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Adaptation and Learning without Assumptions

[*adaptive control methods that improve robustness*]

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Outline

- Part I: Concepts and Issues
- Part II: Theory
- Part III: Design Studies
- Part IV: Conclusions

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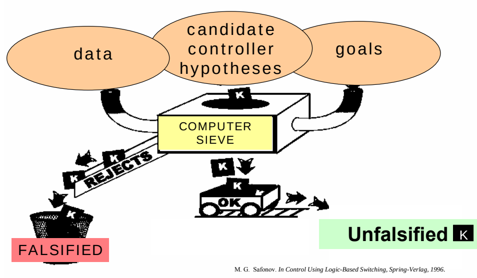
- Part I: Concepts and Issues
- Part II: Theory
- Part III: Design Studies
- Part IV: Conclusions

An Achilles heel of modern system theory has been the habit of 'proof by assumption'

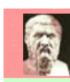
Theorists typically give insufficient attention to the possibility of future observations which may be at odds with assumptions.

Background: Unfalsified Control
ONLY 3 elements



M. G. Safonov. *In Control Using Logic-Based Switching, Spring-Verlag, 1996.*

Control Design Bottleneck



- We have analytic tools for controlling models

- Need <u>DATA-DRIVEN</u> analytic tools needed to close the design loop at the experimental validation stage

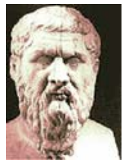
We need
<u>DATA-DRIVEN</u>
analytic design tools

Two ways to learn & adapt: Observation vs. Introspection

Reality is what we observe.

Reality is an ideal, observable only through noisy sensors.

vs.



Galileo: open-eyed **"data-driven"**	Plato: introspective **"assumption driven"**
MODELS approximate Observed Data	Data approximates Unobserved TRUTH
'Curve-Fitting'	'Probabilistic Estimation'

- Traditional control theory ('Platonic'): 
  - contains many assumptions about the plant.
  - some assumptions are unrealistic.
- Unfalsified control theory ('Galilean'): 
  - eliminates hypotheses that are not consistent with evolving experiment data.

Observation vs. Introspection in adaptive control

"Unfalsified: Data Driven"

- **goals are modest:**
  - no guaranteed predictions of future stability
  - just consistency of goals, decisions and data
- **no troublesome assumptions, parsimonious formulation**:
  - **DATA**
  - **GOALS**
  - **DECISIONS**
- **Fast, reliable, exact**

"Traditional: Assumption Driven"

- **goals are ambitious**:
  - guaranteed future stability
  - Cost & estimation convergence
- **many troublesome assumptions**
  - "the 'true' plant is in model set",
  - "noise I.I.D."
  - "bounds on parameters, probabilities"
  - …, "linear time-invariant, minimum-phase plant, order < N"
- **Slow, quasi-static, approximate**

Remarkably, some leading "assumption driven" control theorists have held that observed DATA inconsistent with ASSUMPTIONS should be ignored (cf. M. Gevers et al., "Model Validation in Closed-Loop", ACC, San Diego, 1999)

The Behavioral Approach

- Let the data speak...
- **Unfalsify** (validate) models and controllers against hard criteria:
  - Choose criteria expressible directly in terms of observed data (sensor outputs, actuator inputs)
  - Avoid criteria that that rely on noise model assumptions or other prior beliefs

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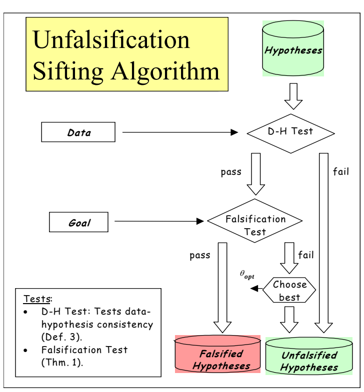
UNFALSIFIED HYPOTHESES:

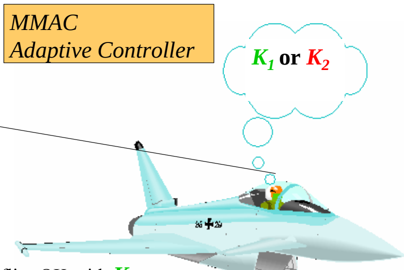
•The ability of each candidate hypothesis to meet the performance goal is tested directly against evolving real-time measurement data.

