

**Monitoring the state of the  
physical plant in a CPS to detect  
and counter benign faults and  
malicious attacks**

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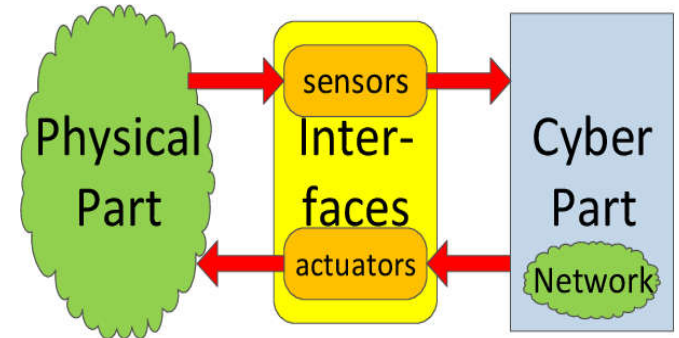
## Outline

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- **Objective** – detect and counter faults in cyber physical systems
- **Fault types**
  - Benign faults – increase reliability
  - Malicious faults – increase security
- **Known techniques to achieve these objectives**
  - High overheads
- **Our approach: Monitor the state of the physical plant**
  - Fit the level of protection to the current state sub-space
- **Main challenge: Determine in real-time the state subspace**
  - Use Machine learning techniques

## Critical CPS applications

- **Many CPSs control life-critical applications**
  - E.g., Aircrafts, Nuclear reactors, Smart Buildings, Automobiles, Medical Devices
  - Must support high levels of safety and provide timely response to benign and malicious faults
- **Common techniques to detect and recover impose high overheads**
  - Hardware, performance, power
  - Most focus on the cyber sub-system ignoring the physical plant
- **Our approach: Detect faults and invoke adaptively proper countermeasures**



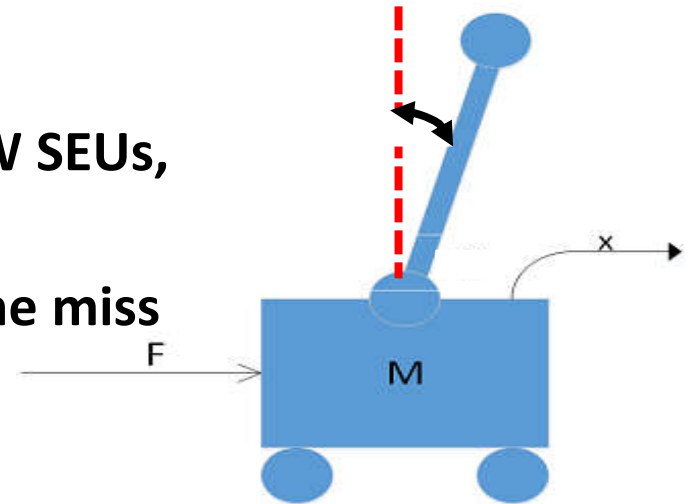
## Failures in Cyber-Physical Systems

### ■ Computing side:

- Erroneous computer outputs due to HW SEUs, SW bugs or maliciously modified SW
- Computational delays causing a deadline miss

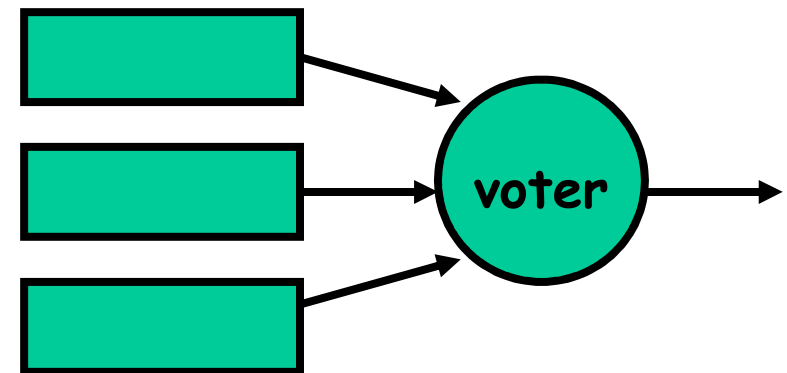
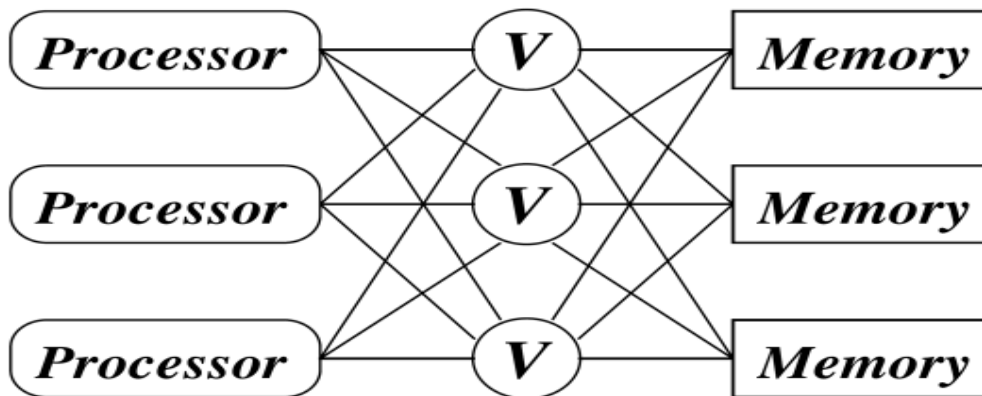
### ■ Physical side:

- Application specific
  - E.g., failure in an inverted pendulum: angle  $\geq 90^\circ$
- **Safety Space Constraints (SSC):** The conditions that the controlled plant must satisfy in order to operate safely
  - E.g., inverted pendulum: angle should be  $\leq 0.5$  rad, or  $30^\circ$ , otherwise it is unsafe



