PERFORMANCE EVALUATION OF AUTONOMOUS SYSTEMS USING ENTROPY

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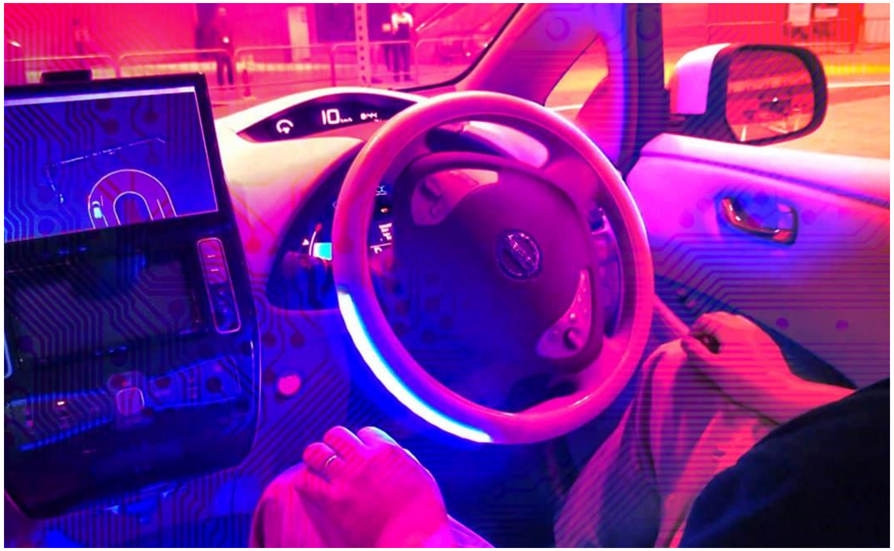
OUTLINE

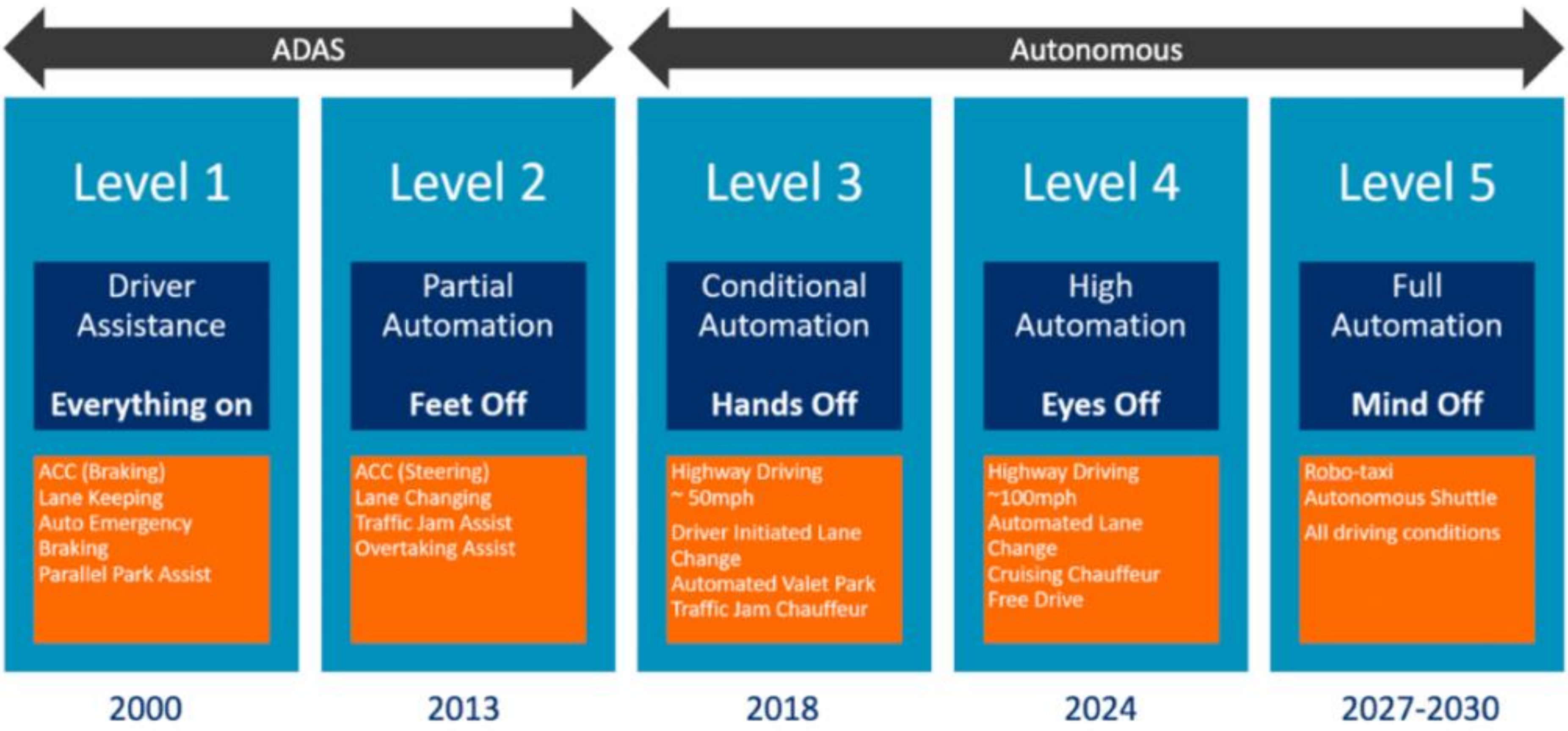
- Putting Everything in Context
- Historical Perspective – Control System Theory: 1950 - today
- Entropy in Thermodynamics
- Shannon Entropy
- Information Theory
- MIT: Alex Levis Group
  - Decision Makers
  - Principle of Bounded Rationality
- Conant – 1976
  - Laws of Information that Govern Performance of Systems (IEEE SMC)
- Intelligent Control – Antsaklis, Saridis
- Autonomy and (Machine / Artificial) Intelligence
  - Autonomy ‘with respect to what’?
  - Levels of Autonomy
- Resiliency – Self Organization – Complex Adaptive Systems
- Need for “Metrics” – The Entropy Perspective
- Connecting the dots: AI then and now (21st century)
- The road ahead.

Example - Autonomous Driving Levels

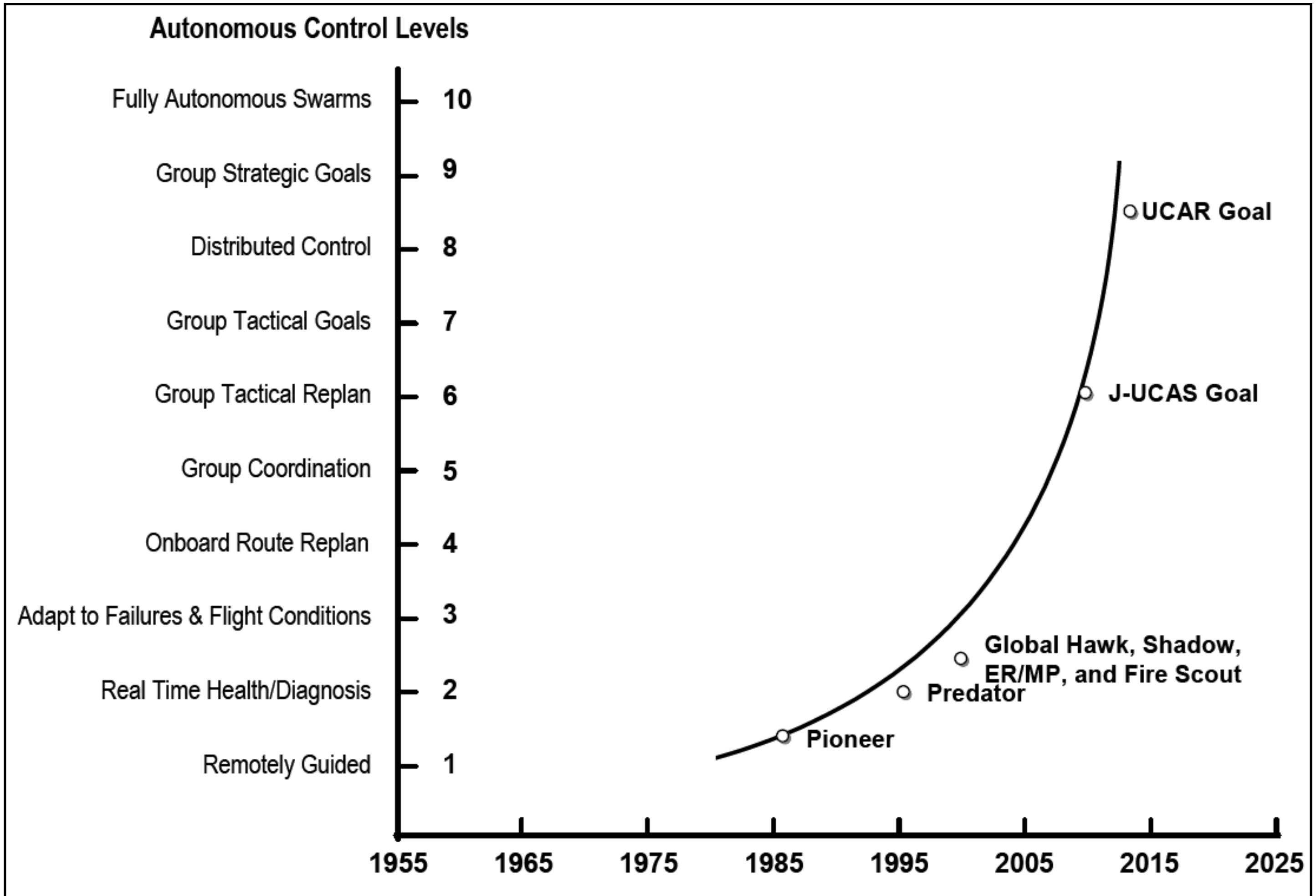


- ❑ **Level Zero - No Automation**
- ❑ **Level One – Driver Assistance:** Vehicle may assist with some functions; driver still in command
- ❑ **Level Two – Partial Automation:** Vehicle may assist with steering/acceleration functions; allow for the driver to disengage from some of their tasks.
- ❑ **Level Three – Conditional Automation:** Vehicle itself controls all monitoring of the environment
- ❑ **Level Four – High Automation:** Autonomous driving system would first notify the driver when conditions are safe, and only then does the driver switch the vehicle into this mode. It cannot determine between more dynamic driving situations like traffic jams or a merge onto the highway.
- ❑ **Level Five – Complete Automation**

Autonomous Driving Levels



DOD ROADMAP – AUTONOMY (Previous)



TREND IN UA AUTONOMY.