* If a hypothesis is a controller, it need not be in the loop to be falsified.



Impact on Adaptive Control

MMAC Adaptive Controller



It flies OK with K_1.
But the adaptive controller says switch to K_2.

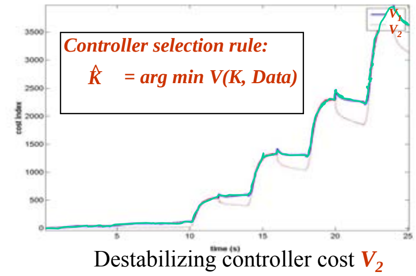
MMAC controller crashes, why?

Answer:
- assumption was wrong
- plant was <u>not</u> close to model

The plane crashes because cost

$$V(K,Data) = e^2(K,Data,t) + \int_0^t \exp^{-\lambda(t-\tau)} e^2(K,Data,\tau)\, d\tau, \quad j = 1,2$$

disregards overwhelming evidence that controller K_2 is destabilizing.



Destabilizing controller cost V_2
is lower than stabilizing controller cost V_1

In life, as in football, you won't go far unless you know where the goal posts are.

— Arnold Glasow —

Goals of adaptive control?

- **Adaptive Control goals**: Ensure stability and desired performance of the closed loop at all times.
- **Problem: Model-Mismatch Instability**
  - ***If <u>assumptions</u> are wrong, then <u>the adaptive loop can cause instability</u>, even when the initial controller is stabilizing***
  - ***Need <u>safe adaptive control</u> laws that recognize instability, and are not blinded by prior assumptions***

Previous Work: Traditional and recent adaptive methods

- Pre-1980's adaptive: Too many assumptions! (non-realistic): LTI, minimum phase; etc.
- Relaxation of assumptions over the years: alternative methods, deal with poor, unreliable models
- Recently, **switching adaptive schemes**:

❈ **Indirect** (MMAC; Identifier-based supervisory; Localization switching)

❈ **Direct** switching schemes (Fu & Barmish, Mårtensson, Safonov) **reduce *a priori* information** need.

Previous Work without assumptions on plant

- Some pre-routed switching schemes essentially had <u>no assumptions</u> on the plant at all (**Fu & Barmish '86, Mårtensson '85**).
  - –Not very practical - use extensive dense search through parameter space: slow convergence.
  - – Only finitely many ***K***'s allowed
- **Stefanovic-Wang-Paul-Safonov '04** solve safe adaptive control via unfalsified adaptive concept
  - – Fast, practical, but still only finitely many ***K***'s

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Adaptive Control

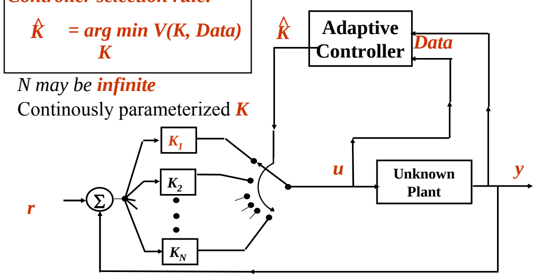
Every adaptive control law minimizes a cost

Controller selection rule:

$$\hat{K} = \arg\min_{K} V(K, Data)$$

N may be infinite

Continously parameterized *K*



Every adaptive control law minimizes a cost

Controller selection rule:

$$\hat{K} = \arg\min_{K} V(K, Data)$$

Choose cost $V(K, Data)$ so that destabilizing controller K_2 cost is greater than stabilizing K_1

Convergence Theorem

(Wang, Stefanovic, Safonov ACC '04)

Assume

1. $V(K,Data)$ is <u>cost detectable</u>
2. **stabilization is feasible,**

then any adaptive controller of the form

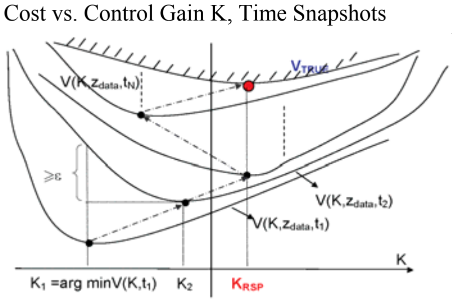
$$\hat{K} = \arg\min_{K} V(K,Data)$$

is stabilizing, <u>irrespective of plant model mismatch</u>.