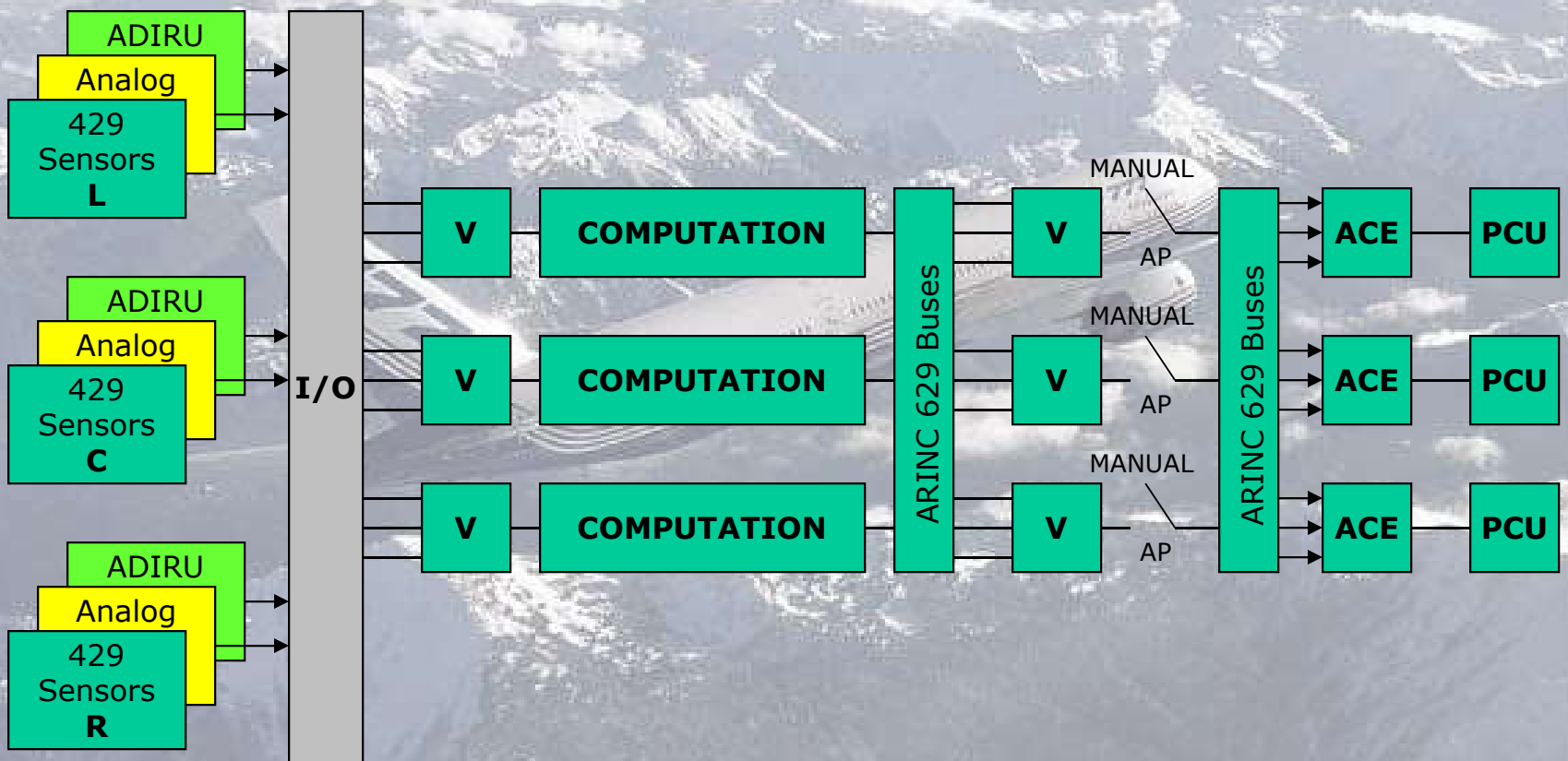
## Fault Tolerance (FT) in CPS

- **Traditional FT - continuous massive redundancy**
  - **Duplex**: two copies of a task running on two cores, can detect faults
  - **TMR**: three copies of a task running on three cores, can mask a single erroneous result

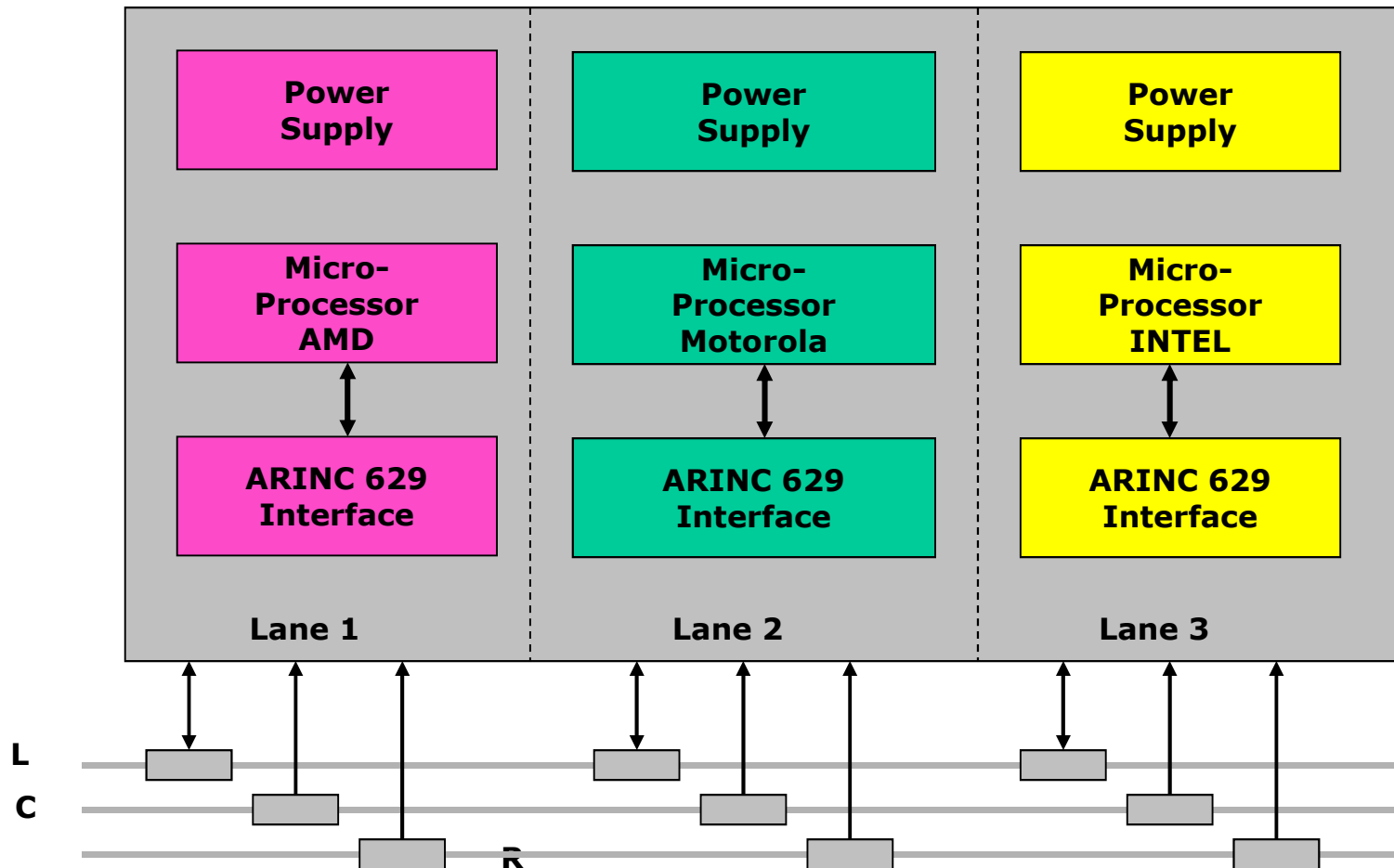


# Example: Boeing 777 (early design)

## Life-critical CPS



# TMR with design diversity



## Our approach – Adaptive Fault Tolerance

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- **Plant state based adaptive FT:**
  - If the plant is **deep** within its **safe region**, can withstand some erroneous control inputs
  - In such a state, a lower level of FT can be deployed
  - Need a definition of
    - Safe region
    - How to determine whether the plant is “deep” in the safe region



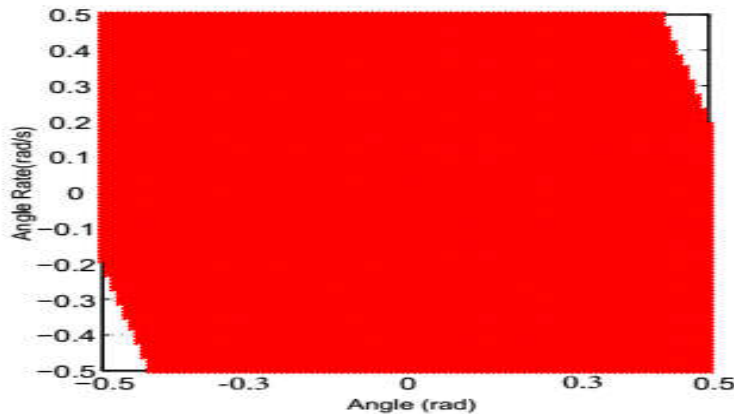
## Physical Plant's Safe State Space ( $S^3$ )

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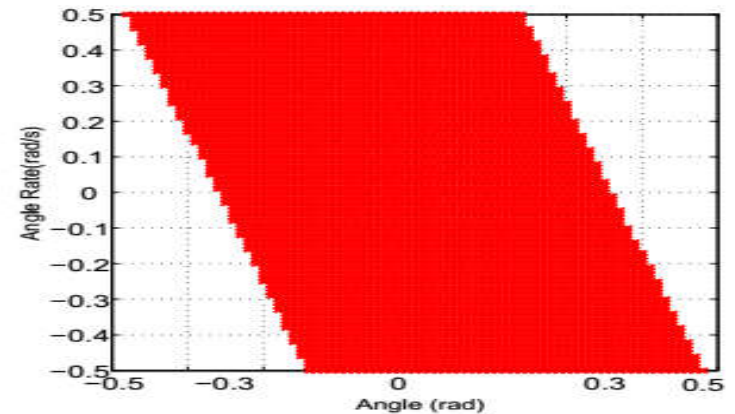
- **Definition:** The sub space of the states of the physical system that meet the SSC (determined by the application engineer)
- **A point is in  $S^3$  if:** **SSC: Safety Space Constraints**
  - 1. The plant satisfies the SSCs at the present time, and
  - 2. Based on
    - (1) the controlled plant control laws,
    - (2) the control algorithm used,
    - (3) the actuator limitations,
    - (4) the control task execution rate, and
    - (5) the limits of the operating environment impactthe plant will continue to satisfy these constraints up to a given horizon, as long as **correct control inputs** are applied

