Adaptive Calibration for Fusion-based Wireless Sensor Networks

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Outline

- **Motivation**
- Background
- Problem Formulation
- Control-theoretical Calibration Algorithm
- Evaluation

Mission-critical Sensing Applications

100 seismometers on UCLA campus [Estrin 02]

acoustic sensors detecting AAV
http://www.ece.wisc.edu/~sensit/

- **Stringent sensing performance requirements**
  - Low false alarm rate, high target detection probability
- **Physical uncertainties**
  - Stochastic noises, hardware biases
  - Environmental changes, dynamics of monitored process
- **Performance of a network must be dynamically calibrated**

State of the Art

- Collaborative signal processing (e.g., data fusion)
  - Improves sensing accuracy by jointly processing **noisy** measurements from **multiple** sensors
  - May not handle system & physical dynamics

- Sensor calibration
  - Often conducted in controlled environments
  - Difficult to repeat after deployment

Exploiting Sensor Heterogeneity

Accelerometer

PIR Acoustic

PTZ camera

Active radar

	Low-end sensors	High-quality (HQ) sensors
Examples	PIR, acoustic	Pan-tilt-zoom camera, active radar
Manufacturing cost	Low	High
Energy consumption	Low	High
Sensing performance	Limited capability, e.g., high false alarm rate	High-accuracy

- Calibrate low-end sensors using HQ sensors' results
- Adaptive calibration in the presence of system/physical dynamics

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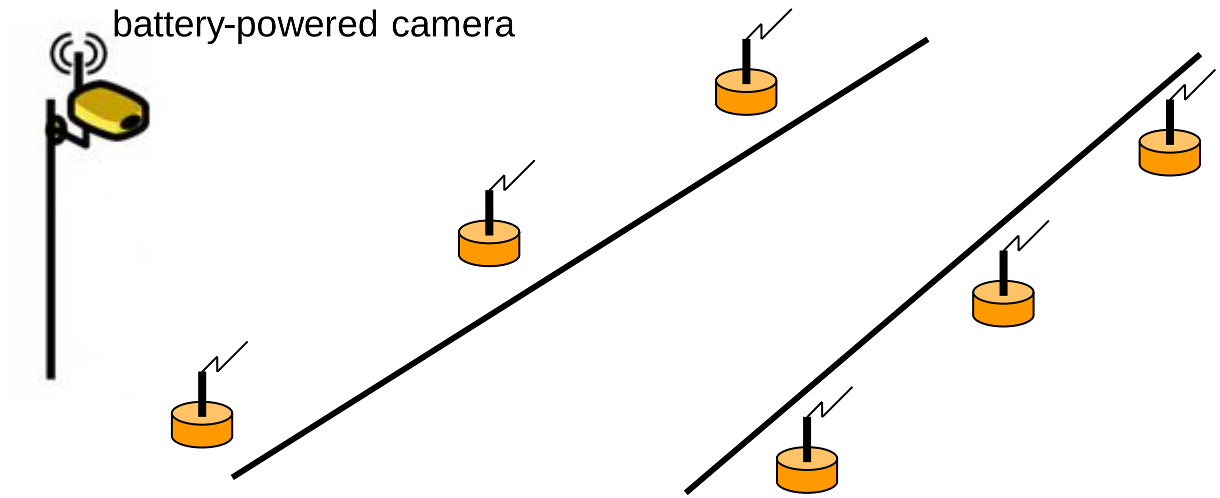
Approach Overview



- Low-end sensors
  - Collaboratively detect target through data fusion
- High-quality sensor
  - Activated when low-end sensors make positive decision
- Feedback
  - Calibrate low-end sensors based on the detection results of HQ sensor