Proof: We apply the 1992 lemma of Morse, Mayne & Goodwin, but with a new L_{2e}-gain type cost $V(K,Data)$ that *<u>detects</u>* <u>instability without plant assumptions</u>.

Idea for proof Prior Result (continued)

Cost vs. Control Gain K, Time Snapshots



With the L_{2e}-gain type cost function, the finite upper bound condition (a) in the 1992 Morse lemma holds even for big "model mismatch"

This is our 'picture' of the Morse-Mayne-Goodwin proof of their hysteresis lemma. **Q.E.D.**

Assumption 1: Cost Detectability

Definition: If

$$V(K,Data) \to \infty \Leftrightarrow \left(\max \left(\|y\|_\tau^2 + \|u\|_\tau^2 \right) / \|r\|_\tau^2 \right) \to \infty$$

then we the cost function $V(K,Data)$ is **<u>cost detectable</u>**.

Key points:

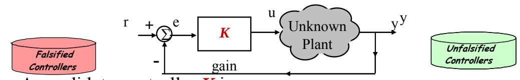
- This $V(K,Data)$ is an L_{2e}-gain type cost function. Irrespective of plant assumptions, it correctly distinguishes stability vs. instability.
- Prior to Safonov & Tsao (1997), cost-detectable cost functions were not used in adaptive control – making them susceptible to model-mismatch instability.

Assumption 2: Feasibility

Definition: An adaptive control problem is said to be **feasible** if the candidate controller set **K** has at least one stabilizing controller.

- *This is the weakest possible assumption required to guarantee adaptive law $\hat{K}(t)$ converges to a stabilizing controller $K \in \mathbf{K}$*
- *If the initial controller works prior to closing the adaptive loop, then feasibility assumption is satisfied*

Unfalsified Cost Level *V(K,Data)*



A candidate controller ***K*** is **FALSIFIED** with repect if to cost level V_o if

$V(K,Data) = \max \left(\|y\|_\tau^2 + \|u\|_\tau^2 \right) / \|\tilde{r}(K,Data)\|_\tau^2$

when the ***Data:=(y,u)*** proves existence of a 'fictitious'

$\tilde{r}(K, Data) = y + K^{-1}u$

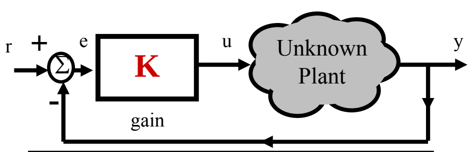
that would violate performance spec ***V(K,Data)<*** V_o if the ***K*** were in the loop.

- Controllers may remain **UNFALSIFIED** with repect to cost level V_o until the data proves otherwise.
- Or, fading memory may be used to reinstate previously falsified controllers

Key points:

- A controller need not be in the loop to be falsified.
- Even a single data point can falsify many controllers.

Trivial Example



- Plant Data: at time t=0, (u,y)=(1,1)
- Candidate **K**'s: u=**K**e real gain
- Goal: |e(t)/r(t)| < V_o = 0.1 for all r(t)

Relations: e=u/**K**=1/**K** , r=y+e=y+u/**K**= 1+1/**K**

=> **K is** unfalsified if |1/(1+**K**)| < 0.1

=> unfalsified **K**'s: **K>9** or **K<-11**

Cost-Detectable *V(K,Data)* Solves…

Problem of Safe Adaptive Control:

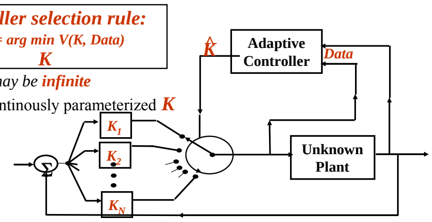
Design adaptive controllers that never destabilize when the adaptive loop is closed (**model-mismatch instability**), with no assumptions on the plant.