# Example: $S^3$ for inverted pendulum, horizon 15sec

Control task period

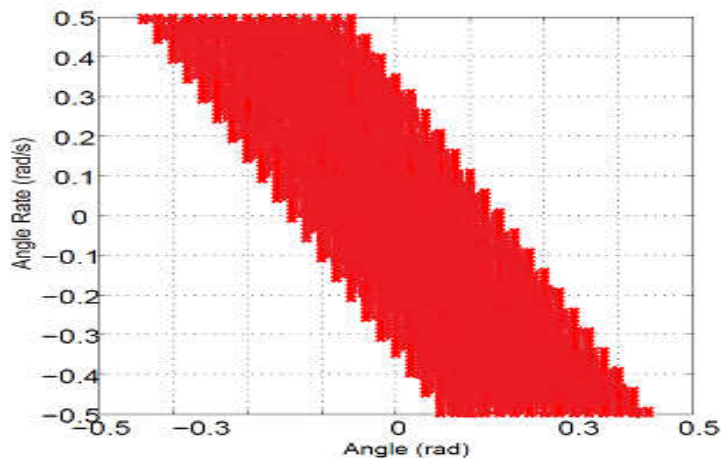


(a) Period = 10ms

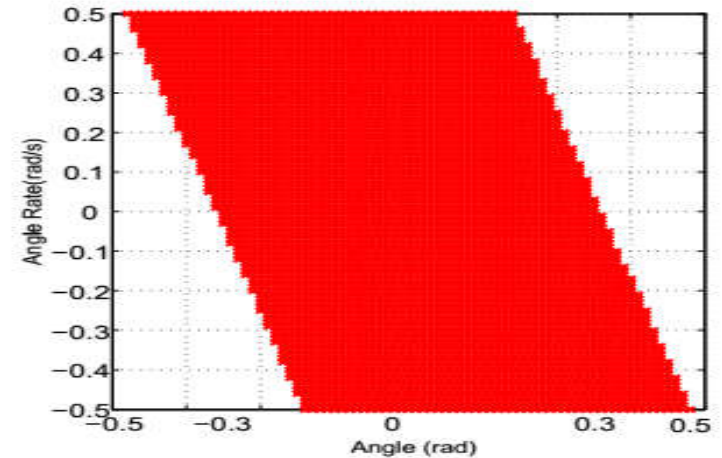


(b) Period = 30ms

Actuator bound



(c)  $u_{lim} = 2.5 \text{ N}$



(f)  $u_{lim} > 10 \text{ N}$

## Sub-spaces of $S^3$

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- **S1:** Even if the controller generates the **worst-case** control input until the next iteration of the control task, the plant will not leave its  $S^3$
- **S2:** If the controller generates a default output (e.g., zero or repeat the previous output), the plant remains in  $S^3$
- **S3:** If the controller produces an incorrect output, the plant is not guaranteed to stay in  $S^3$
- **(Benign) Fault Tolerance implications:**
  - **S1:** No fault-tolerance is required
  - **S2:** It is sufficient for the computer to be fail-stop
  - **S3:** Fault fault-masking is necessary

## Security in CPS

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- **Unique characteristics of CPS**
  - Limited computing resources
  - Often limited power
  - Often inaccessible location
  - Network connectivity
  - Physical exposure

- **Vulnerabilities**
  - Network intrusion
  - Exhaustion attack
  - Information theft
  - Modifying software (code injection or reprogramming)
  - Physical tampering (side channel attacks)
  - Modifying sensor output

## Classifying Security Threats in CPS

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- **Distinguish between two malicious objectives**
  - **Harming physical plant operation** vs.
  - **Stealing propriety information**
    - Stealing information - well-known threat in general computing systems
    - Various cryptographic schemes can be employed
- **Threats to the physical plant operation can be detected by**
  - **Common techniques to detect intrusion & software modification**
    - E.g., code analyzers, anomaly detection, sandboxing
    - Often have a high overhead for constrained CPSs
    - Never achieve 100% coverage as new attacks are developed (hard to update countermeasures)

## Our approach to deal with security threats in CPS

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- **Must first detect the threat and if possible recover**
- **Monitor the state of the plant and identify **marginal states****
  - **The marginal state is likely to be the result of a fault**
  - **The exact nature of the fault is unknown**
    - **(1) A benign fault** requiring fault tolerance measures
      - **E.g., execute two copies of the control task on two cores**
    - **(2) A malicious attack** on the control task
      - **Must use a different version of the control task**

## Counteracting security threats in CPS

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- **Assume first that it is a benign fault** – duplicate the control task
  - **If the state remains marginal** – replace the current version of the control task by a second version
  - Second version should follow a simpler control algorithm
    - More robust, shorter execution time but lower quality
    - Can be useful even for dealing with benign SW bugs
  - **If the plant state is still marginal** execute **emergency procedure**
    - Use a default control (even an open-loop scheme)
    - Inform remote operator
- **Detecting a threat** to the safe operation of the physical plant is the most significant step

## Challenge: Determine current sub-space in real-time

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- **Given the current state of the physical plan how to decide which sub-space it belongs to?**
  - Storage constraints
  - Timing constraints
- **Use machine learning schemes to identify boundaries between sub-spaces**
  - Hopefully requiring only a few parameters
- **Standard Machine Learning (ML) algorithms for classification problems:**
  - E.g., Logistic Regression, Neural Networks, Support Vector Machine (SVM)



## Safety Critical Issues

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- **Can not guarantee 100% classification accuracy**
- **Need a way to make it conservative**
- **Misclassification from S1 to S2 or even S3 is allowed, only wasting computing resource; from S3 to S1 is not allowed**
- **Classification algorithms produce a 1 if the calculated probability is greater than a threshold**
  - **Default 0.5**
- **Can iteratively adjust this threshold value, until no dangerous misclassifications exist**

## Real-Time Task Optimization - example

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### ■ Inputs:

- Number of available copies & number of versions for each task
- Power consumed by each version of every task
- Current temperature of each processor  $T_{proc}(t)$

### ■ Output:

- Preferred version for each task (Note: need to generate classifier for each version of every task)

### ■ System objective: e.g., minimize aging of processors due to high operating temperature

- All circuit fault mechanisms rates exponential in  $T$  (e.g., electro-migration, dielectric breakdown and stress migration)
- Thermal Age Acceleration Factor (TAAF)

$$TAAF = e^{\left(-\frac{E_a}{kT_{proc}(t)}\right)}$$

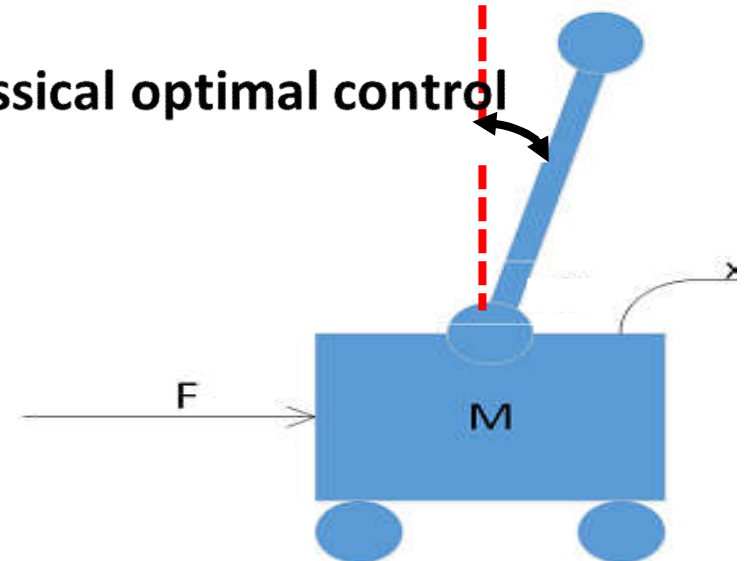
## Examples of online plant state classification

