. Reasoning
  5. Problem solving
  6. Knowledge representation

Cognitive CPS - Key Principles

- Definition: CPS that have *cognitive functions and capabilities*.
- CPS can be explicitly designed and/or can learn to possess cognitive functions.
- Need for specific cognitive functions and capabilities will depend on the problem.
- Cognitive CPS's may learn from each other, from humans, and also form collaborative networks.
- Hypothesis: Cognitive CPS will be better able to augment humans and lead to human flourishing.

Cognitive CPS concept offers the most expansive and ambitious program for integrating ML/AI with CPHS for realizing Smart-X Systems.

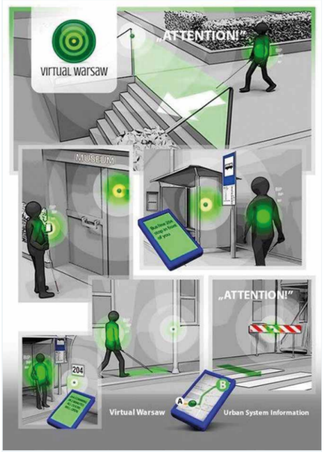
Perception in ML

- Deep learning is revolutionizing perception.
- Compositionality is built-in.
- Examples of very impressive progress in:
  - Computer vision.
  - Speech recognition and processing.
  - Language translation.
- Architectures:
  - Convolutional neural networks
  - Long Short Term Memory (LSTM) recurrent neural networks.

Perception in CPS

- CPS with multiple, distributed sources of sensed information.
- Immediately possible to leverage DL advances.
- Prior knowledge plays a very large role in cognitive theories of perception.
- Neural network techniques could be combined with relational prior knowledge for improved context awareness in sensor rich CPS.
- Potential tools and techniques for relational priors:
  1. Neural networks with symbolic front ends with priors to learn the symbolic front end.
  2. Graph networks, e.g., scene graphs.

Example: Virtual Warsaw — Smart City Helping Visually Impaired



© Virtual Warsaw visual demo.

"City of Warsaw launched "Virtual Warsaw", a virtual smart city based on Internet of Things (IoT) technology . . . city is deploying a network of hundreds of thousands of beacon sensors . . . to help visually impaired residents move independently about the city with assistance from their smartphones. "

EMBRACING INNOVATION IN GOVERNMENT: GLOBAL TRENDS, OECD

Attention in ML

- Attention is the key to focussing on the most relevant information from multiple distributed sources of information.
- Neurocomputational models to show that attention is important in cognition.
- Numerous research advances in ML.

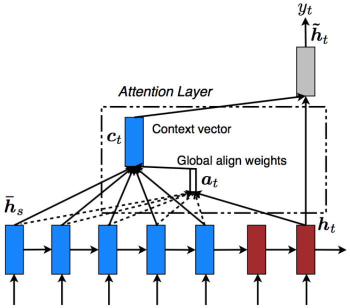


Figure: Attention based Machine Translator

Attention in CPS

- Two levels of attention:
  - First level - selection and focus on a particular task.
  - Second level - top-down search for relevant information.
- Attention for detecting changing conditions and contexts.
- Attention for fault detection and/or resilience.
- Attention models that are hierarchical and programmable will be required for CPS.

Memory

- Memory is central to intelligent behavior.
- Multiple memory mechanisms in human cognition:
  - short-term
  - long-term
  - episodic (content-addressable)
  - semantic
- Examples: LSTM, differential neural computers (DNC), experience replay
- Key idea: Explicitly incorporate external memory systems in CPS architectures.

Memory in CPS: Episodic Control

- Episodic control - re-enact successful episodes from memory storage.
- Episodic control has potential relevance to “small data” learning and control.
- Model-free episodic control — recorded experiences are used as value function estimators.
- Neural episodic control – combining deep learning model and lookup tables of action values.

Problem Solving and CPS

- Problem solving is key to enable CPS to make the optimal decisions.
- Reinforcement learning ideas and techniques are relevant in the context of goal oriented tasks.
- RL algorithms that are efficient and scalable will be necessary.
- Safety is critical for CPS.
- Potential approaches:
  1. Model based RL
  2. Safe RL algorithms
  3. Hierarchical RL

Knowledge Representation

- Knowledge representation plays a role in CPS, e.g., smart manufacturing
- Knowledge representation can be of varied types: concepts, logic, rules, procedures.
- Traditional approaches, e.g., expert systems, had limited successes.
- Learning knowledge graphs from data and priors.
- Transfer learning using knowledge graphs.
- Connectionist models for dense distributed representations.
- Compositionality of knowledge representation.