Unmanned Systems

Challenge of Autonomy (U.S. DoD)

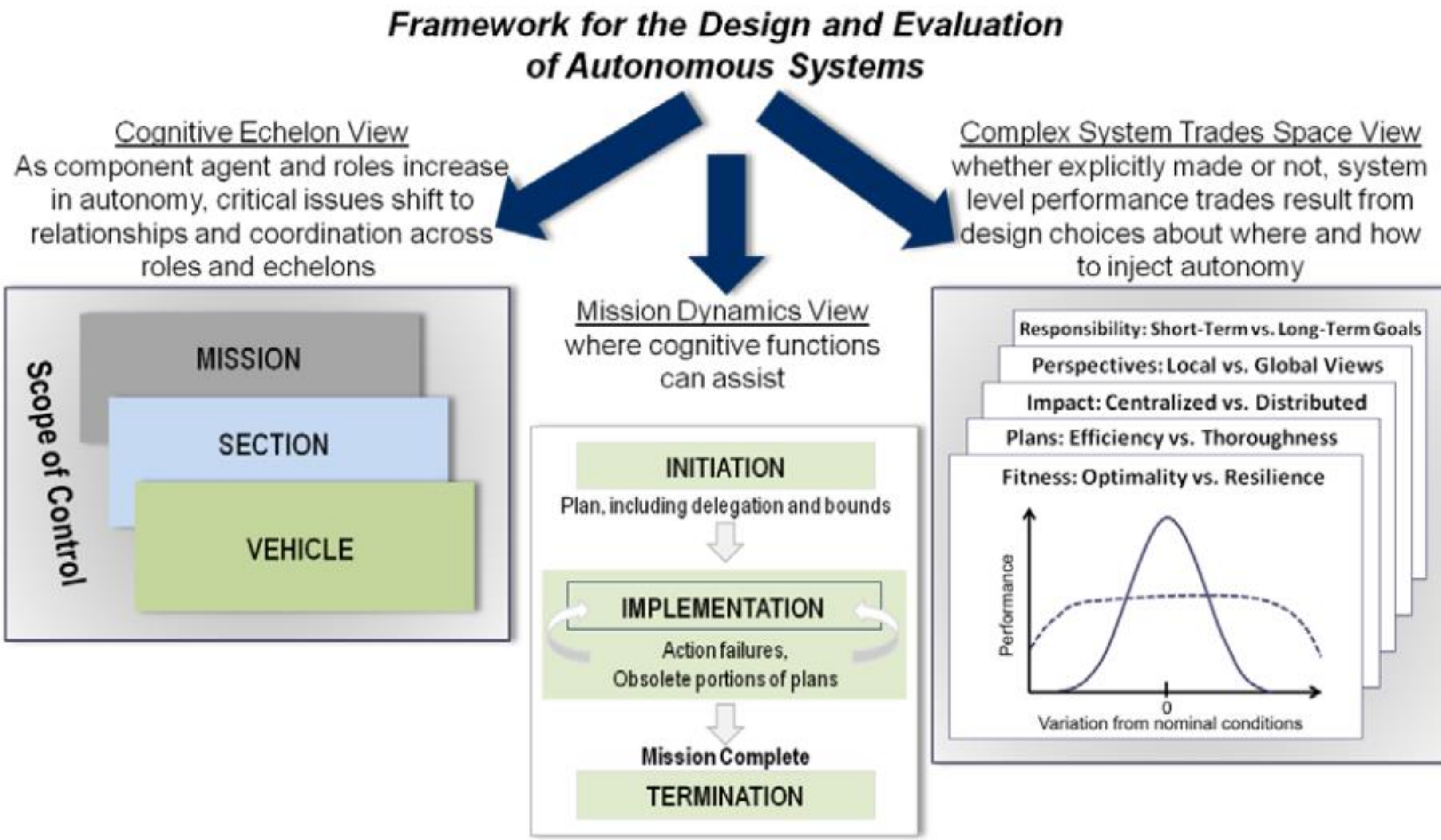


Figure 1-1 Framework for the Design and Evaluation of Autonomous Systems

Challenge of Autonomy (U.S. DoD)

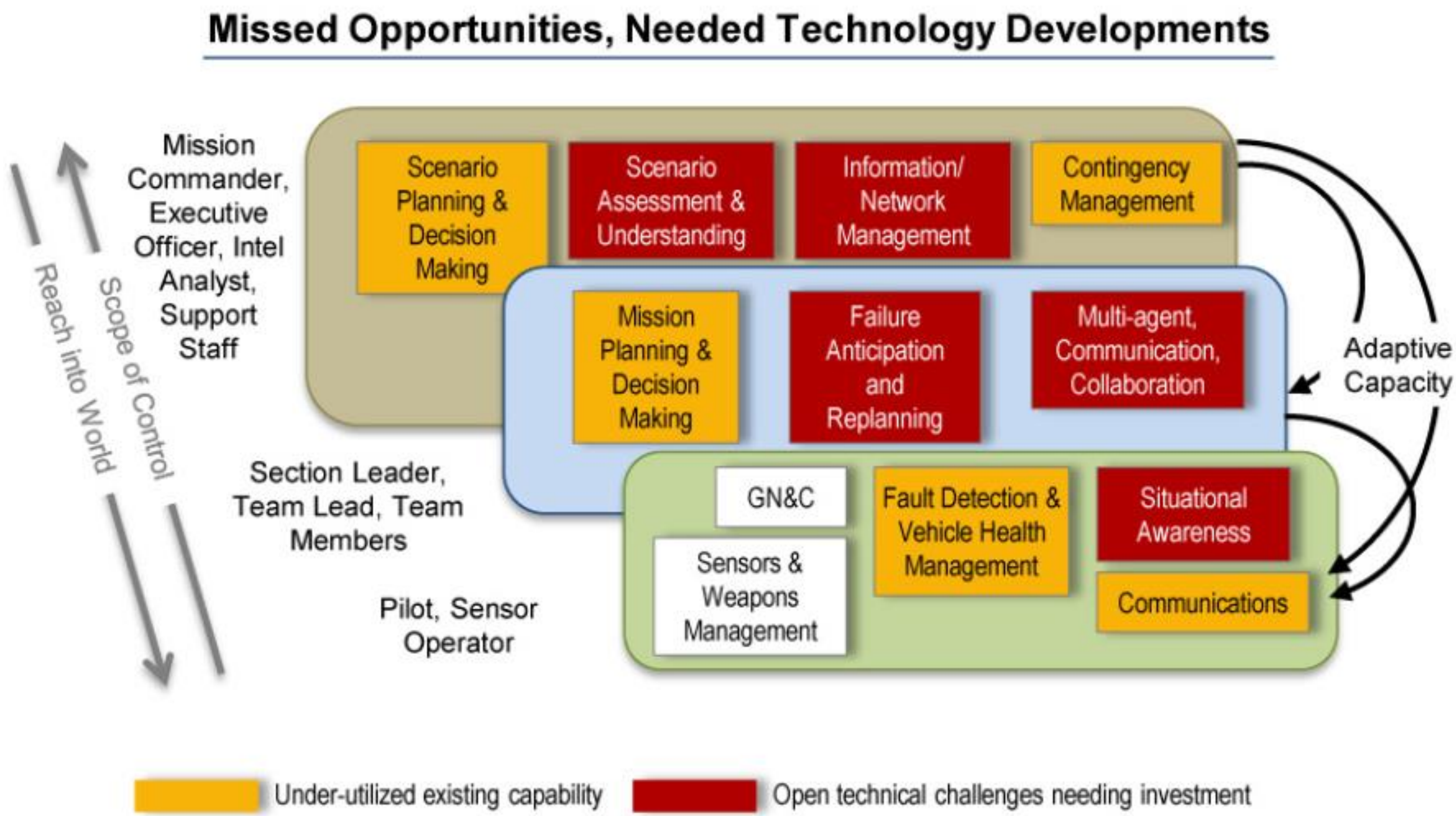


Figure 1-3 Status of Technology Deployment and Remaining Challenges

US DOD Autonomy Roadmap: 2027-2042

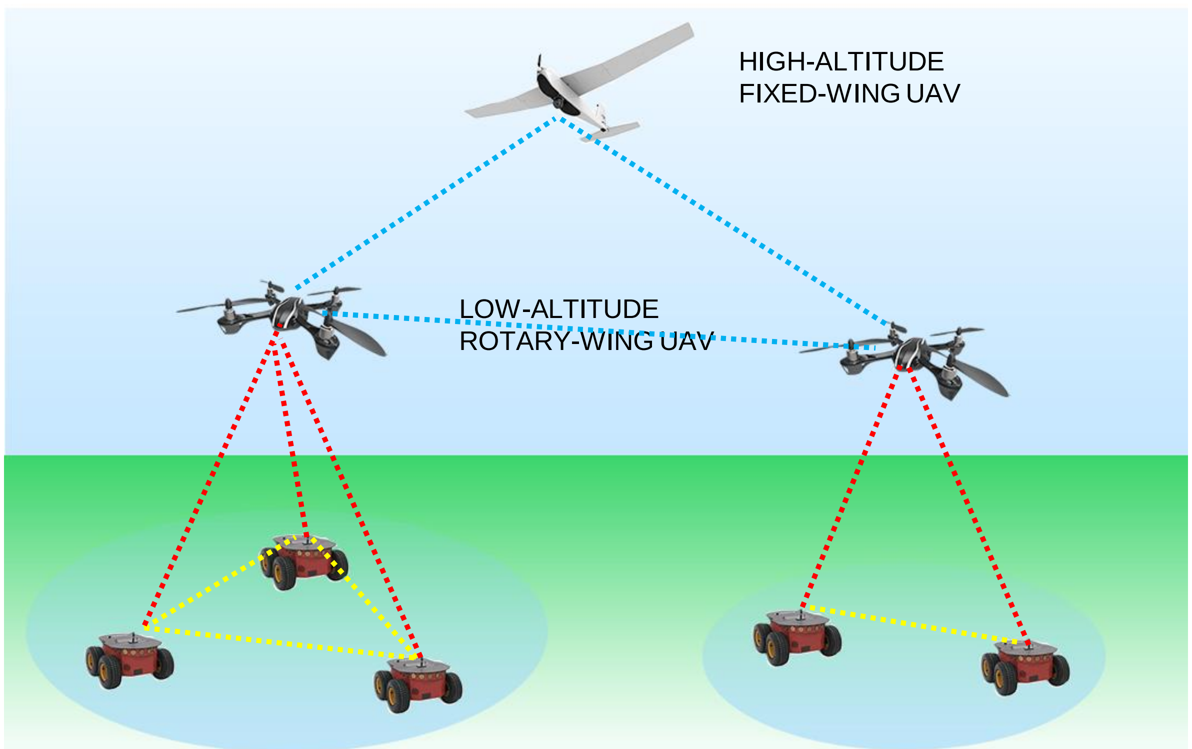
		2017 - - - - - - - - - - NEAR-TERM	2029 - - - - - - - - - - MID-TERM	2042 FAR-TERM
AUTONOMY	Artificial Intelligence/ Machine Learning	-Private Sector Collaboration -Cloud Technologies	-Augmented Reality -Virtual Reality	-Persistent Sensing -Highly Autonomous
	Increased Efficiency and Effectivness	-Increased Safety & Efficiency	-Unmanned Tasks, Ops -Leader-Follower	-Swarming
	Trust	-Tasking Guidance and Validation, Ethical Requirements for Human Decisions		
	Weaponization	-DoD Strategy Consensus -LAWS assessment	-Armed Wingman/Teammate (Human Decision to Engage)	

Table 3: Comprehensive Roadmap for Autonomy

Updated

UAV-UGV Testbed

- Different types of UGVs and UAVs (helicopters, quadrotors, fixed-wing airplanes) referred to as *agents/nodes* of a generic/sparse distributed multi-robot system.



UGVs - SUBTEAM 1

UGVs - SUBTEAM 2

- UGVs may form sub-teams, may function in loose and/or dynamically reconfigurable (2-D) formations, each team having specific objectives
- UAVs provide the 'eye-in-the-sky' component flying at fixed or different altitudes (in 2-D or 3-D formations)
- Communication System between agents made by **ZigBee/Wireless/Bluetooth/Radio (915 MHz)**

Grant #: 37240A, org. 272901, Notre Dame - DU

Autonomy/AS with Respect to What?