Controller selection rule:

$\hat{K} = \arg\min_{K} V(K, Data)$

*N may be **infinite***

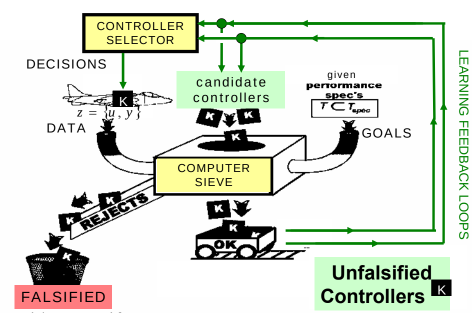
Continously parameterized ***K***



The Behavioral Approach to Adaptive Control

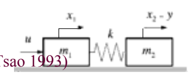
- **Data Driven:** Let the data speak...
  - Don't let modeling beliefs trump observation
- **Unfalsify** (validate) models and/or controllers against hard criteria:
  - Choose criteria expressible directly in terms of observed data (sensor outputs, actuator inputs)
  - Avoid criteria that that rely on "noise model" and other prior beliefs

Unfalsified Adaptive Control

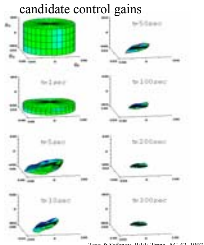


with repect if to cost level V_o

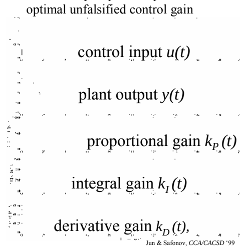
Simulation Example: ACC Benchmark (Safonov & Tsao 1993)



time-history of unfalsified candidate control gains



time-history of plant response and optimal unfalsified control gain



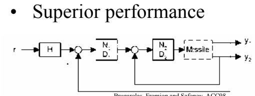
Evolution of unfalsified set

Time responses

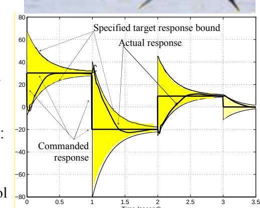
Another Example: Missile

Brugarolas, Fromion & Safonov, ACC 1998

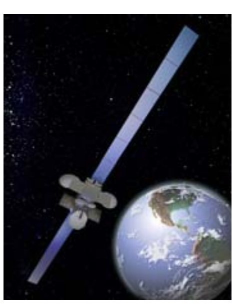
- Learns control gains
- Adapts quickly to compensate for damage & failures
- Superior performance



Unfalsified adaptive missile autopilot:
- discovers stabilizing control gains as it flies, nearly instantaneously
- maintains precise sure-footed control

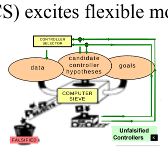


Another Example: Satellite

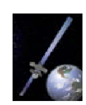


Boeing Satellite Systems 702

- Large flexible appendage of uncertain mode frequency (>25%)
- Relatively fast closed-loop response required
- Reaction Control System (RCS) excites flexible modes



Antenna Mapping Control Problem



(AIAA GNC Conf., 2003)

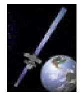
PD Control Law: $$u = C_p(r - y) - C_d\,\dot{y} \quad (8)$$

Performace Spec: $$\begin{cases} |T_{er}(j\omega)| < |W_1^{-1}(j\omega)| \\ |T_{ur}(j\omega)| < |W_2^{-1}(j\omega)| \end{cases}, \forall\omega \quad (9)$$

In time domain, the performance spec is equivalent to

$$\left\| \begin{bmatrix} \hat{w}_1 * (r - y) \\ \hat{w}_2 * u \end{bmatrix} \right\|_{L_2[0,t)} \Big/ \|r\|_{L_2[0,t)} < 1, \forall t, \forall r \quad (10)$$

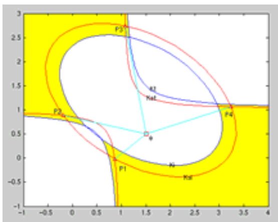
Antenna Mapping Control



Controller Parameter Vector Switching

When the currently used controller vector is falsified (i.e. not satisfying (12))

==> switch to an element within the unfalsified controller parameter set.