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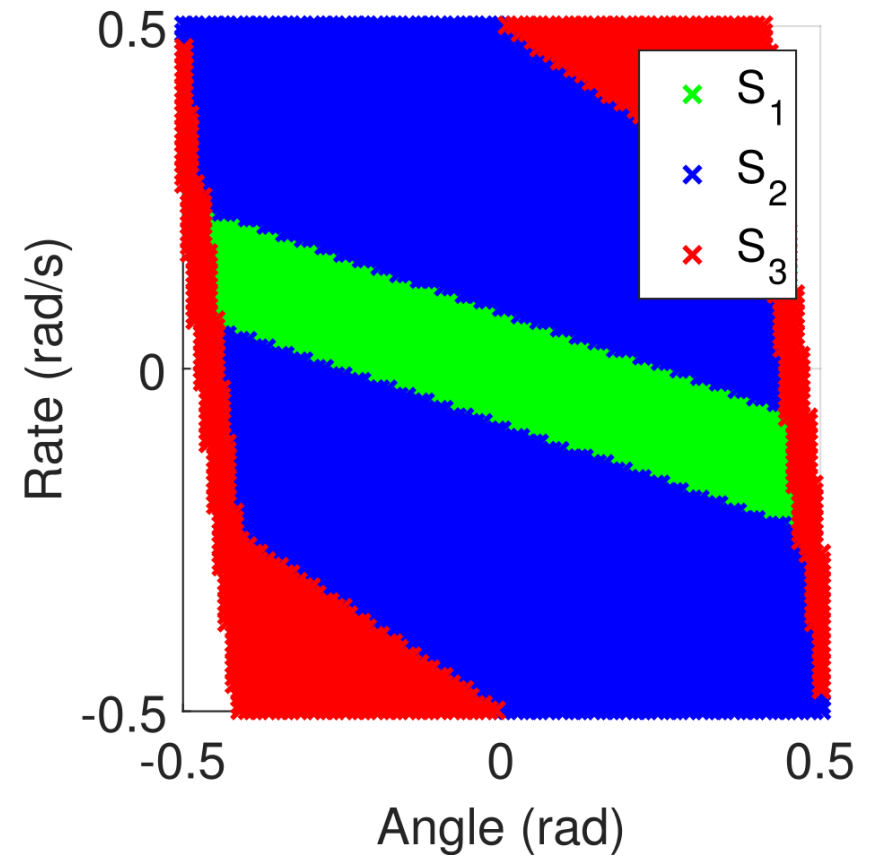
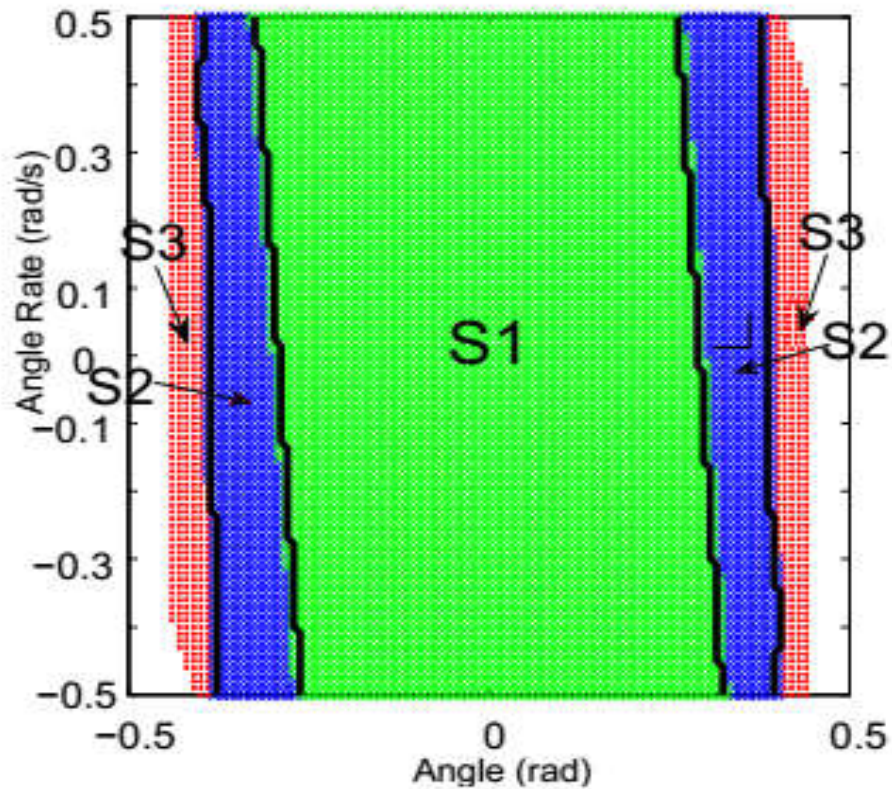
- **Inverted pendulum**
- **Anti-lock Braking System (ABS) in a car**
- **Highway platoon**
- **Humanoid Robot**

## Inverted Pendulum

- **Real-time control algorithm:**
  - Linear Quadratic Regulator (LQR) - classical optimal control algorithm
- **Safe State Constraints (SSC):**
  - $-0.5 \leq \phi \leq 0.5 \text{ rad}$
- **Upper and Lower Bounds of the control force:  $\pm 40 \text{ N}$**



# Sub Spaces and Decision Boundaries



Max Cart velocity  $\rightarrow 0$

## Training Algorithms (Inverted Pendulum)

	<i>LR</i>	<i>NN</i>	<i>SVM</i>
Trained Parameters Size	15	153	788
Training Accuracy	85.8%	99.92%	99.98%

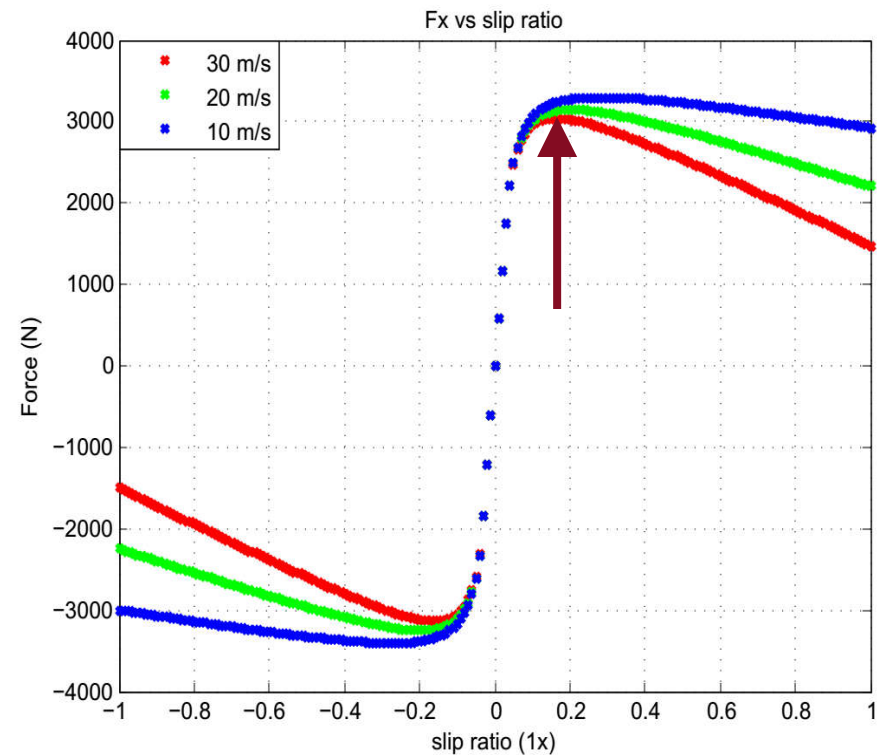
COMPARISON OF LEARNING ALGORITHMS FOR  
INVERTED PENDULUM

<i>Angle</i>	<i>Angle Rate</i>	<i>Predicted</i>	<i>Actual</i>
-0.3900	-0.1800	3.0000	2.0000
-0.3100	0.1600	3.0 <b>S3</b>	2.0 <b>S2</b>
0.3100	-0.1600	3.0	2.0
0.3900	0.1800	3.0000	2.0000

TRAINING PERFORMANCE OF NEURAL NETWORKS FOR  
INVERTED PENDULUM

## Anti-Lock Braking System (ABS)

- Prevent wheels from locking up during hard braking
- Also maximize braking forces generated by the tires to get small stop distance
- The most important parameter is the Slip ratio
  - **Slip\_ratio:**  $\sigma_x = \frac{r_{eff}\omega_w - \dot{x}}{\dot{x}}$
  - $\omega_w$  is the wheel speed,  $\dot{x}$  is the car speed
  - Largest longitudinal friction force is achieved for a slip value around 0.15