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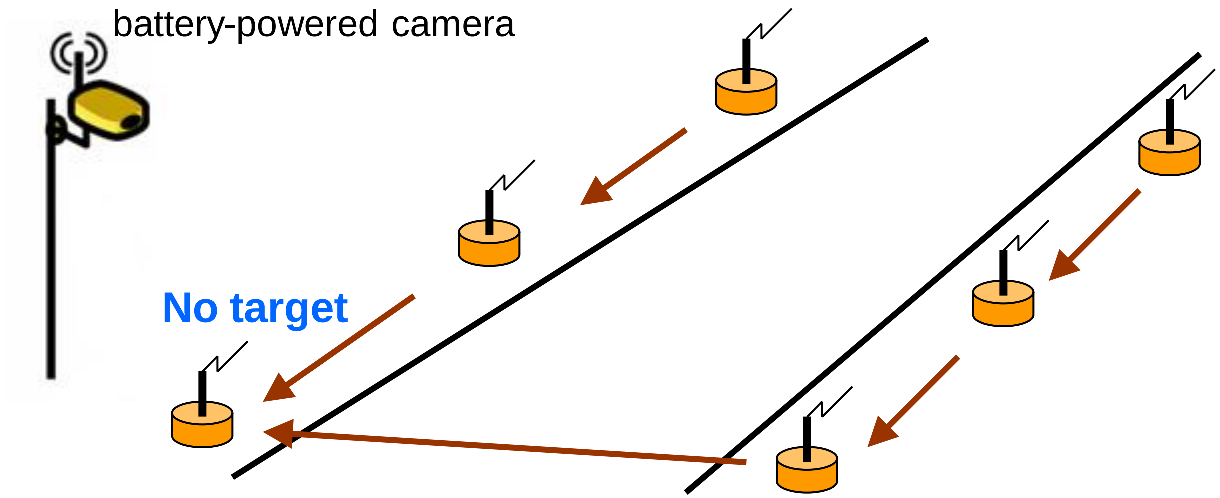

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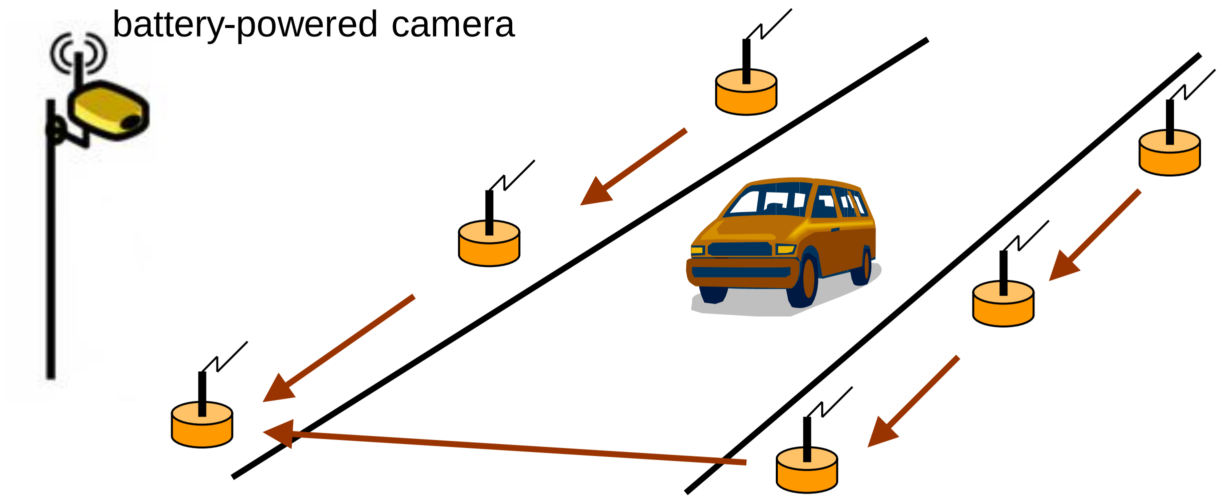