Selected Methodological Challenges

- Approaches for combining model-based and model-free techniques.
- Approaches to combine hierarchical and distributed architectures and algorithms.
- Reducing the need for large amounts of data.
- Leveraging meta learning paradigm: “learning to learn”.

Example: Enabling Resilience in Smart Grids

- Three phases: pre-event, during event, and post-event
- Use of multi-sensory perception pipelines for reliable multi-time scale decisions
- Episodic control and decision making to learn from past experiences.
- Learning resilience strategies by RL on large scale simulation data.
- Meta learning methods for long-term resilience adaptation strategies.

Example: Smart Transportation

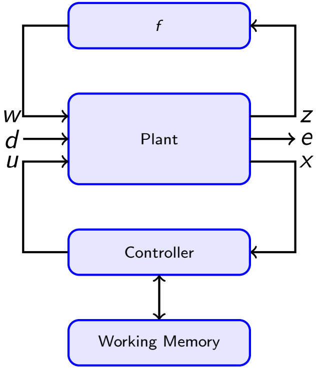
- Greater perceptual awareness at various levels in the transportation system using distributed, connected sensors.
- Example direction for improving perception: inference on scene graph embeddings, semantic front ends.
- Meta learning methods for adaptation to novel circumstances.
- Use of cognitive functions in self-driving cars for better interactions with human driven cars.

Our Recent Work

External Memory in Control

Theme: External memory to improve learning/adaptation in control systems.

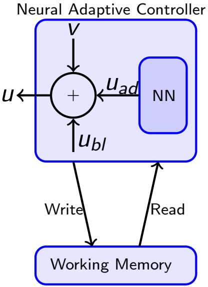
- Plant represents the system to be controlled. u: control input, x: system state.
- Function f is the uncertainty in the system model.
- Traditionally, the dynamic state of the controller constitutes the "memory".
- Idea: Controller can read from and write to the *external working memory.*



Working Memory Augmented Neural Adaptive Control

- u_{bl}: baseline control input using standard model-based (robust) control design.
- u_{ad}: control term for compensating the uncertainty f. It is the output of NN.
- v: robustness term for nullifying the higher order residual terms.
- Memory read is used to modify the output u_{ad} from NN
- Control equation:

$$u = u_{\text{bl}} + u_{\text{ad}} + v \tag{1}$$



Working Memory Structure

Working memory with six memory locations. Upper row is the matrix h of content vectors. Lower row is the matrix k of key vectors. Key k_i serves as an indentifier for content vector h_i.

$$\overbrace{\underbrace{\begin{array}{|c|c|c|c|c|c|}\hline h_1 & h_2 & h_3 & h_4 & h_5 & h_6 \\ \hline k_1 & k_2 & k_3 & k_4 & k_5 & k_6 \\ \hline \end{array}}_{k}}^{h}$$

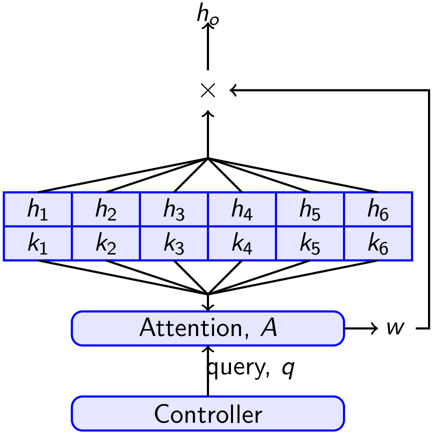
$h = [h_1, h_2, ..., h_6],\ k = [k_1, k_2, ..., k_6]$

Interface Operation: Memory Read

- A query q generated by the controller to read from memory
- Memory read equation:

$$h_o = hw = \sum_i w_i h_i \tag{2}$$

- Vector of weights w determined by an *attention mechanism:* $w_i = A_i(q, k)$
- Hard and soft attention mechanisms.