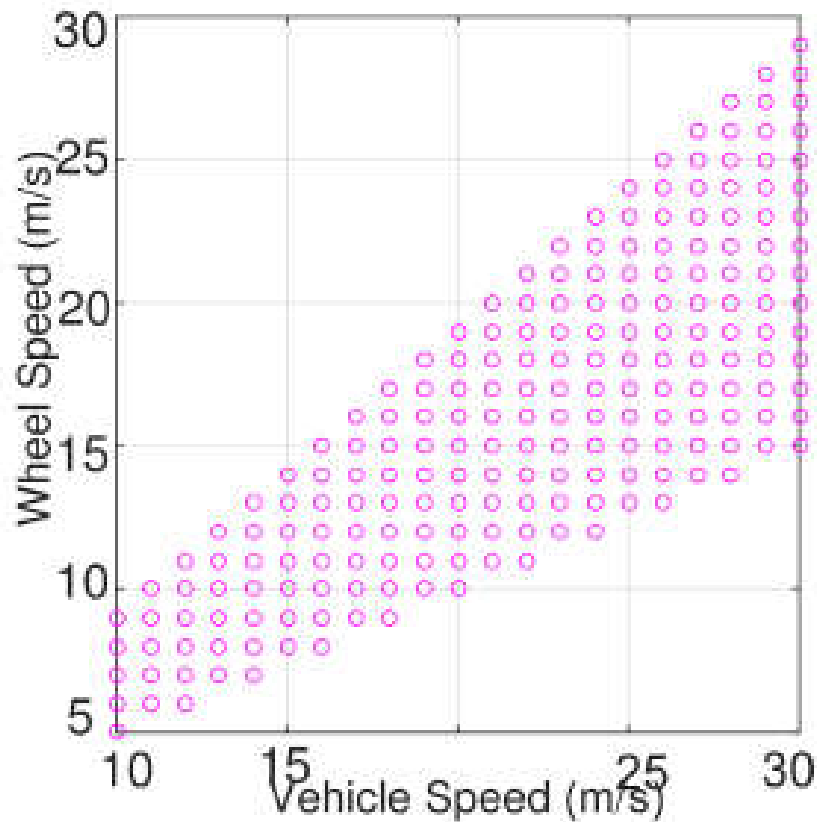
## ABS in a Car

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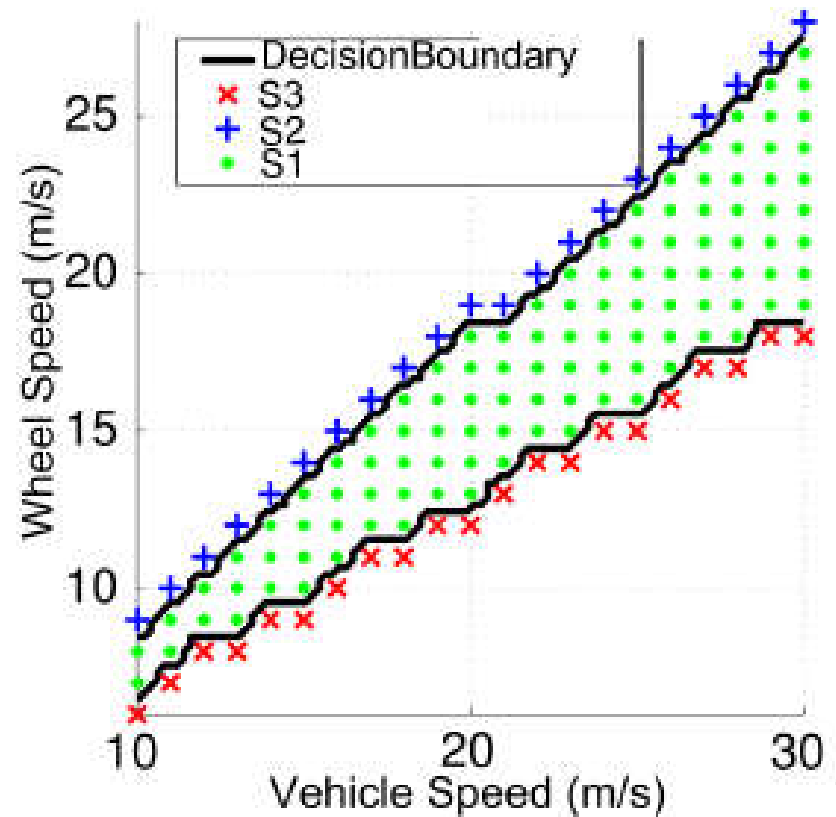
- **State vector**
  - [vehicle speed  $v$ , wheel speed  $\omega$  ]
- **Real-time control algorithm:**
  - Proportional Integral Derivative (PID)
- **SSC: in order to have a final stopping distance smaller than a threshold, the slip ratio must be within a certain range**
  - Slip ratio = [0.05, 0.25]



## SSC and the state sub-spaces



(a) SSC



(b) Sub-spaces in  $S^3$

## Training process for 3 ML techniques

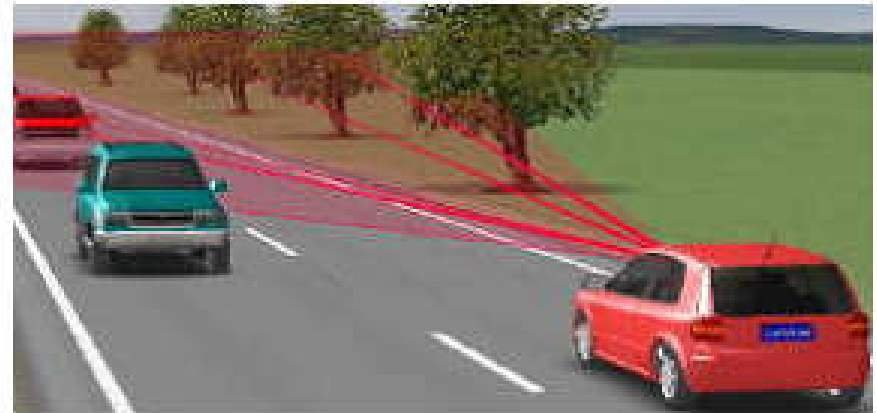
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- **Logistic Regression, Neural Networks, SVM**  
all achieved **100% training accuracy**
- **Using 15, 93 or 138 parameters**

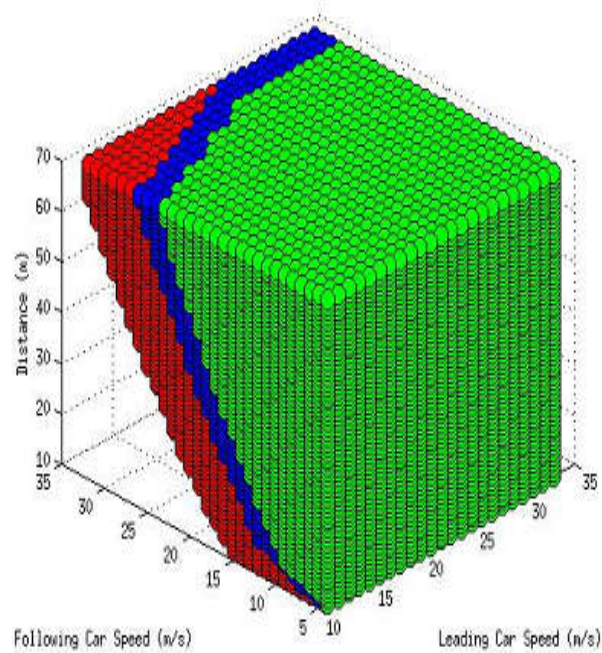
Algorithm	<i>LR</i>	<i>NN</i>	<i>SVM</i>
No. of Parameters	15	93	138
Accuracy	100%	100%	100%