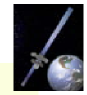


Unfalsified set is in yellow color

An Approach

1. Find the intersections of current set Kt with all previous set Kτ
3. Use a slightly larger set (left plot red-colored) to calculate intersection to avoid switching too frequently
3. Switch to the nearest interstction

Simulation Results



Bode plots of closed-loop S=1/(1+GK)

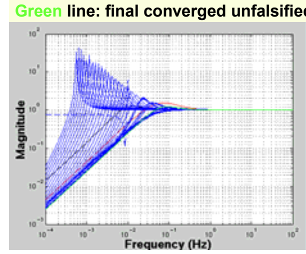
Dashed blue line: initial transfer function

Red line: W_1^{-1}

Solid blue lines: Ter at each switching, under $W1^{-1}$ at end

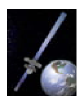
Black line: nominal non-adaptiveTer

Green line: final converged unfalsified T_{er}

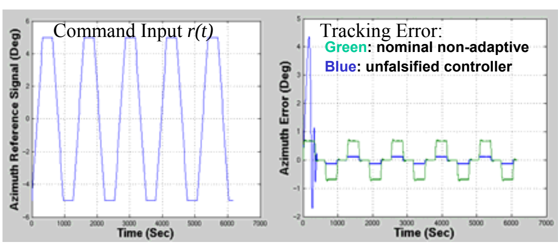


Converged unfalsified Ter lies under non-adaptive Ter and under W_1^{-1}

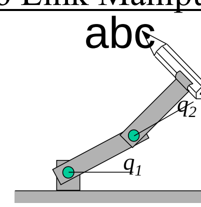
Simulation Results



After initial transients, unfalsified controller shows smaller tracking error than the nominal non-adaptive PD controller



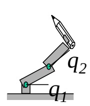
Another Example: Two Link Manipulator



$$u_a = H(q)\ddot{q} + C(q,\dot{q})\dot{q} + g(q)$$
$$= Y(q,\dot{q},\ddot{q})\theta$$

Tsao and Safonov, *Int. J. Adaptive Contr. & Signal Proc.*, 2001

Background: Computed-Torque Robot Control



- Control Law

$$u = H(q)\left(\ddot{q}_d + 2\lambda\dot{\tilde{q}} + \lambda^2\tilde{q}\right) + C(q,\dot{q}) + g(q)$$

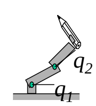
$\tilde{q} = q - q_d$, tracking error; q_d desired trajectory

- Performance

$$H(q)\left(\ddot{\tilde{q}} + 2\lambda\dot{\tilde{q}} + \lambda^2\tilde{q}\right) = d$$

tracking error converges exponentially fast to a region proportional to the size of disturbance *d*

Simulation



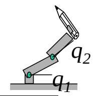
- Tip mass m moves between 2 and 20 every 0.5 sec

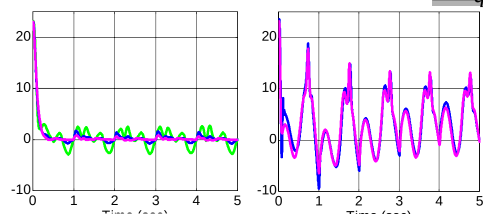
  at m=2, $\theta^*=[3.34,\ 0.97,\ 1.0392,\ 0.6]^T$
  at m=20, $\theta^*=[30.07,\ 9.7,\ 10.392,\ 6]^T$
  $\hat{\theta}(0) = [0.5,\ 0.5,\ 0.5,\ 0.5]^T$

  $\Theta(0) = \{\theta \mid -200 \le \theta_i \le 200, i = 1,\cdots,4\}$

- $q_{d1}=30°\ (1-\cos 2\pi t)$, $q_{d2}=45°(1-\cos 2\pi t)$
- $q(0)=[0,\ 0.4]^T$, $dq/dt(0)=[0,\ 0]^T$

Joint 1 Tracking Error(deg)





Unfalsified   Slotine et al's

τ=0   τ=1/(40π)   τ=1/(10π)

Another Example:
Unfalsified 'PID Universal Controller'

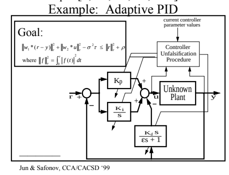
- Unfalsified adaptive control loop stabilizes in real-time
- Unstable Plant 30 Candidate PID Controllers:

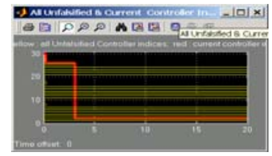
  K_I =[2, 50, 100]

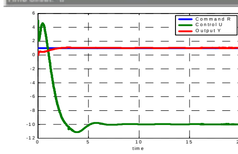
  K_D = [.5, .6]

  K_P = [5, 10, 25, 80, 110]