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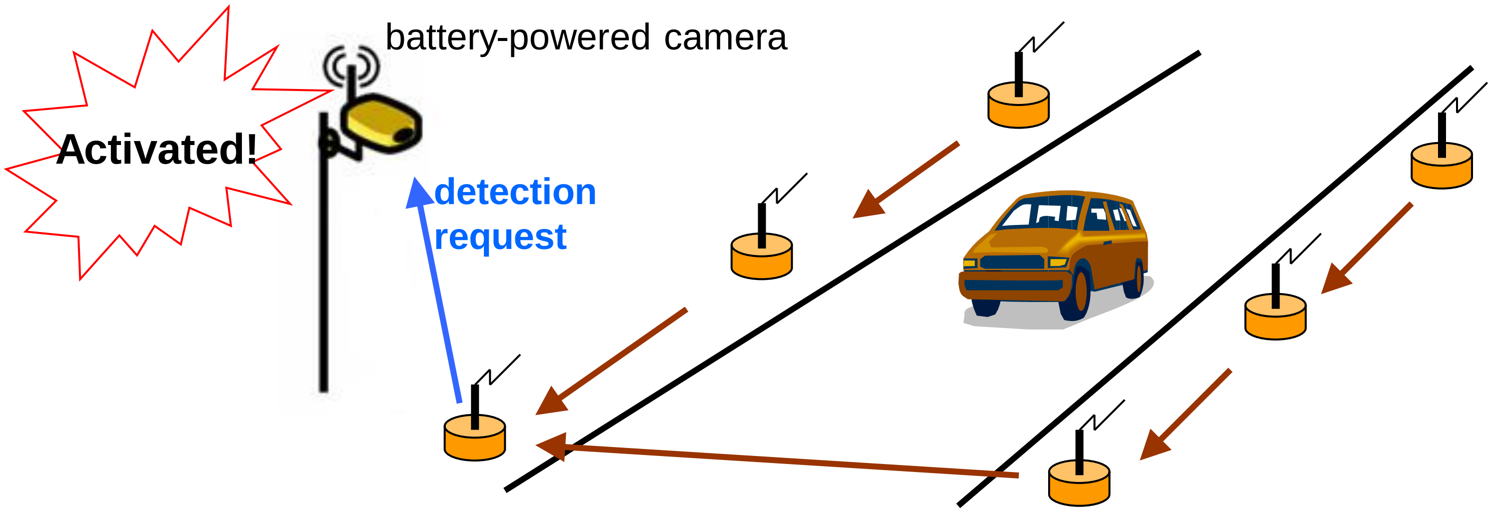

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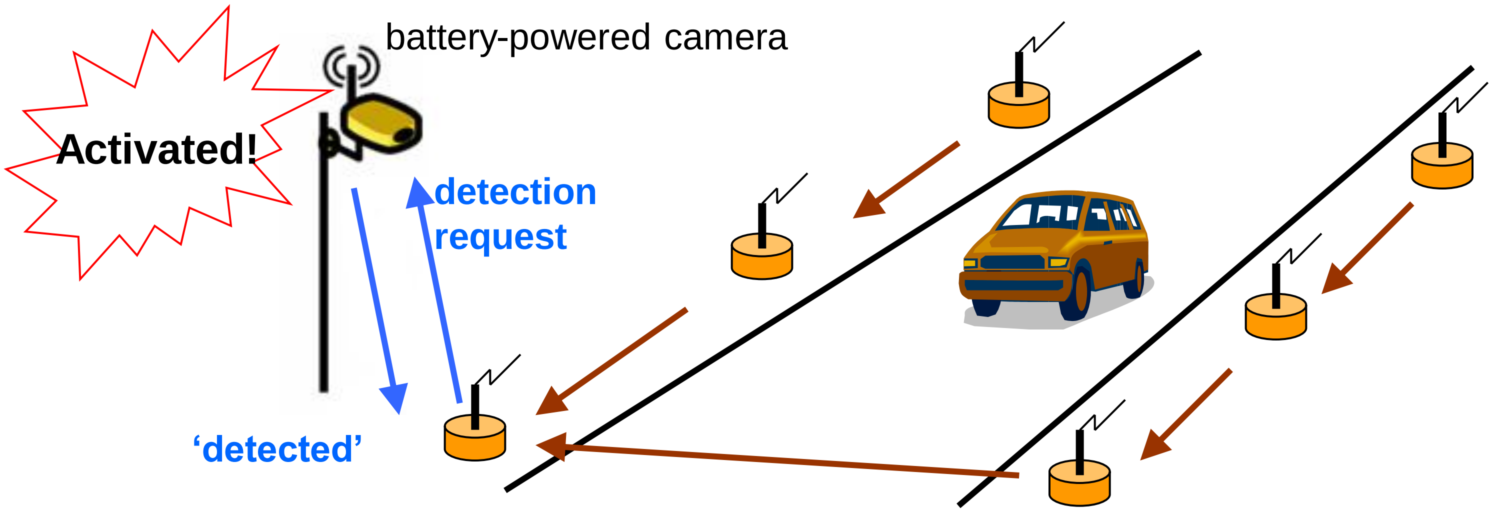