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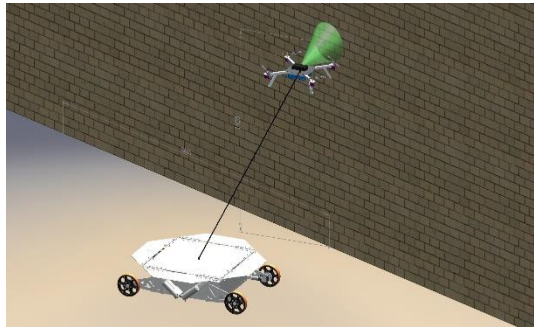

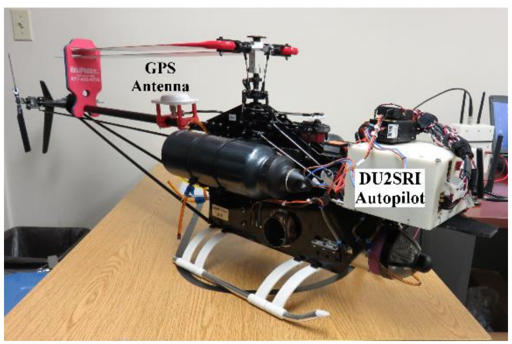

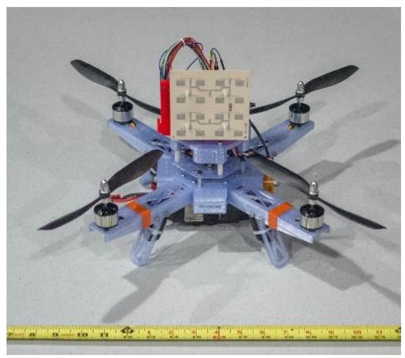

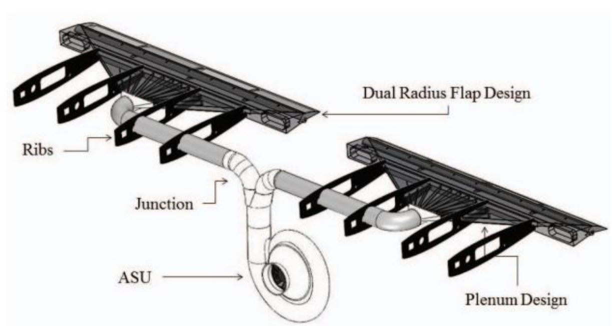

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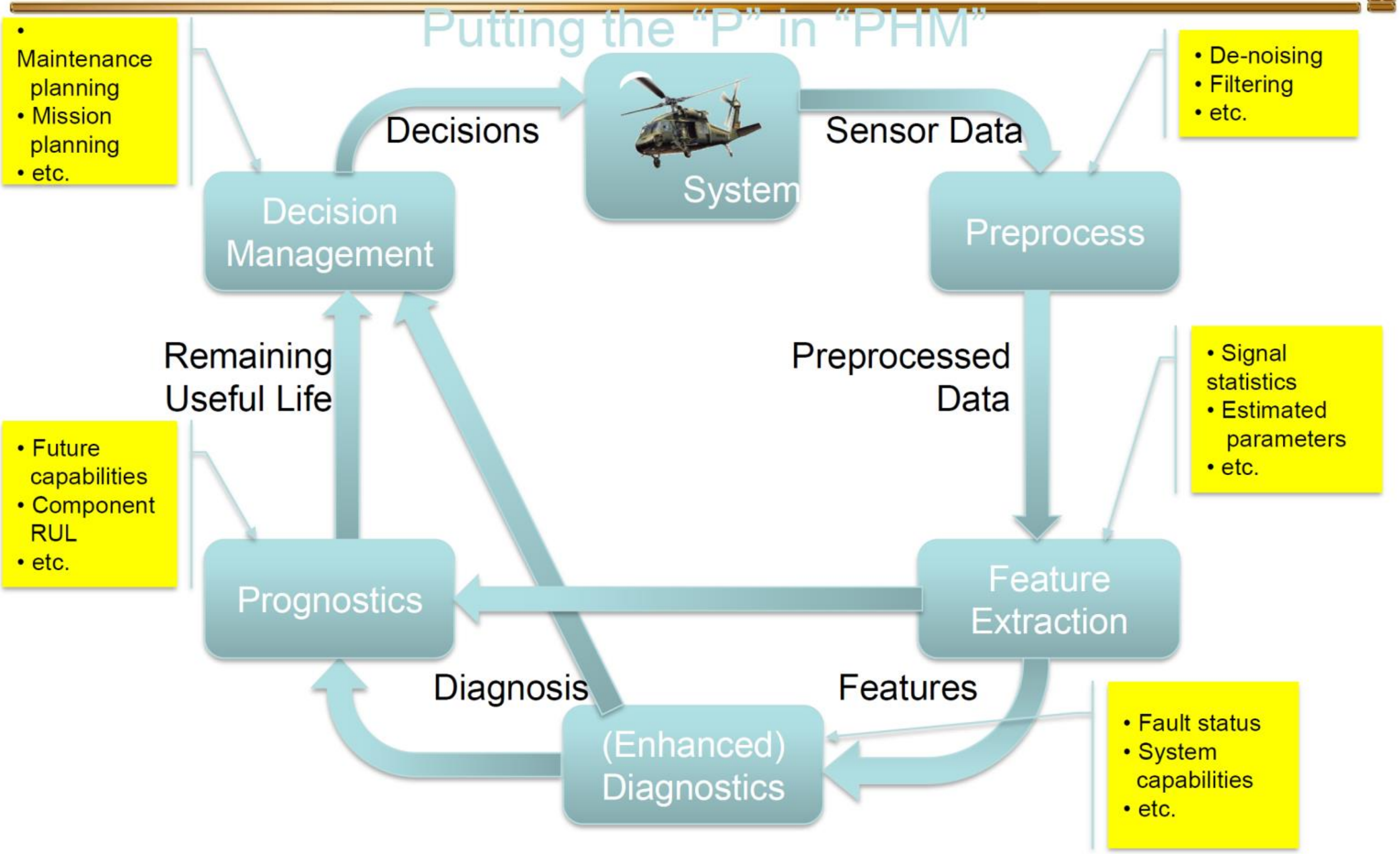
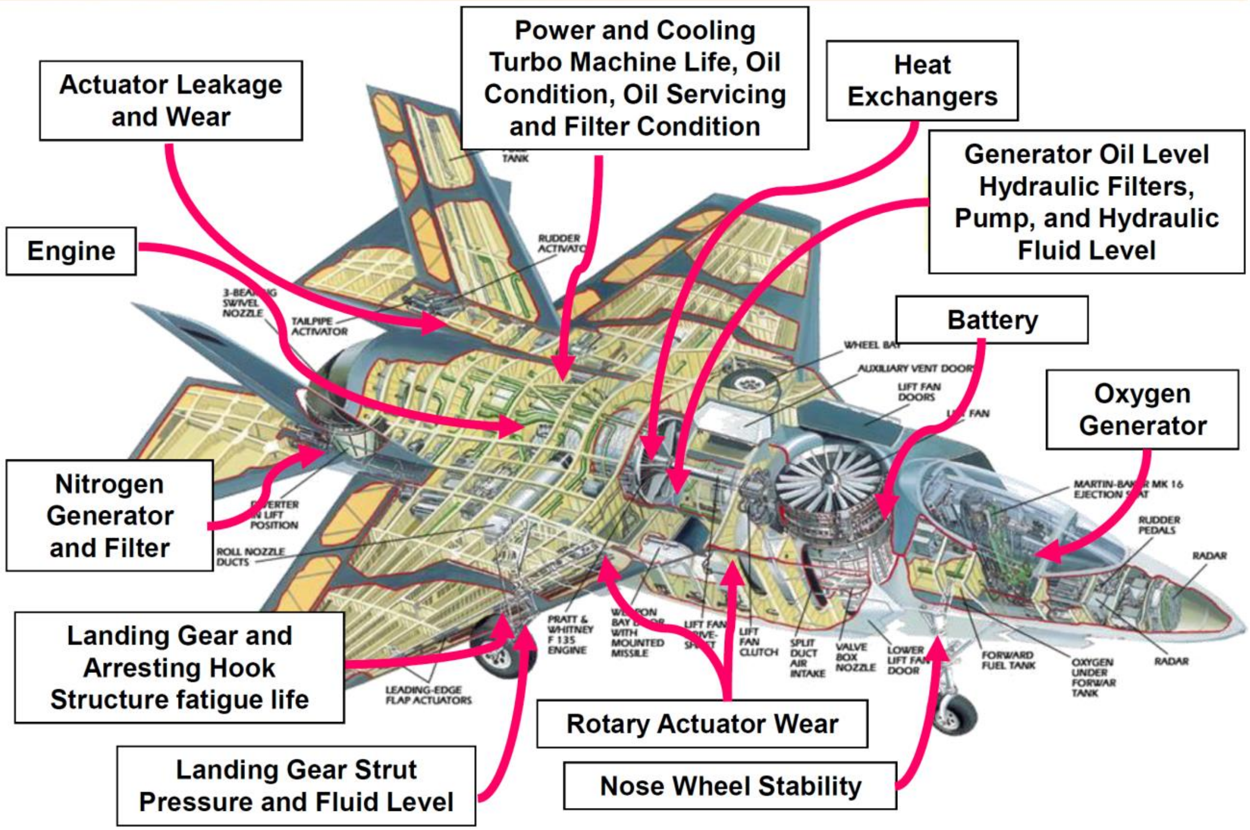
The Overall Concept: IVHM



F-35 Prognostic Candidates



Human Operator Challenge

There is nothing unmanned in a UAS/RPAS

- ❑ *4-to-1 operators-to-one UAS (U.S. Air Force)*
- ❑ In the future (as the U.S. Army wants) *1-to-4*

Unnamed Systems (UAVs, UGVs, AUVs/ROVs)

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- **Sample Challenges**
  - Uncertainty
  - Computational Complexity
  - Performance Guarantees
  - Implementation / Testing

Fleet/Team Uncertainty

Environment Uncertainty +

Individual System Uncertainty

Individual Vehicle Uncertainty

Component/sub-system uncertainty

Individual Sensor Uncertainty

Uncertainty ‘increases’