## Platoon System (Automated Highway)

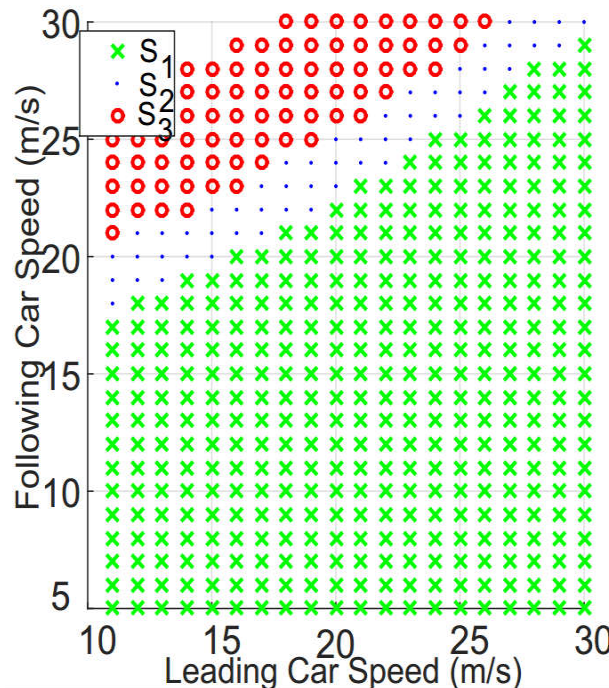
- An example of an application with multiple individuals systems communicating with each other
- **Carsim**: a commercial software for automotive design, can simulate automated highway - integrated with our SW tool
- **Experiments:**
  - A leader-follower system
  - Ensure safety - do not allow cars to collide
  - Following car uses a sensor to measure distance from leading car
  - Leading car sends its speed wirelessly to following car



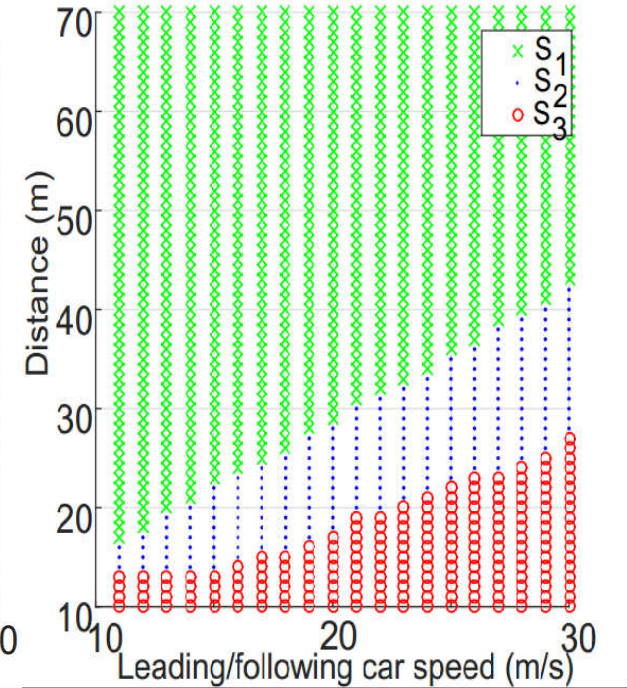
# Sub-spaces of the Following Car



(a) 3D Plot for Sub-spaces



(b) Cross Section Plot with Distance Fixed at 40 meters



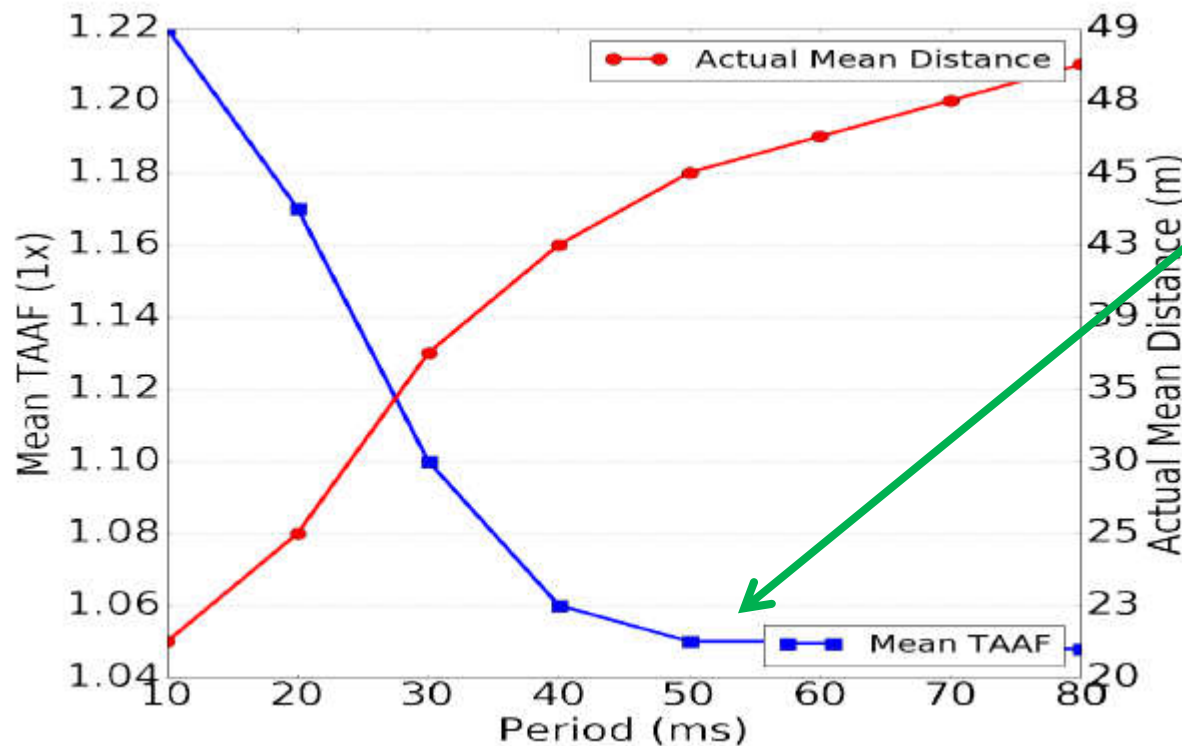
(c) Cross Section Plot with Leading Car Speed Same as Follower

## Platoon Case Study with Multiple Task Versions

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- **Each control task has two versions:**
  - **Version 1 (complex version):**
    - **Constant Time Gap algorithm for Adaptive Cruise Control**
    - **Period: 10 ms to 80 ms**
  - **Version 2 (the simple version):**
    - **PID with pre-determined desired velocity and distance**
- **The distance between two cars is the quality of control constraint**
- **The version for the control task will switch during the drive depending on the current sub-space**