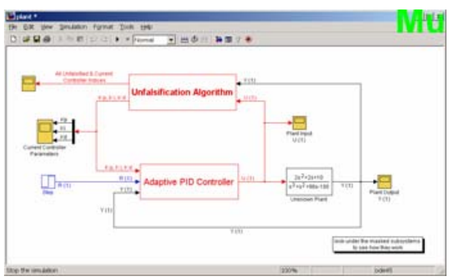
Example: Adaptive PID





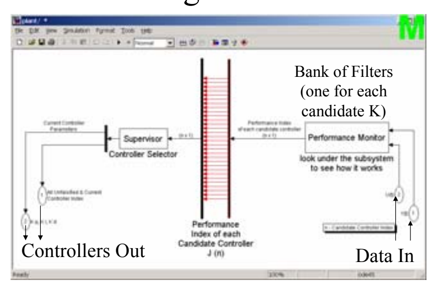


How Unfalsified Works



ftp://routh.usc.edu/pub/safonov/PID_Demo_for_MATLAB6.zip

Inside the Unfalsification Algorithm Block



Others peoples' design studies (off-line 'run-to-run'):

- Emmanuel Collins et al. (Weigh Belt Feeder adaptive PID tuning, CDC99)
- Kosut (Semiconductor Mfg. Process run-to-run tuning, CDC98)
- Woodley, How & Kosut (ECP Torsional disk control, adaptive tuning, ACC99
- Razavi & Kurfess, Int. J ACSP, Aug. 2001

USC is the only one doing <u>real-time</u> unfalsified adaptive control.

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What's Wrong:
Adaptive Control Counter-Examples

Despite "proofs" of stability and convergence, modern adaptive control methods fail to achieve goals when there is large "model mismatch".

Assumptions Fail.

Modern adaptive methods are blinded by assumptions.

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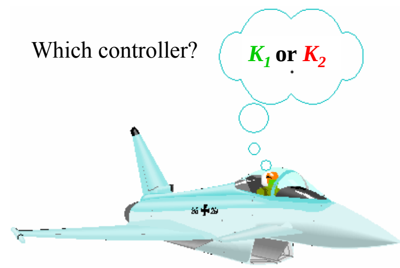
Which controller?



It flies OK with K_1. But the adaptive law says switch *to* K_2.

MRAC chooses c_2 and crashes finally, why?

Wrong assumption: Plant was not close to the model!

In life, as in football, you won't go far unless you know where the goal posts are.

— Arnold Glasow —

THE FIX

Remember your goals:

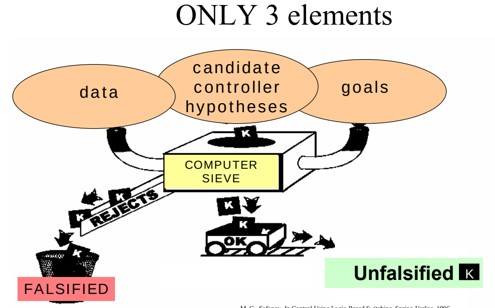
- Switch (or tune) to a stabilizing controller, based on observation
- Don't be blinded by prior assumptions (expect model mismatch)
- **And, above all, choose a cost function that detects instability when it happens:**

You need *cost detectability*

You need an L_{2e}-gain type cost function ***V(K,Data)***

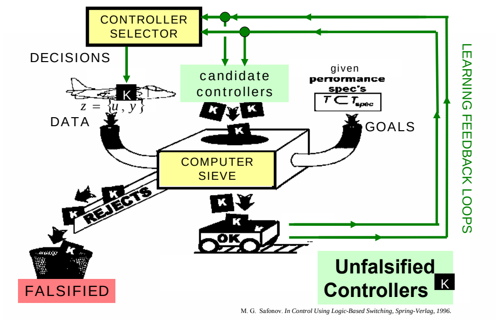
Background: Unfalsified Control

ONLY 3 elements



M. G. Safonov. *In Control Using Logic-Based Switching*, Springer-Verlag, 1996.

Unfalsified Adaptive Control



M. G. Safonov. *In Control Using Logic-Based Switching*, Spring-Verlag, 1996.

Conclusions

- Introspective models are not adequate for analyzing adaptation

- To explain learning and adaptation, we need the open-eyed, data-driven scientific logic of unfalsification

- Unfalsified adaptive control robustifies
- It remembers where the goal posts are
- No plant assumptions needed

Selected References

http://routh.usc.edu

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