Different sources of uncertainty

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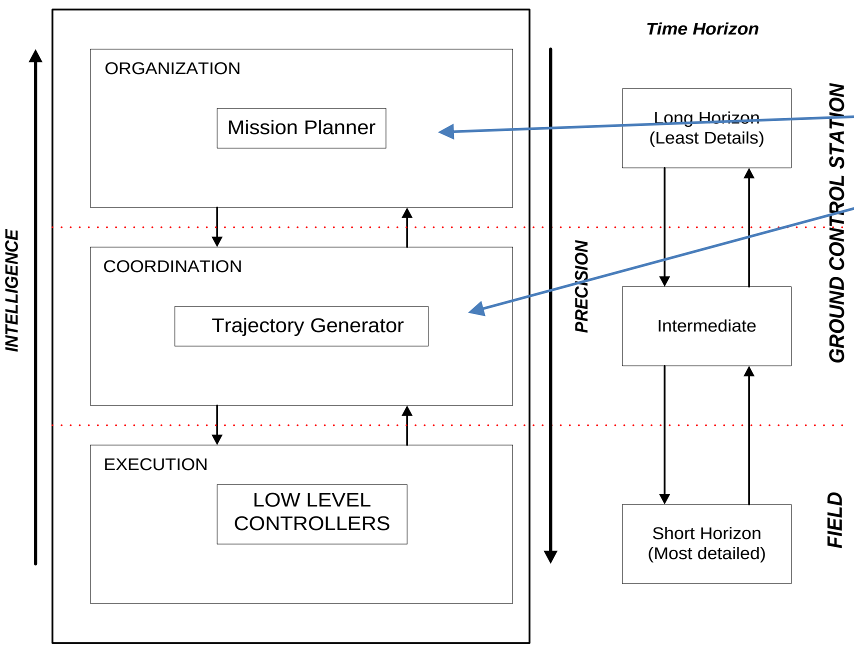
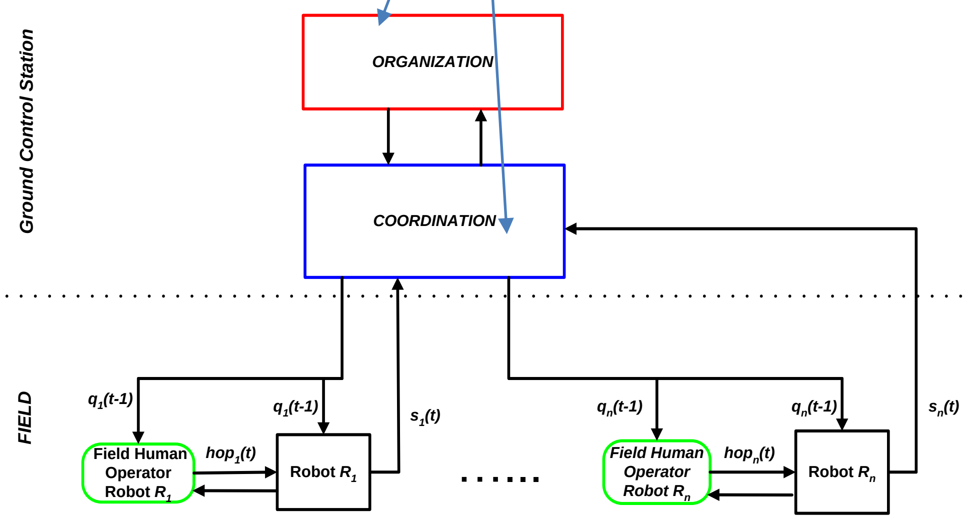
MULTI-LEVEL CONTROL SYSTEM CONFIGURATION



Supervisory controller blocks



Entropy in Thermodynamics

Boltzmann (*theory of statistical thermodynamics*): defined Entropy, *S*, of a perfect gas changing states isothermally at temperature *T* in terms of Gibbs energy ψ, the total energy of the system *H* and Boltzmann's universal constant *k*, as

$$S = -k\int_x \{(\psi - H)/kT\}\, e^{(\psi - H)/kT} dx$$

$$S = -k\int_X p(x) \ln p(x) dx$$

$$p(x) = e^{(\psi - H)/kT}$$

Shannon Entropy

$$H(X) = -\sum_x p(x) \log p(x) \qquad or \qquad H(X) = \int f(x) \ln f(x)\,dx$$

Conditional Entropies

$$H_Y(X) = -\sum_{x,\,y} p(x, y) \log p(x/y) = -\sum_{y} p(y) \sum_{x} p(x/y) \log p(x/y)$$

Transmission of Information

$$T(X : Y) = H(X) + H(Y) - H(X, Y) = H(X) - H_Y(X) = H(Y) - H_X(Y)$$

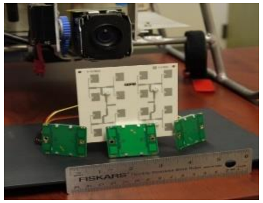
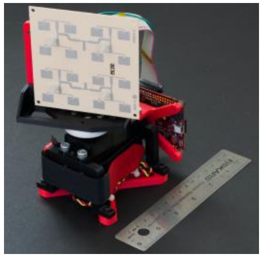
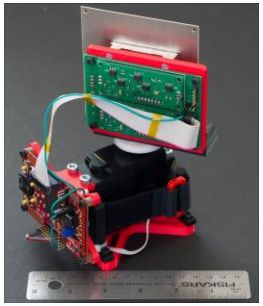
Control Systems and Intelligent Machines

- Since 1960's, progress in robotics and automation, despite several challenges and drawbacks, has produced unparalleled results; technology has, today, matured to the point of building fully autonomous systems.
  - High-confidence systems (DARPA perspective)

- **Efforts to develop a theory of intelligent machines (IMs), build on**:
  - Foundations of classical control (1950's),
  - Adaptive and learning control (1960's),
  - Self-organizing control (1970's),
  - Intelligent control (1980's).
    - Integration of concepts/ideas from Science, Engineering and Mathematics
      - AI
      - Control Systems
      - Operations Research

Long-Term Objectives

- **Central Objective: Assured Autonomy**
  - Progression of automation from the human to the machine
    - Transition from human-in-the-loop to human-on-the-loop
      - Levels of autonomy
  - End goal: High-confidence systems
    - Resilient vs robust design (crucial)
- **Required attributes (not exclusive)**
  - Reasoning, (Re-) Planning, Decision-making, Adaptation and Learning, Situational Awareness, Self-organization, Reconfigurability, Fault-tolerance, PHM/IM
- **The "Tool": Intelligent Control**
  - Bring under one ensemble and implement, concepts and ideas from Science, Engineering, Mathematics, OR, Game Theory, Complexity Theory, Complex Adaptive Systems
- **Challenge: Metrics to Measure/Evaluate Autonomy**
  - Robust autonomy and robust intelligence







Fundamentals, Challenges

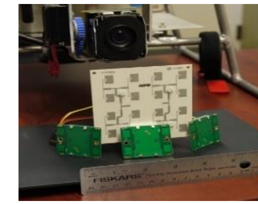
- **Tools and Technology**
  - Control Theory, Adaptive Control, Learning Control, Self-Organizing Control, Command and Control; C^3, C^3I, C^4I, Intelligent Control
  - Decision Makers; Bounded Rationality; Hierarchical Multi-level Systems
  - Intelligent Machines, Intelligent Robotic Systems
  - AI, Expert Systems, Knowledge-Based Systems; Cognitive Systems
- **Why not 'then', or thus far? – Lack of computational power**
- **Why 'now'? – Computational power; almost no limit on computational complexity; understanding of complex system collective behavior; understanding of event- vs time- based systems; understanding of formal designs with performance guarantees**
- **(Sample of) Open questions:**
  - How is autonomy / intelligence defined?
    - How are levels of (robust) autonomy/intelligence defined?
  - How is uncertainty handled?
  - How is autonomy/intelligence modeled and evaluated?
    - Single vs multiple metrics
  - How are today's complex systems modeled?
    - Single, nominal vs family of system models
    - Unstructured uncertainty

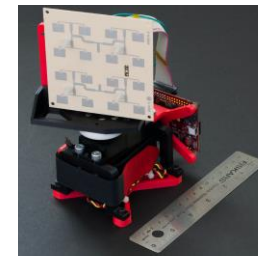
The ‘History’ – Intelligent Control

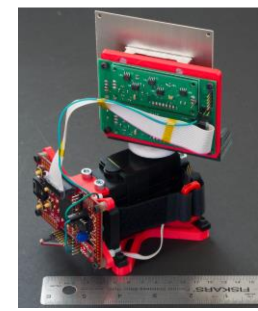
- Foundations of classical control – 1950’s
- Adaptive and learning control – 1960’s
- Self-organizing control – 1970’s
- Intelligent control -1980’s
- K. S. Fu (Purdue) - 1970’s coins the term ‘intelligent control’
- Alex Levis and his Group: Decision Makers (Info Theory, then PNs)
- G. N. Saridis (Purdue) introduces ‘hierarchically intelligent control systems’ (PhDs: J. Graham, H. Stephanou, S. Lee)
- The 1980’s
  - J. Albus (NBS, then NIST)
  - Antsaklis – Passino
  - Meystel
  - Ozguner – Acar
  - Saridis – Valavanis then Lima, Moed, McInroy, Wang

Common theme: multi-level/layer architectures; time-based and event-based considerations; mathematical approaches

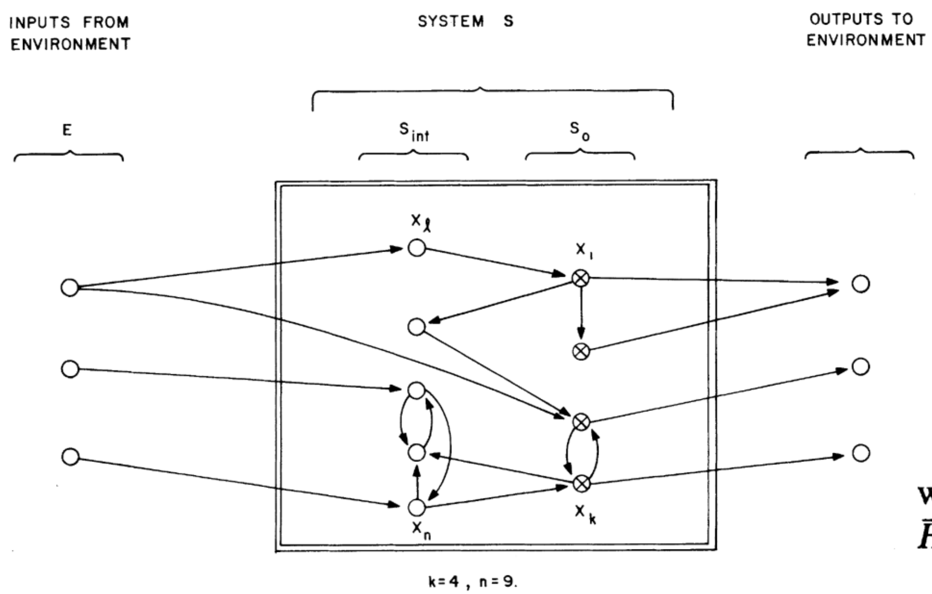
Common limitation: lack of computational power (very crucial)







Conant (1976) – The pioneer



$$H(X_1,X_2,X_3) = H(X_1,X_2) + H_{X_1,X_2}(X_3)$$
$$= H(X_1) + H_{X_1}(X_2) + H_{X_1,X_2}(X_3)$$

$$\overline{H}(X) = \lim_{m\to\infty} \frac{1}{m} H(X(t),X(t+1),\cdots,X(t+m-1))$$

with units of bits per step [14]. The *conditional entropy rate* $\overline{H}_{X_1}(X_2)$ is defined by

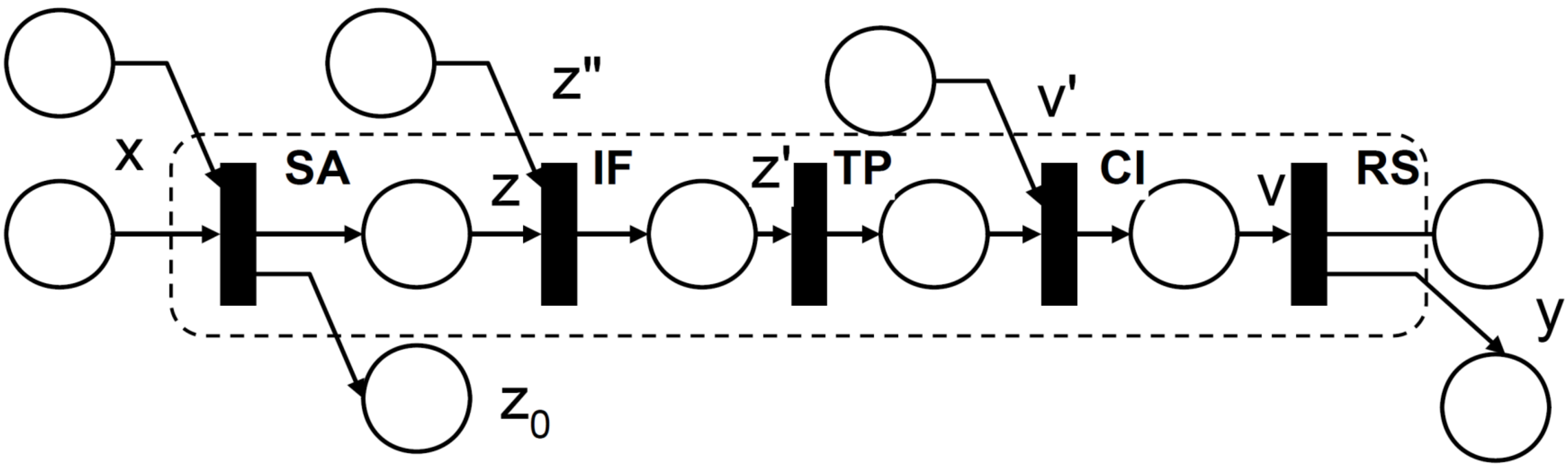
$$\overline{H}_{X_1}(X_2) = \overline{H}(X_1,X_2) - \overline{H}(X_1)$$