Interface Operation: Memory Write

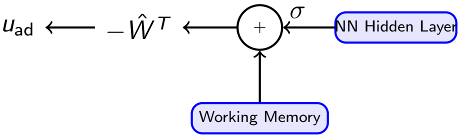
- The write vector that carries the new information is denoted by h_w
- Write operation is modeled by a differential equation with a forget term, an update term and an additional third term that is an update by the learning algorithm,

$$\dot{h}_i = -w_i h_i + c_w w_i h_w + w_i \hat{W} h_e^T \tag{3}$$

  where w_i are the same attention weights
- The factor c_w is a design parameter that controls the extent to which the write vector can update the memory.

Modification of Control Input in Neural Adaptive Control

- Two layer NN: $\hat{W}^T \sigma(\hat{V}^T x + \hat{b}_v)$
- Memory Read output, h_o
- Memory Read h_o modifies the context for the output layer of the NN



- *Memory augmented adaptive control:*

$$u_{ad} = -\hat{W}^T \left(\sigma(\hat{V}^T x + \hat{b}_v) + h_o \right) \tag{4}$$

Application to Flight Control

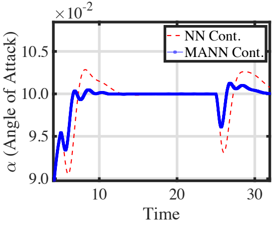


Figure: Comparison of MRAC flight controllers with and without Memory. Reference Signal (s): 0.1 deg

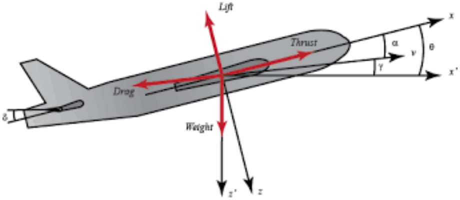


Table: Flight Controller Performance

Metric	Peak Deviation	Settling Time (1 % error)
NN cont.	0.54^o	6.61 s
MANN Cont.	0.38^o	3.45 s
Reduction	$\sim$ 30%	$\sim$ 48%

Application to Two Link Planar Robot Arm

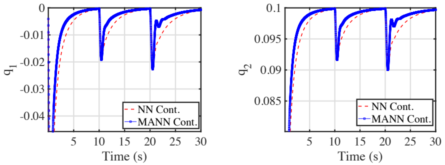


Figure: Joint angle responses for controllers with and without memory. Left: joint variable x_1, right: joint variable x_2. Reference signal, $s_1 = 0, s_2 = 0.1$

Table: Robot Arm Controller Performance, Settling Time (1 % error), First abrupt change

Joint Angle	1	2
NN cont.	17.6 s	15.2 s
MANN Cont.	16.3 s	13.7 s
Reduction	7.8%	10.4%

Table: Robot Arm Controller Performance, Settling Time (1 % error), Second abrupt change

Joint Angle	1	2
NN cont.	29.7 s	26.72 s
MANN Cont.	28.5 s	24.9 s
Reduction	4%	6.8%

Peak deviations are nearly identical

Publications for More Details

1. D. Muthirayan and P. P. Khargonekar, “Working Memory Augmentation for Improved Learning in Neural Adaptive Control,” IEEE Conference on Decision and Control, 2019, to appear.
2. D. Muthirayan, and P.P. Khargonekar, “Memory Augmented Neural Network Adaptive Controllers: Performance and Stability”, arXiv preprint arXiv:1905.02832, 2019
3. D. Muthirayan, and P.P. Khargonekar, “Memory Augmented Neural Network Adaptive Controller for Strict Feedback Nonlinear Systems,” arXiv preprint arXiv:1906.05421, 2019
4. D. Muthirayan, S. Nivison and P. P. Khargonekar, “Improved Attention Models for Memory Augmented Neural Network Adaptive Controllers,” arXiv preprint arXiv:1910.01189, 2019

Concluding Remarks: Cognitive CPS as Vision for the Future

- Cognitive CPS is a potential vision for the future of human-augmenting CPS.
- Recent advances in ML/AI offer building blocks for cognitive CPS.
- Cognitive CPS could offer new directions as ML/AI meet the physical world.
- Need to bring in (computational) cognitive science.
- Applications should drive selection of problems and development of technologies.
- Gradual development of various cognitive capabilities in cognitive CPS likely.

We are in the early stages of this exciting journey.

Thank you!

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