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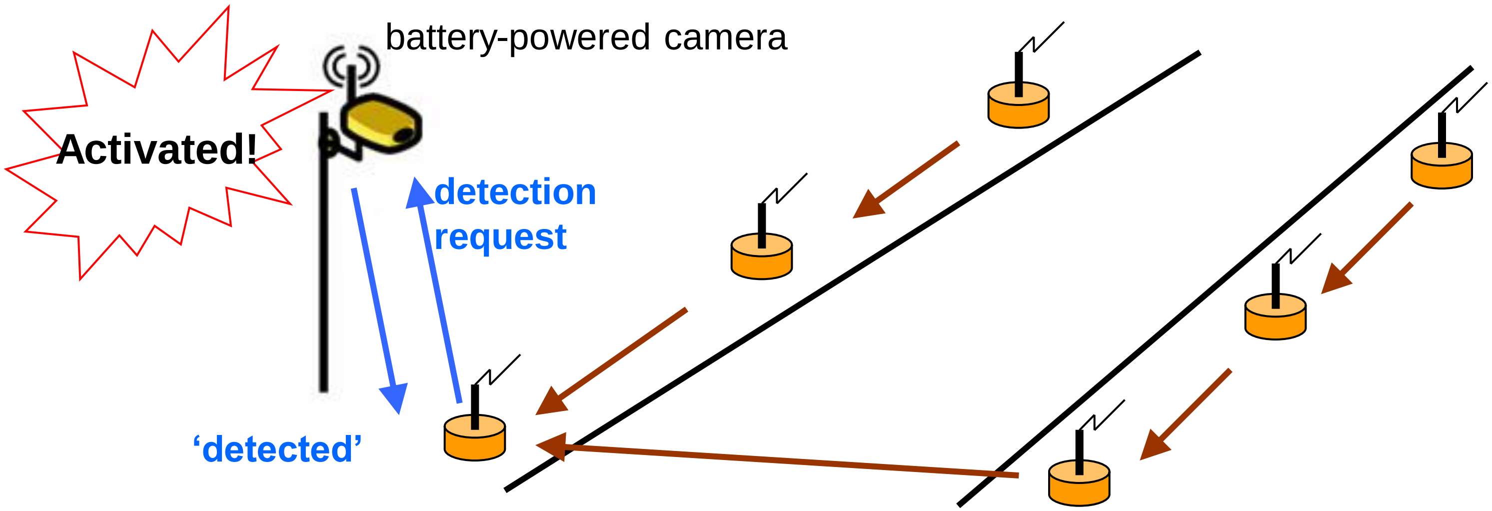

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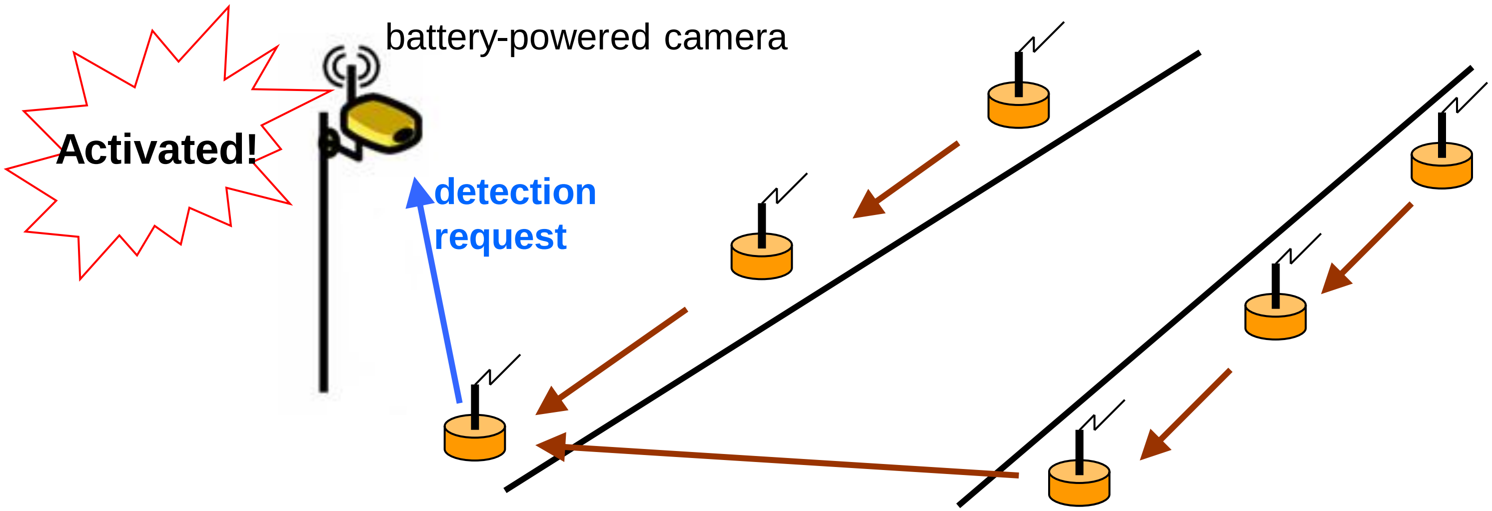