$F = \sum_{j=1}^{n} \overline{H}(X_j)$		total rate (of "information flow"),
F_t	$= \overline{T}(E:S_0)$	thruput rate,
F_b	$= \overline{T}_{S_0}(E:S_{int})$	blockage rate,
F_c	$= \overline{T}(X_1:X_2:\cdots:X_n)$	coordination rate,
F_n	$= \overline{H}_E(S)$	noise rate,

and with these, the PLIR can be expressed as

$$F = F_t + F_b + F_c + F_n. \qquad (9b)$$

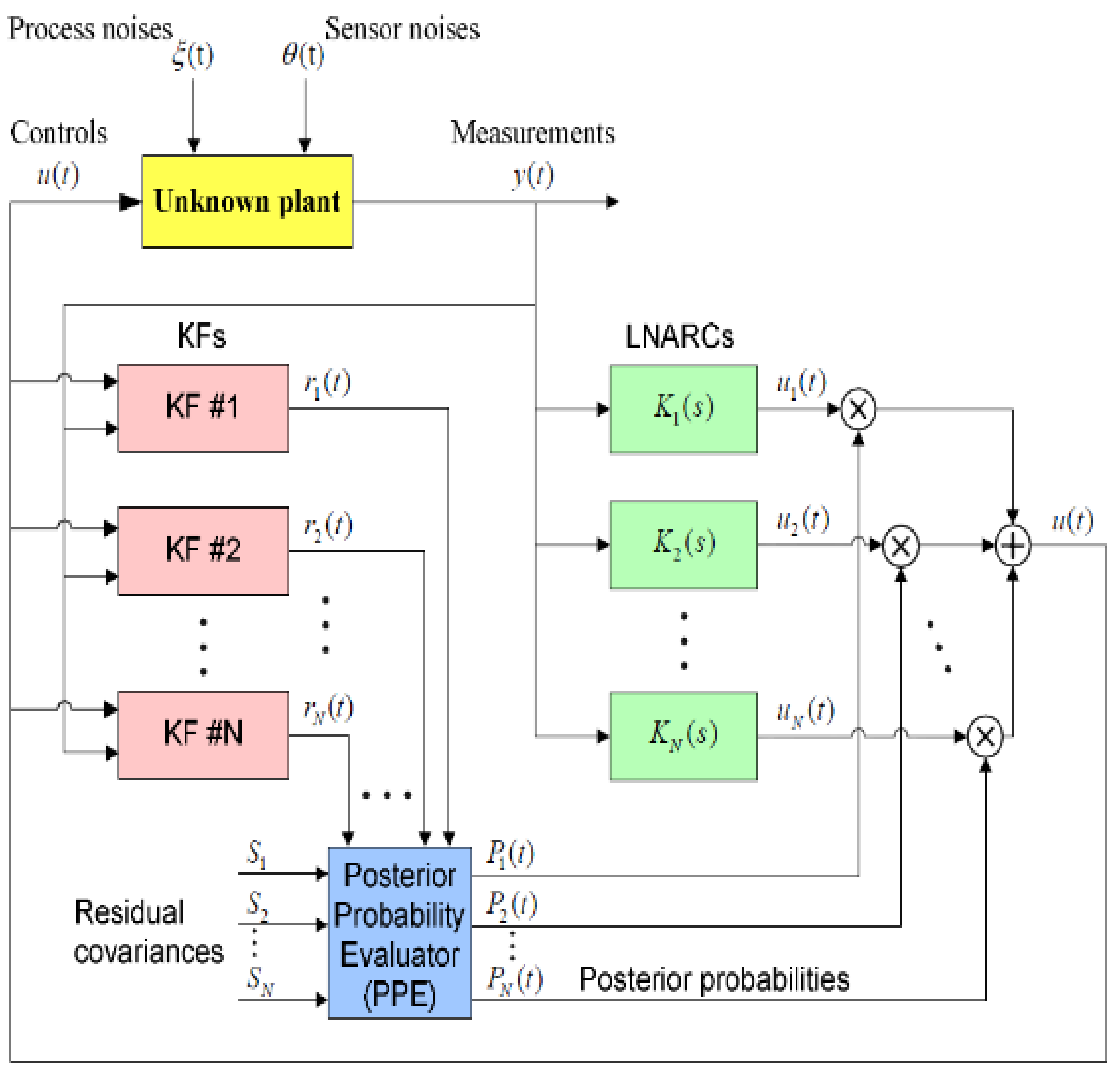
The A. Levis Approach (MIT, GMU)



- Situation Assessment (SA)
- Information Fusion (IF)
- Task Processing (TP)
- Command Interpretation (CI)
- Response Selection (RS)

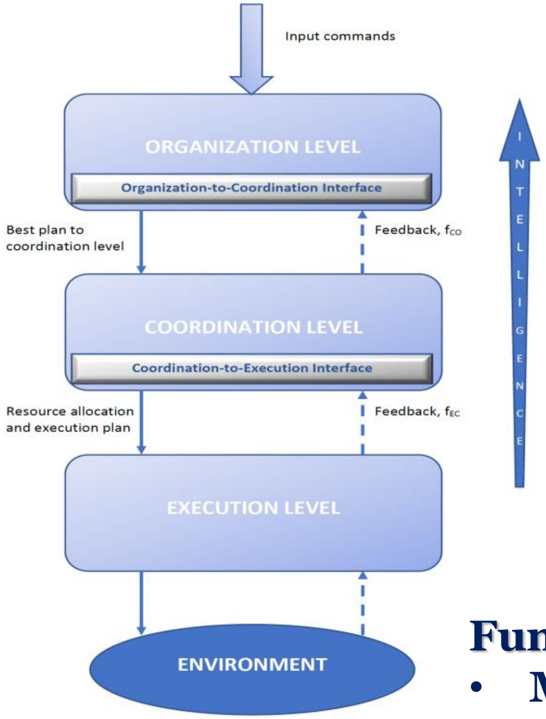
Not enough credit given to this group. The first to use/apply Conant's Law and use information theory to determine throughput, coordination, blockage and noise of I/O information.

… very fast forward, S. Fekri and M. Athans

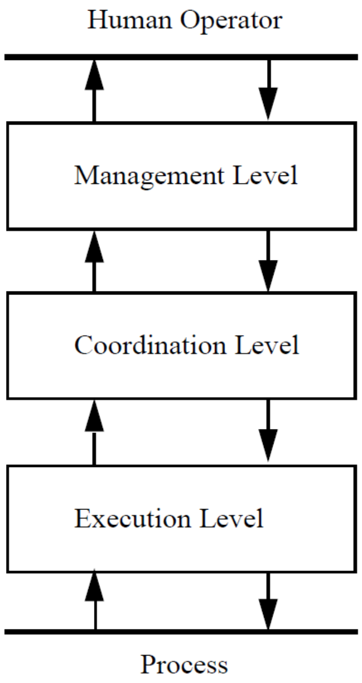


Hierarchical Architectures

Saridis - Valavanis



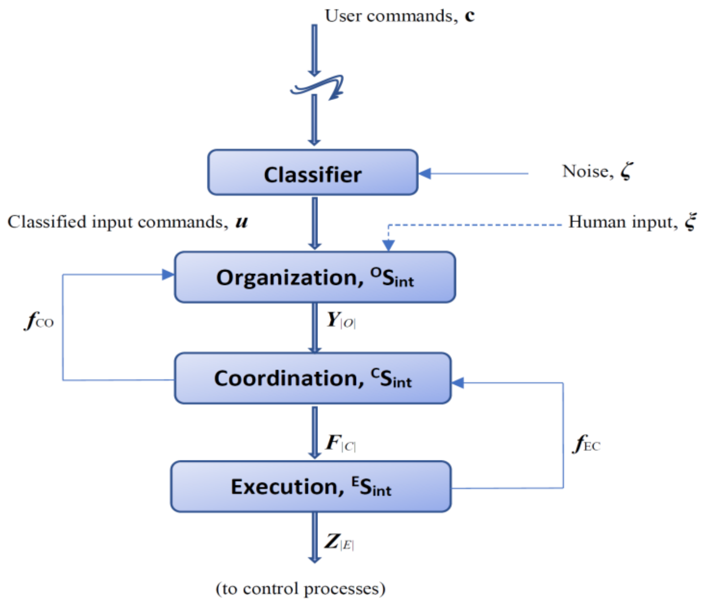
Antsaklis – Passino (autonomicity)

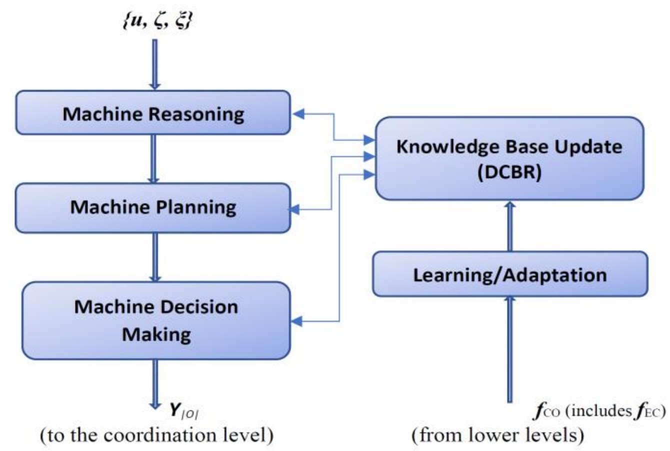


Functionality – One Framework

- Modular
- Spatio-temporal
- Explicit human interaction modeling
- Event-based and Time-based
- On-line / Off-line components
- Vertical/horizontal functionality
- Independent of specific methodologies used for implementation

Hierarchical Architecture





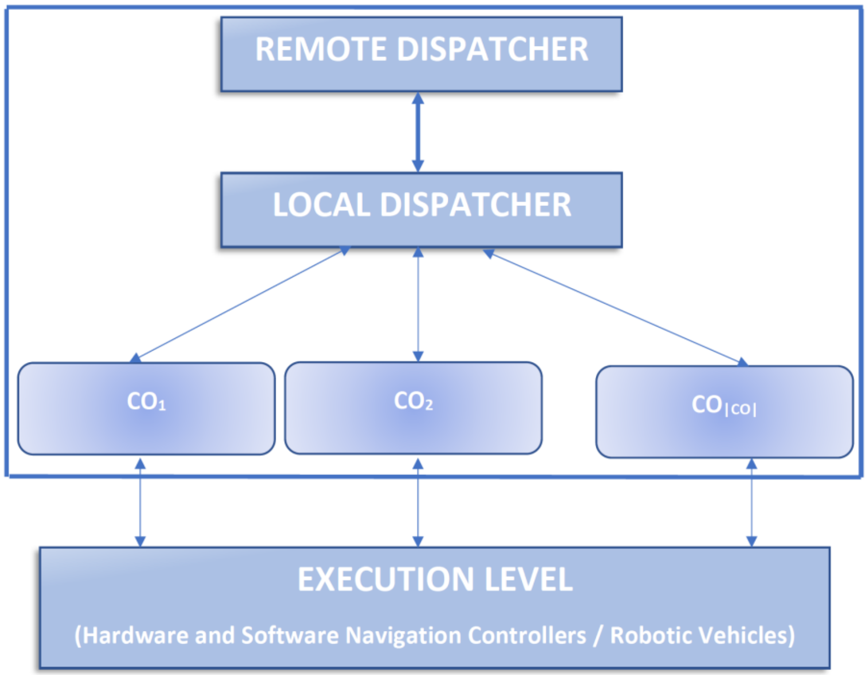
$$p(k+1/u_i) = p(k/u_i) + \beta_{i+1}[\xi - p(t/u_i)]$$