# Trade-off between Reliability & Quality of Control



Execute the simpler version (PID) more often

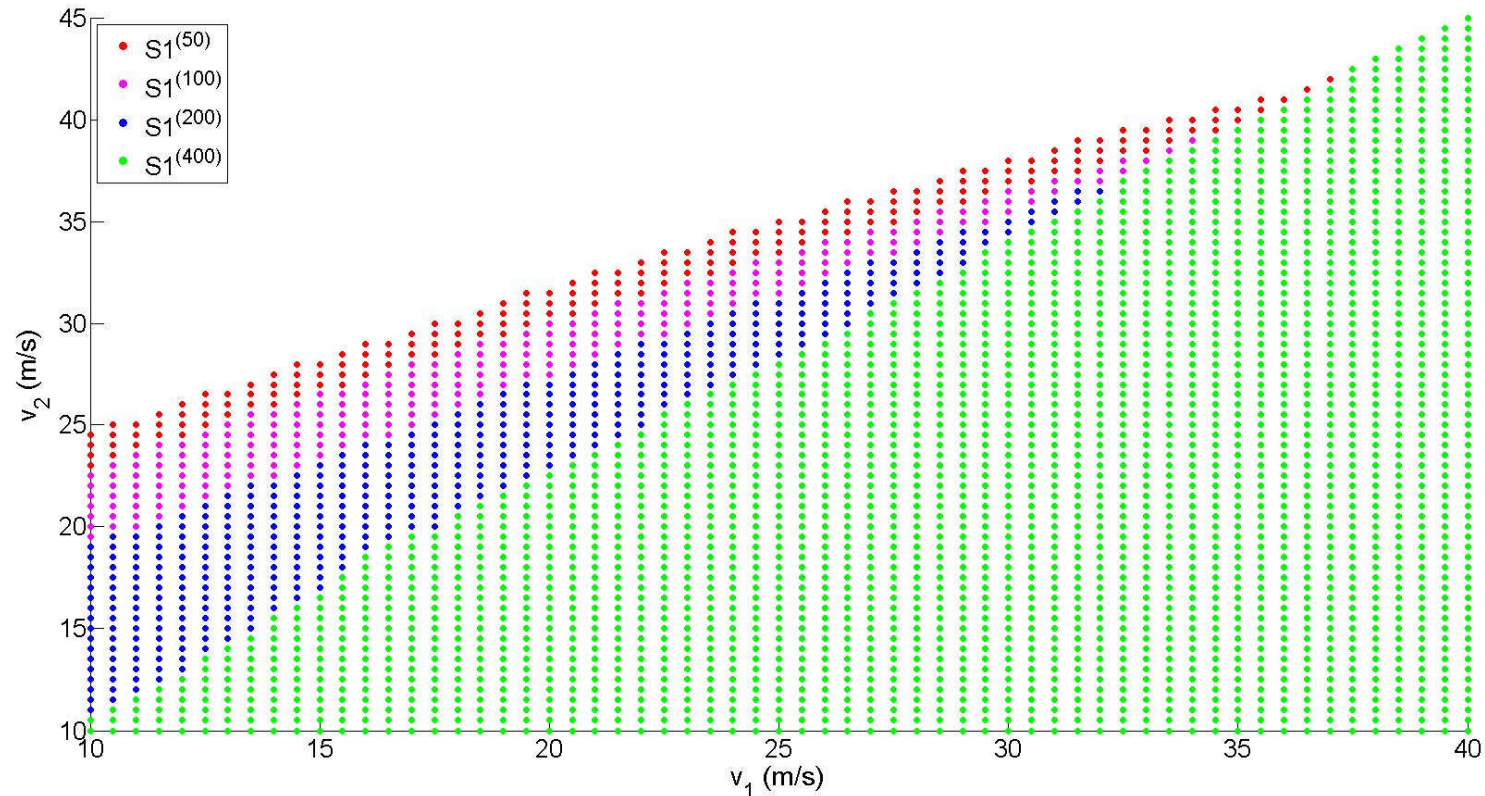
TAAF: Thermal Age Acceleration Factor

## Comparing classification schemes - Platoon

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Algorithm	<i>LR</i>	<i>NN</i>	<i>SVM</i>
No. of Parameters	15	153	788
Accuracy	78.56%	99.58%	99.62%

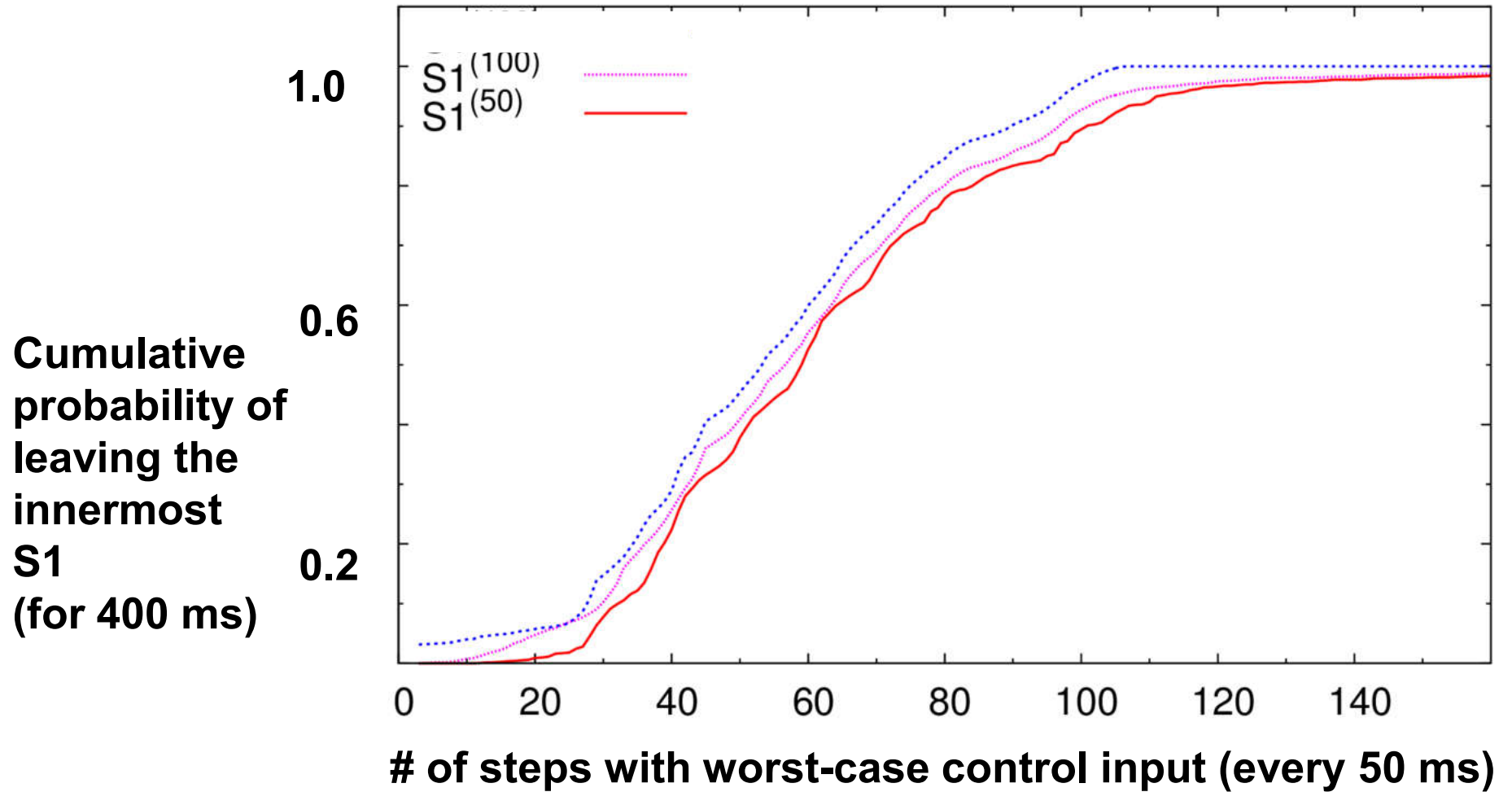
# Check for benign faults and then for malicious ones



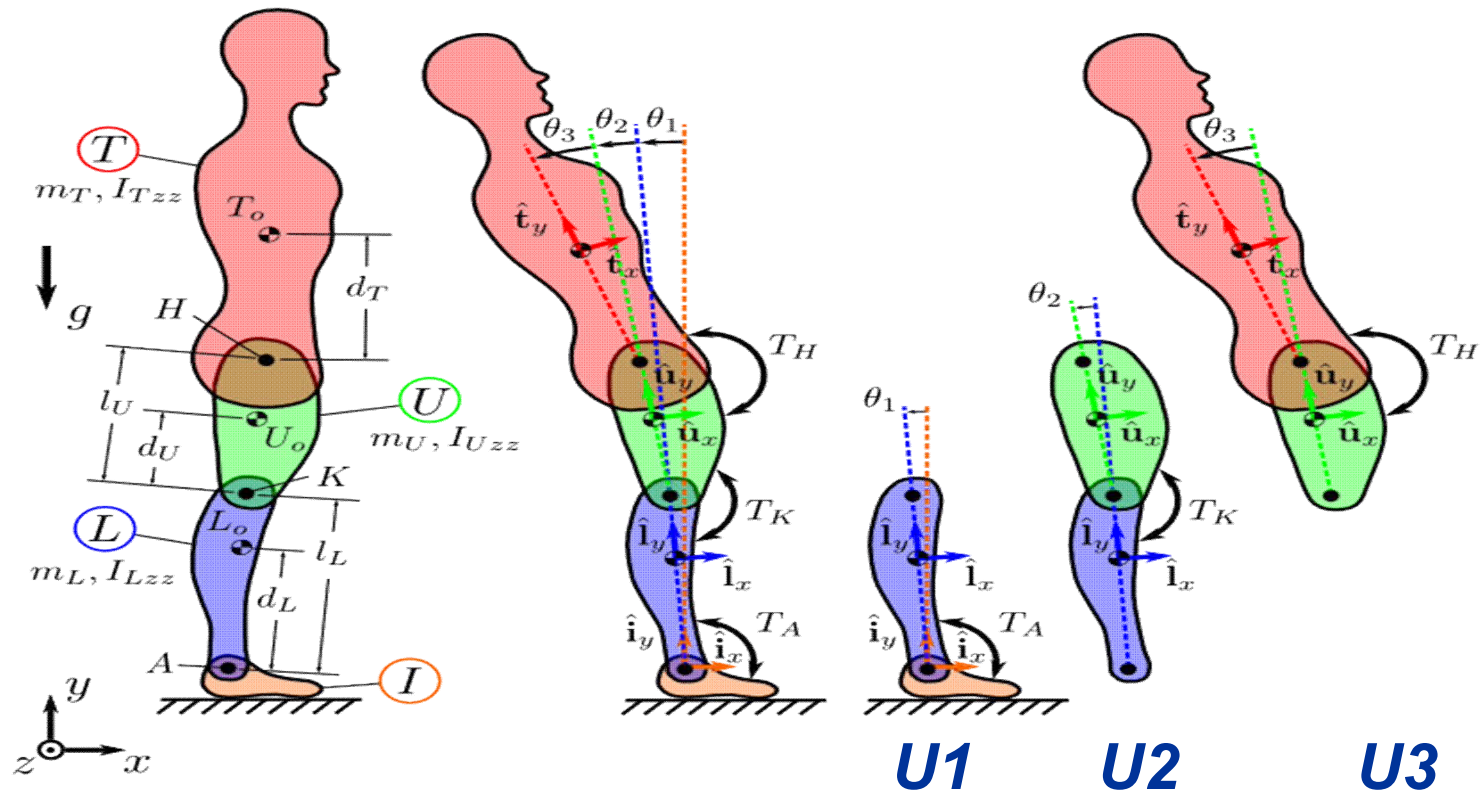
**Task\_period=50ms; Innermost S1 defined for Task\_period=400ms**