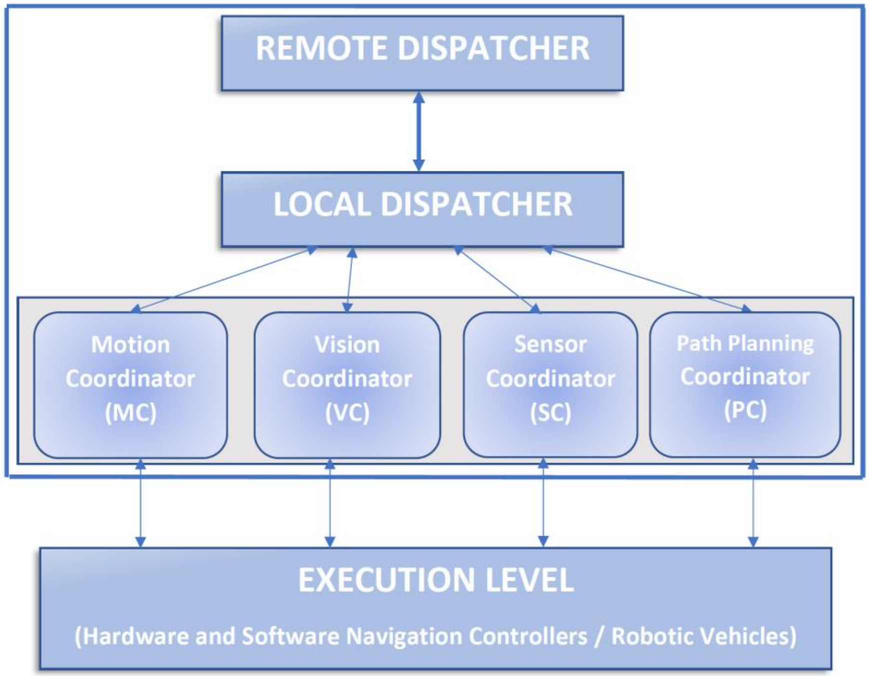
$$J(k+1/u_i) = J(k/u_i) + \gamma_{i+1}[J_{obs}(k+1/u_i) - J(k/u_i)]$$

Modeling Framework

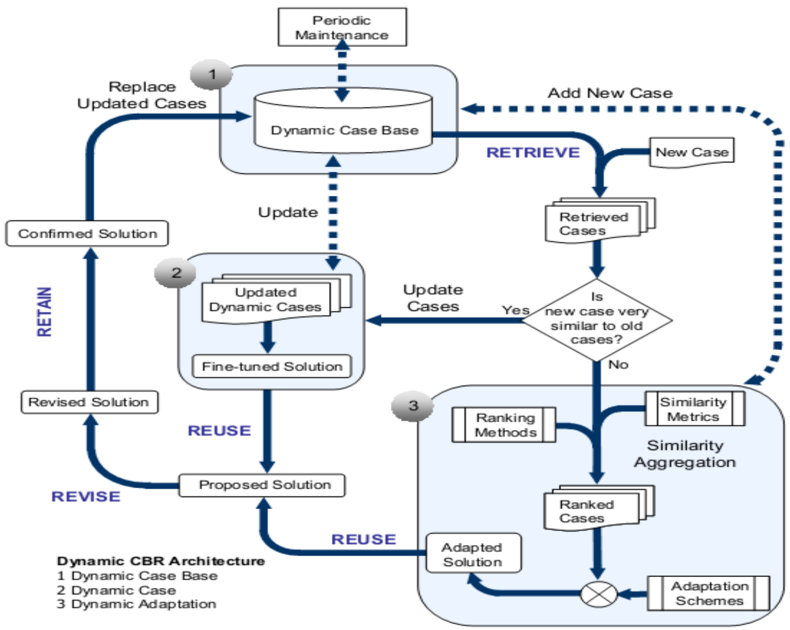
- Probabilistic
- Fuzzy-Logic Based
- N-Dimensional Information Theory Based

Coordination Level





Adaptation/Learning (Vachtsevanos et al, 30 years later….)



Ent_e is a new case, Ent_j represents previous cases; El_i is a feature; $n_{i,pert}$ is a pertinence weighted variable associated with the description element El_i; $n_{i,pred}$ is a predictive weighted variable associated with each case in memory, which is increased as the corresponding element (feature) is favorably selecting a case, and decreased as this selection leads to a failure; α is an adjustable parameter. Incremental learning will occur whenever a new case is processed, and its results are identified.

$$sim(Ent_e, Ent_j) = \frac{\sum_{k=1}^{n} \alpha \times sim(El_{i,k}, El_{l,k}) + \sum_{k=1}^{n} n_{k_i,pred} \times n_{i,pert} \times sim(El_{i,k}, El_{l,k})}{\alpha \times n + \sum_{k=1}^{n} n_{k_i,pred} \times n_{i,pert}}$$

Incremental learning will be pursued using Q-Learning, a popular reinforcement learning scheme for agents learning to behave in a game-like environment. Q-Learning is highly adaptive for on-line learning since it can easily incorporate new data as part of its stored database.

Advantage: COMPUTATIONAL POWER!!!

Adaptation/Learning (GaTech, Vachtsevanos, et al)

Expected reward: "cost-to-go" function

Immediate reward

Learning

Discount factor

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right]$$

Current state *Current action* *Next state* *Next action*

Q(s, a) will be first initialized (with 0's or random values) for all states $s \in S$ and for all actions $a \in A(s)$; then, for each case s will be initialized, and for each step in a case a will be chosen from s using a policy derived from Q. Then, action a will be taken and the resultant state s' and the reward r will be observed. The next step will be to evaluate/update $Q(s, a) \leftarrow Q(s, a) + \alpha[r + \gamma \max_{a'} Q(s', a') - Q(s, a)]$, followed by updating the state ($s \leftarrow s'$).

...35 years later (Lin–Antsaklis–Valavanis– Rutherford)

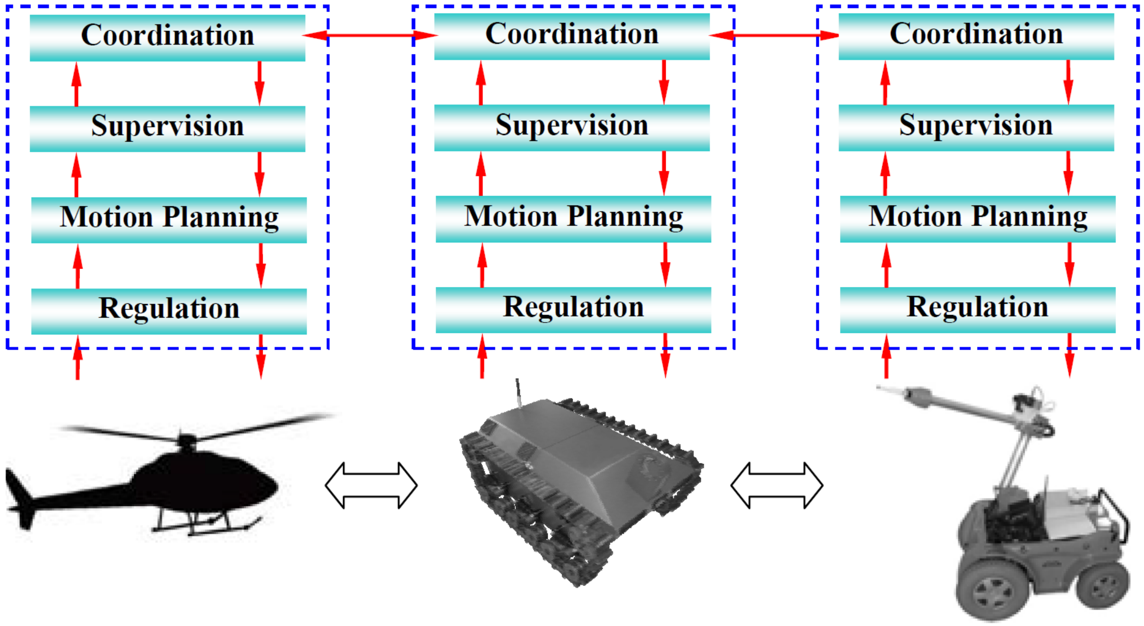


Figure 1: Hybrid hierarchical control architecture for multi-robot systems. The red arrows between layers represent the information flow and feedback between layers. The red arrows between coordination layers of two robots stand for communication between robots, while the physical interactions and passive reactions are denoted as arrows between physical robots.

Advantage: COMPUTATIONAL POWER!!!

Why Entropy?

- Duality of the concept of Entropy
  - Measure of uncertainty as defined in Information Theory (Shannon). Measures throughput, blockage, internal decision making, coordination, noise, human involvement etc., of data / information flow in any (unmanned) system. Minimization of uncertainty corresponds to maximization of autonomy / intelligence.
  - Control performance measure, suitable to measure and evaluate precision of task execution (optimal control, stochastic optimal control, adaptive control formulations)
  - Entropy measure is INVARIANT to transformations – major plus

- Deviation from 'optimal' is expressed as cross-Entropy and shows autonomy robustness / resilience
- Additive properties
- Accounting for event-based and time-based functionality
- Horizontal and vertical measure
- Suitable for component, individual layer, overall system evaluation
- Independent of specific methodologies used for implementation
- One measure fits all!

Metrics to evaluate Autonomy/Intelligence (Vachtsevanos – Valavanis – Antsaklis)

- **Performance and Effectiveness metrics**
  - **Confidence (expressed as reliability measure, probabilistic metric)**
  - **Risk is interpreted via a 'value at risk level', which is indicative of not nominal situation, i.e., fault, failure, etc.**
  - **Trust and trust consensus are evaluated through Entropic measures indicating precision of execution, deviation from optimal, information propagation, etc.**
  - **Remaining Useful Life (RUL) of system components, sub-systems**
  - **Probabilistic measure of resilience (PMR) - to quantify the probability of a given system being resilient to forecasted environmental conditions, denoting the ratio of integrated real performance over the targeted one – thus, expressed as Entropy, too**

$$R(T) = \int_0^T P_R(t)dt \Big/ \int_0^T P_T(t)dt$$

Entropy for Control

Boltzmann (*theory of statistical thermodynamics)*: defined Entropy, *S*, of a perfect gas changing states isothermally at temperature *T* in terms of Gibbs energy ψ, the total energy of the system *H* and Boltzmann's universal constant *k*, as

$$S = -k\int_x \{(\psi - H)/kT\}\, e^{(\psi-H)/kT} dx$$

$$S = -k\int_X p(x) \ln p(x) dx$$

$$p(x) = e^{(\psi-H)/kT}$$

Saridis' pioneering work!
Valavanis' PhD Thesis

Entropy for Control - 2

When applying dynamical theory of thermodynamics on the <u>aggregate</u> of the molecules of a perfect gas, an average Langangian, *I*, may be defined to describe the performance over time of the state *x* of the gas

$$I = \int L(x, t)dt$$

$$S = -k\int_x \{(\psi - H)/kT\} e^{(\psi - H)/kT} dx \qquad \textit{and} \qquad I = \int L(x, t)dt$$

are equivalent leading to

$$S = I/T$$

***T is* constant temperature of the isothermal process of a perfect gas.**

Entropy for control - 3

Objective: Express performance measure of a control problem in terms of Entropy, i.e.:

Consider the optimal feedback deterministic control problem with accessible states for an *n*-dimensional system with state vector *x(t)* and *u(x, t)* the *m*-dimensional control law.