# # of steps with wrong control to exit innermost S1

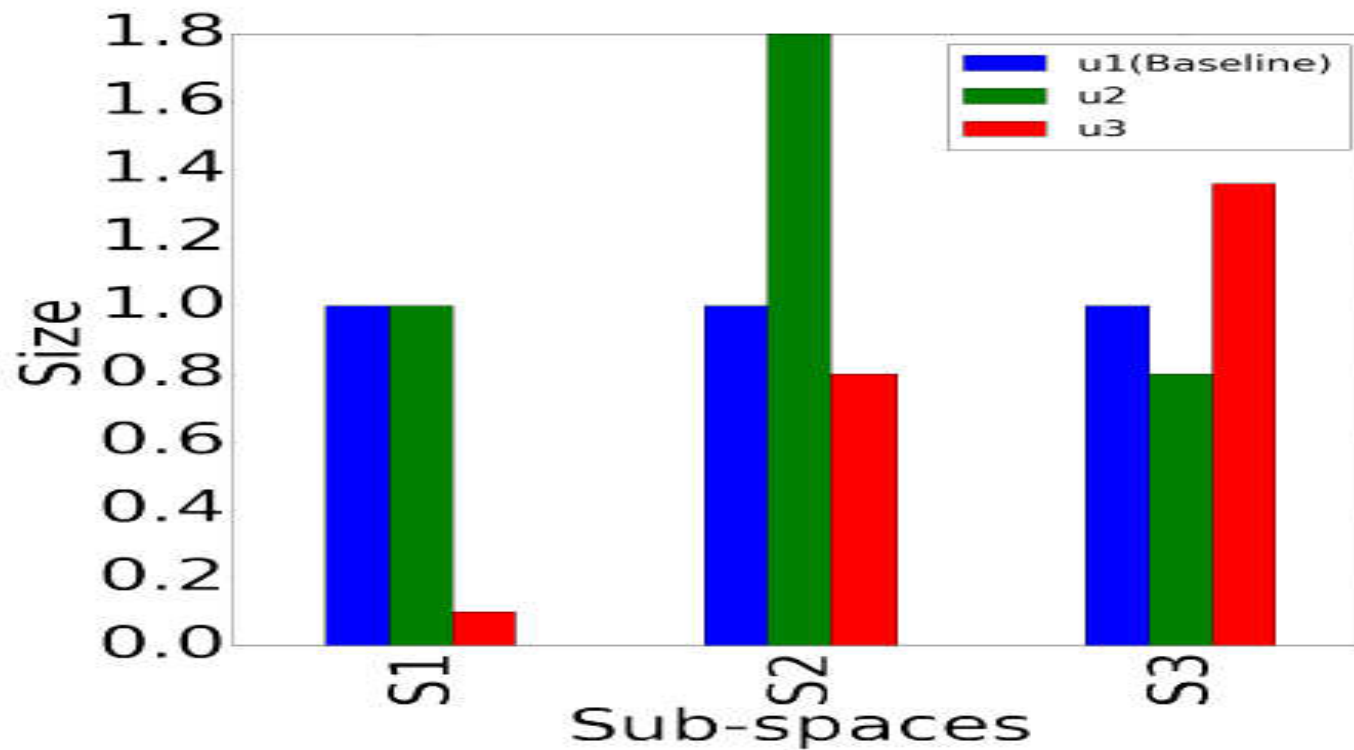


# Humanoid Robot



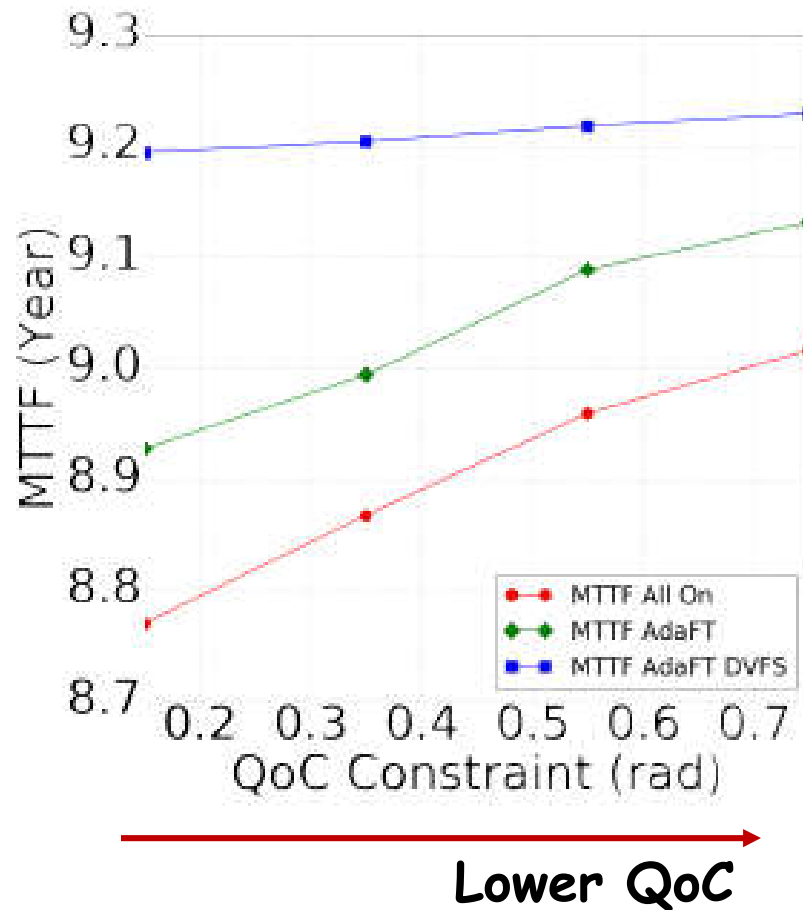
Three control tasks,  $U1$ ,  $U2$  and  $U3$ , adjusting the torques at the ankle, knee and hip, respectively

## Sub-spaces and classification schemes



Algorithm	Neural Network	Random Forest	Decision Tree
Accuracy	99.6%	97%	97%
Prediction Time	3ms	1ms	0.0096ms

## Reliability vs Quality of Control (QoC)



Developed the **AdaFT** tool that includes the classification process and system optimization to determine the tasks' version and rate

## Conclusions

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- **Benefits of monitoring the current state of the physical plant**
  - **Achieve high reliability at a lower cost**
  - **Detect malicious attacks targeting the physical plant's operation (rather than attempts to access proprietary information)**
    - **Such attacks are dangerous in a CPS**
  - **Allow recovery from some malicious attacks**
    - **Can always detect and invoke emergency response**
  - **Must have an efficient scheme to classify the state sub-space in real-time**