Then, $dx/dt = f(x, u, t)$, $x(t_o)=x_o$

and cost function

$V(u, x_o, t_o) = \int L(x, u, t)dt$ (Integral is defined over $[t_o, T]$)

An optimal control $u^*(x, t)$ minimizes the cost

$V(u^*; x_o, t_o) = \min_u \int L(x, u, t)dt$ (Integral defined over $[t_o, T]$)

Entropy for control - 4

Saridis proposed to define the differential Entropy for some *u(x, t)* as

$$H(x_o, u(x, t), p(u)) = H(u) = - \int_{\Omega u}\int_{\Omega x} p(x_o, u) \ln p(x_o, u) dx_o du$$

(Integrals are defined over Ω_u and Ω_x

Found necessary and sufficient conditions to minimize

$$V(u(x, t), x_o, t_o)$$

by minimizing the differential Entropy

$$H(u, p(u))$$

where *p(u)* is the worst Entropy density as defined by Jayne's Maximum Entropy Principle.

Entropy for control - 5

By selecting the worst-case distribution satisfying Jaynes' Maximum Entropy Principle, the performance criterion of the control is associated with the Entropy of selecting a certain control law."

Minimization of the differential Entropy results in the optimal control solution.

Note: The Adaptive Control problem is also formulated in terms of Entropy.

$$\textit{Entropy Interval} = H_{max} - H_{min}$$

Kullback-Leibler (K-L) measure of cross-Entropy (1951) and Kullback's (1959) minimum directed divergence or minimum cross-Entropy principle, MinxEnt

Intelligence and Robust Intelligence - 2

Human intervention introduced mathematically via additional probabilistic constraints,

p_i, $i=1, 2, 3\ldots, n$, $\sum p_i=1$

$\sum c_i p_i=c$

c_i's are weights and c is a bound, which are imposed on (unconstraint) probability distributions and influence/alter the $H_{max} - H_{min}$ interval.

Example: *$p = (p_1, p_2\ldots, p_n)$ and $q = (q_1, q_2, \ldots, q_n)$ may be measured (and evaluated) via the K-L measure $D(p:q) = \sum p_i ln(p_i/q_i)$. For example, when q is the uniform distribution (indicating maximum uncertainty), then $D(p:q) = lnn-H(p)$ where $H(p)$ is Shannon's Entropy.*

Intelligence and Robust Intelligence - 3

Under this information theory related approach, which connects Entropy with the event-based attributes of multi-level systems, the system starts from a state of maximum uncertainty and through adaptation and learning, uncertainty is reduced as a function of accumulated and acquired knowledge and information over time.

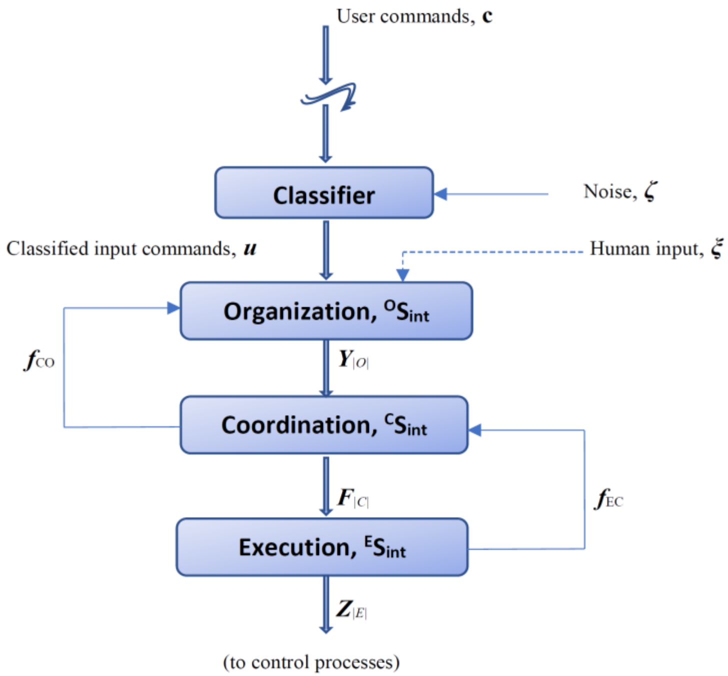
Entropy for control, cont….

$DS = \{S_O, S_C, S_E\}$ - $S_O = \{\boldsymbol{u}, \zeta, \xi, \boldsymbol{f}_{\mathrm{CO}}, {}^{\mathbf{O}}\mathbf{S}_{\mathbf{int}}, \boldsymbol{Y}_{|O|}\}$ - $S_C = \{\boldsymbol{Y}_{|O|}, \boldsymbol{f}_{\mathrm{EC}}, {}^{\mathbf{C}}\mathbf{S}_{\mathbf{int}}, \boldsymbol{F}_{|C|}\}$

$S_E = \{ \boldsymbol{F}_{|C|}, {}^{\mathbf{E}}\mathbf{S}_{\mathbf{int}}, \boldsymbol{Z}_{|E|}\}$

$DS = \{S_O, S_C, S_E\} = \{\boldsymbol{u}, \zeta, \xi, \boldsymbol{f}_{\mathrm{CO}}, \boldsymbol{f}_{\mathrm{EC}}, {}^{\mathbf{O}}\mathbf{S}_{\mathbf{int}}, {}^{\mathbf{C}}\mathbf{S}_{\mathbf{int}}, {}^{\mathbf{E}}\mathbf{S}_{\mathbf{int}}, \boldsymbol{Z}_{|E|}\}$

Augmented input is $\boldsymbol{U} = \{\boldsymbol{u}, \zeta, \xi\}$, internal variables are $S_i = \{ \boldsymbol{f}_{\mathrm{CO}}, \boldsymbol{f}_{\mathrm{EC}}, {}^{\mathbf{O}}\mathbf{S}_{\mathbf{int}}, {}^{\mathbf{C}}\mathbf{S}_{\mathbf{int}}, {}^{\mathbf{E}}\mathbf{S}_{\mathbf{int}}\}$ and the output is $\boldsymbol{Z}_{|E|}$.



GPLIR considers external and internal noise; internal control strategies and internal coordination of the levels and between the levels to execute the requested mission

GPLIR may be derived for each top-down and bottom-up function of the organizer

GPLIR is also derived for the coordination and execution levels.

Entropy for control, cont….

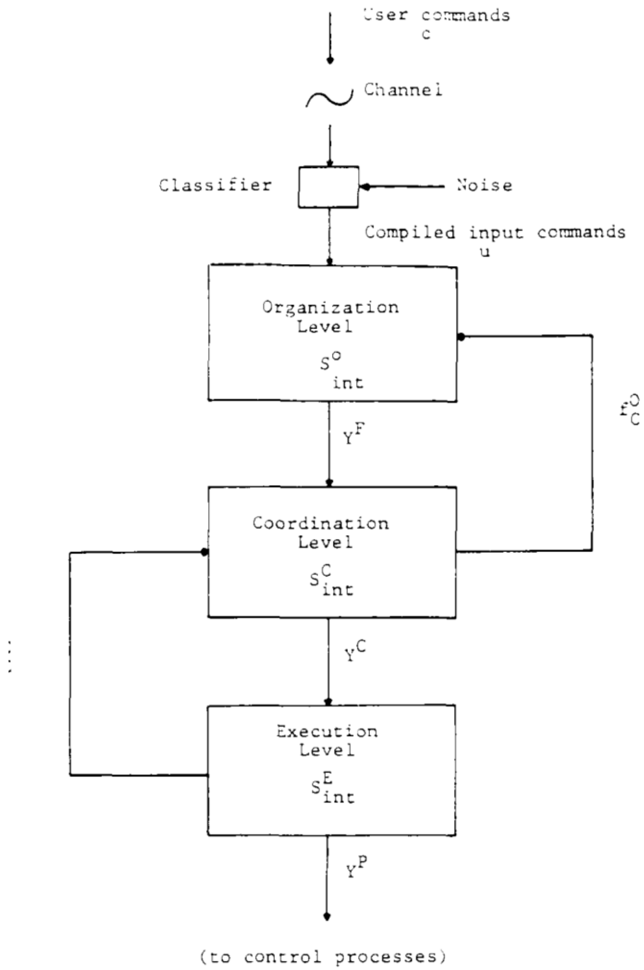


Fig. 1. Block diagram of intelligent machine.

The *total rate of activity* of the IRS F is expressed as the entropy rate of all internal variables:

$$F = \sum_{S_i} \overline{H}(S_i)$$

$$S_i = \left(S_{0i}, S_{Ci}, S_{Ei}, Y^F, Y^C, Y^P\right). \qquad (15)$$

Entropy for control, cont….

User commands $\boldsymbol{c}$ - c_i, $i = 1, 2, 3, \ldots |c|$

Classified input commands **u**, u_j, $j = 1, 2, 3, \quad \ldots |u|$. Note that $|c| = |u| = M$

$c_i \rightarrow u_i$ or $c_i \rightarrow u_j$, $i \neq j$

Primitive events $\boldsymbol{e}$, represented as binary random variable $\boldsymbol{x}$, $\{e_i \leftrightarrow x_i\}$, $i = 1, 0$,

Plans formulated as sets of primitive events that form activities $\boldsymbol{A}$, ordered activities ${}^{O}\boldsymbol{A}$ and augmented ordered activities ${}^{O}\boldsymbol{A}_A$

A general learning algorithm of the form $p(k+1/u_i) = p(k/u_i) + \beta_{i+1}[\xi - p(t/u_i)]$

β_{i+1} is a sequence satisfying Dvoketcky's condition for convergence, ξ is either 1 when $J' = \min J_c$, or, otherwise 0, and J' is the actual cost of execution of the plan.

$p(k/u_i)$. Thus, $J(k+1/u_i) = J(k/u_i) + \gamma_{i+1}[J_{obs}(k+1/u_i) - J(k/u_i)]$,

Entropy for control, cont....

The *total noise rate* throughout the IRS F_n represents the uncertainty that remains in the IRS variables when all external inputs, i.e., the compiled input command and feedback information are known. It is expressed as

$$F_n = \overline{H}\left(S_{0i}, Y^F, S_{Ci}, Y^C, S_{Ei}, Y^P / u_j, f_{C0}, f_{EC}\right). \quad (16)$$

$$F_n = F_n' + F_D \quad (17)$$

where

$$F_n' = \overline{H}\left(Y^P / u_j, f_{C0}, f_{EC}\right) \quad (18)$$

$$F_D = \overline{H}\left(S_{0i}, Y^F, S_{Ci}, Y^C, S_{Ei} / u_j, f_{C0}, f_{EC}, Y^P\right). \quad (19)$$

Entropy for control, cont….

The *total throughput rate* of the IRS is the amount by which the output of the IRS is related to its compiled input command and feedback information. It is expressed as

$$F_t = \overline{T}\left(u_j, f_{C0}, f_{EC} : Y^P\right) \tag{21}$$

and it is decomposable into two terms as

$$F_t = \overline{H}(Y^P) - F_n'. \tag{22}$$

Entropy for control, cont….

The *total blockage rate* of the IRS is thought of as the amount of information in the input to the IRS that is not included in the output. It is expressed as

$$F_b = \overline{T}\left(u_j, f_{C0}, f_{EC} : Y^F, S_{0i}, Y^C, S_{Ci}, S_{Ei} / Y^P\right) \quad (23)$$

and it is decomposed further into two terms expressed as

$$F_b = \overline{H}\left(u_j, f_{C0}, f_{EC} / Y^P\right) - F_D. \quad (24)$$

The first term indicates the joint uncertainty about the compiled input command and related feedback when the execution level processes are known.

Entropy for control, cont….

The *total coordination rate* of the IRS denotes the transmission of information (knowledge processing) within the IRS, i.e., the amount by which all of the internal variables of the IRS constrain each other. It is expressed as

$$F_c = \overline{T}(S_i : Y^P) \tag{25}$$

$$F_c = F_c^0 + F_c^C + F_c^E + \overline{T}(S_0 : S_C : S_E). \tag{26}$$

The last term of (26) is simplified further to give

$$\begin{aligned} \overline{T}(S_0 : S_C : S_E) &= \overline{T}(S_0 : S_C) + \overline{T}(S_0, S_C : S_E) \\ &= \overline{H}(S_C) - \overline{H}(S_0 / S_C) \\ &\quad + \overline{H}(S_E) - \overline{H}(S_E / S_0, S_C) \end{aligned} \tag{27}$$

where

$$\overline{T}(S_0 : S_C) = \overline{H}(S_C) - \overline{H}(S_C / S_0) \tag{28}$$

$$\overline{T}(S_0, S_C : S_E) = \overline{H}(S_E) - \overline{H}(S_E / S_0, S_C). \tag{29}$$

Alternatively

Knowledge $\boldsymbol{K} = -\alpha - \ln p(\boldsymbol{K})$, $p(\boldsymbol{K})$ is the pdf of knowledge, α appropriately chosen constant

$p(\boldsymbol{K})$ must satisfy Jaynes principle of maximum Entropy $p(\boldsymbol{K}) = e^{-\alpha-\boldsymbol{K}}$, $\alpha = \int e^{-\boldsymbol{K}} ds$ integral is over the space of knowledge, Ω_s.

Knowledge between states $K_{ij} = ½\, w_{ij} s_i s_j$ with w's serving as state transition coefficients, 0 or 1

Total system knowledge $\boldsymbol{K} = ½\, \Sigma_i \Sigma_j\, w_{ij} s_i s_j$ form of energy of all underlying events.

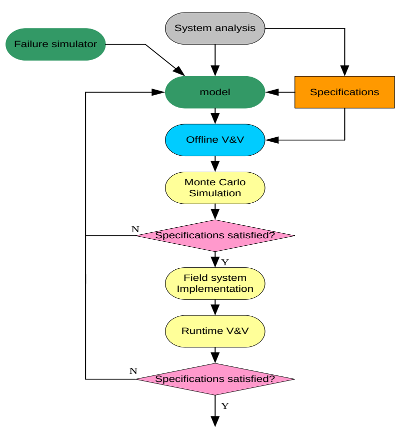
$R_{ij} = K_{ij}/T$, $R_i = K_i/T$ and $\boldsymbol{R} = \boldsymbol{K}/T$ - rate of knowledge $\boldsymbol{R}$ chosen as the main variable of the system with discrete states, defined over a fixed interval of time T.

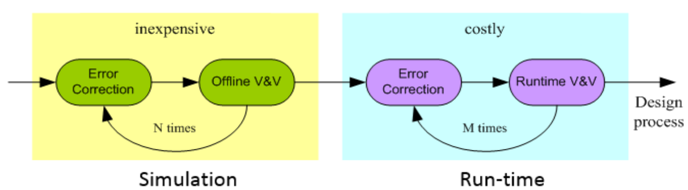
R must satisfy the relation *(**MI**):(**DB**) to (**R**)*, ***MI***, defined as the process of analyzing, organizing and converting data into knowledge – it is the set of rules that operates on a Data Base (***DB***) of events/activities to produce flow of knowledge (***R***)

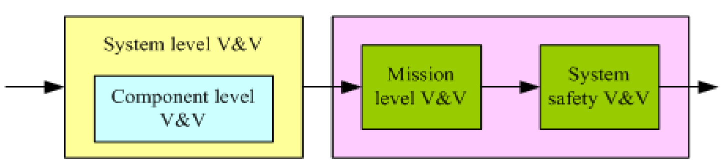
$Prob(\boldsymbol{MI}, \boldsymbol{DB}) = Prob(\boldsymbol{R})$ and consequently $H(\boldsymbol{MI}/\boldsymbol{DB}) + H(\boldsymbol{DB}) = H(\boldsymbol{R})$.

Autonomy for Unmanned Systems

- ❑ Autonomy in the context of a RPAS/UAS is the capability of its components or sub-systems to operate independently from external control.
  - ❑ Spectrum of autonomy from basic automation (mechanistic execution of action or response to stimuli) to partial autonomy, to flexible autonomy and to fully autonomous systems able to act independently in dynamic/uncertain environments.
- ❑ Foundational Framework
  - ❑ Set of goals vs environment uncertainty (to define levels of autonomy)
  - ❑ Integrity Management
    - ❑ Prognostics and Health Management (PHM) / Remaining Useful Life (RUL)
  - ❑ Metrics: Risk; Confidence; Trust and Trust Consensus; Measure of Resilience; Entropic Measures; Kolmogorov Complexity
  - ❑ Deep Learning; Q-Learning; Convolutional Neural Networks
  - ❑ Supervisory controllers (to 'translate' time-based to event-base and vice versa)
  - ❑ Off-line and run-time V&V

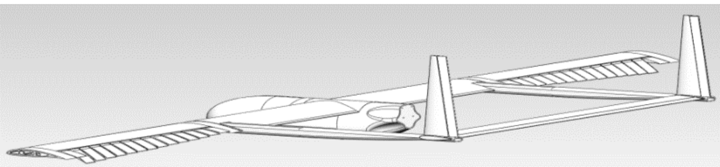


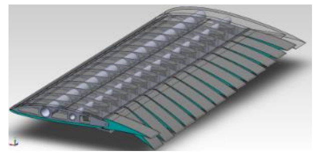


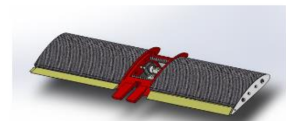


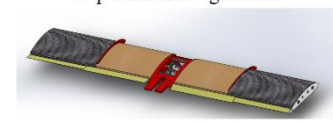
Autonomy for Unmanned Systems

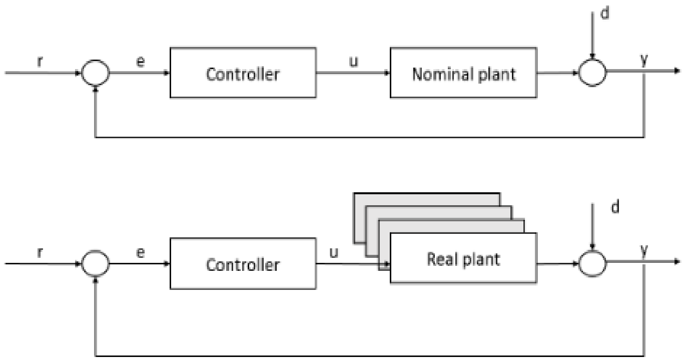
The NextGen - New Reality for Autonomy - Example

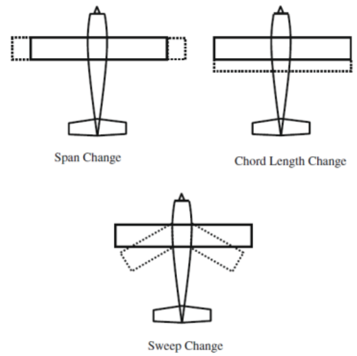


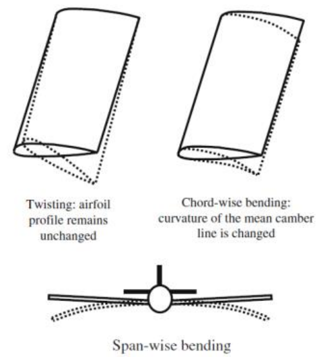




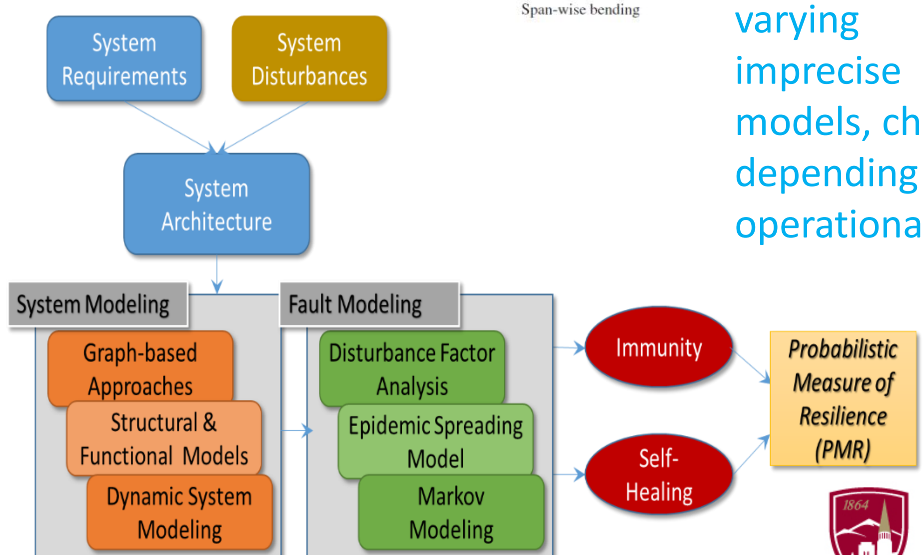








Autonomy will also be built in a bottom-up way to accommodate in real-time unstructured uncertainties (non model-based), time-varying parameters, imprecise system models, changing models depending on operational regime.



Autonomy for Unmanned Systems

Functionality of the UAS: "… as if there were a pilot on-board" - The Human-Machine interface Challenge

AI as a Tool Allows for:

- **Designing effective / efficient HMIs to reduce AVO workload.**
- **Automation progression - decision making shifts to the 'machine'**
- **High confidence systems**

- ❑ ***4-to-1 operators-to-one UAS (U.S. Air Force)***
- ❑ **In the future (as the U.S. Army wants) *1-to-4***

- ❖ Reconfigurable software- programming architectures
- ❖ Combine hardware, control and software reconfiguration strategies
- ❖ Design for reconfigurability: the complexity paradigm
- ❖ Design for self-organization (that includes adaptation and learning)
- ❖ A confluence of tools/methods from large-scale system theory, complexity theory, coordination and control, etc.

On Autonomy–Immediate steps

- Choose candidate testbed system (i.e., unmanned vehicle)
- Define desired functionality (goals – environment uncertainty) and desired levels
- Develop modeling and architectural framework with vertical and horizontal functionality details
- Develop algorithmic and procedural framework, and software architecture, adaptation and learning, etc.
- Define metrics (quantitative)
- Start testing the candidate system under different set of goals to be achieved and under different environment conditions
- Evaluate progression of automation and establish the trust level after which the human allows for the machine to make decisions without interaction with the operator
- Change goals and environment and repeat considering
    - Ability to self-organize
    - Reconfigure itself
    - Self-build / update the knowledge base (DCBR) based on similarity from previous experience, etc.
    - Test resilience
    - Redesign / modify and retest the system

THANK YOU