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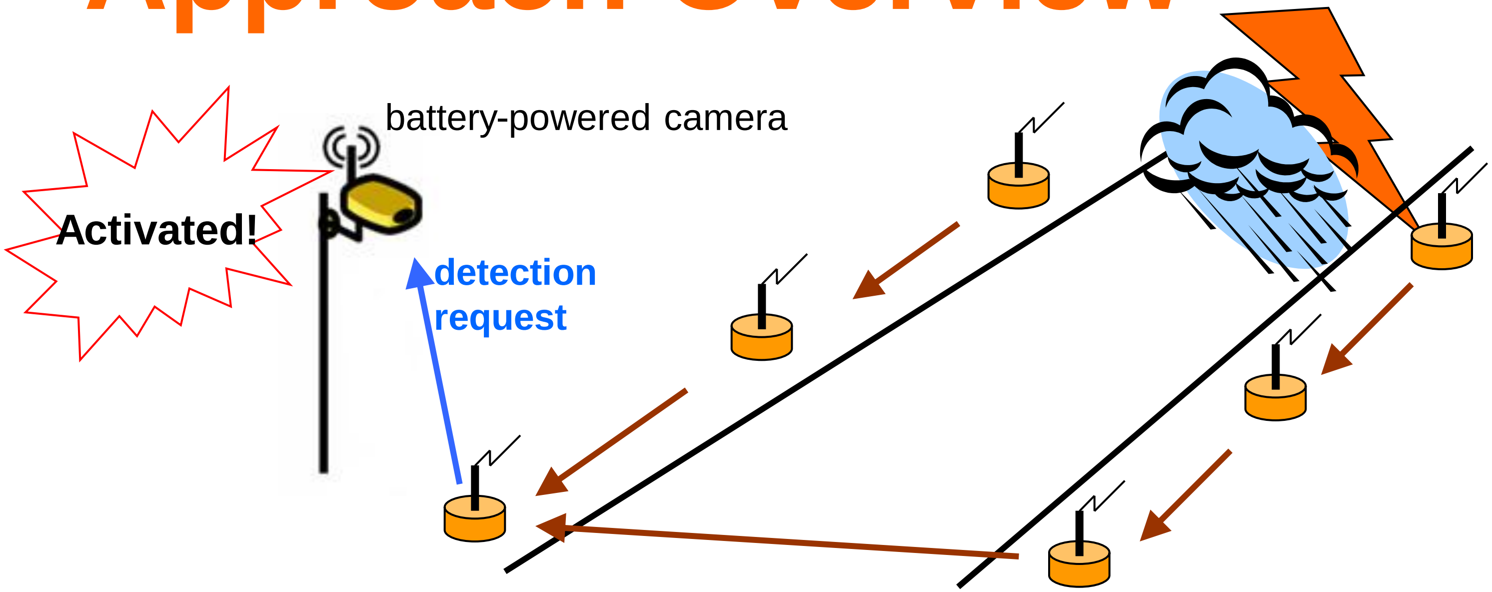

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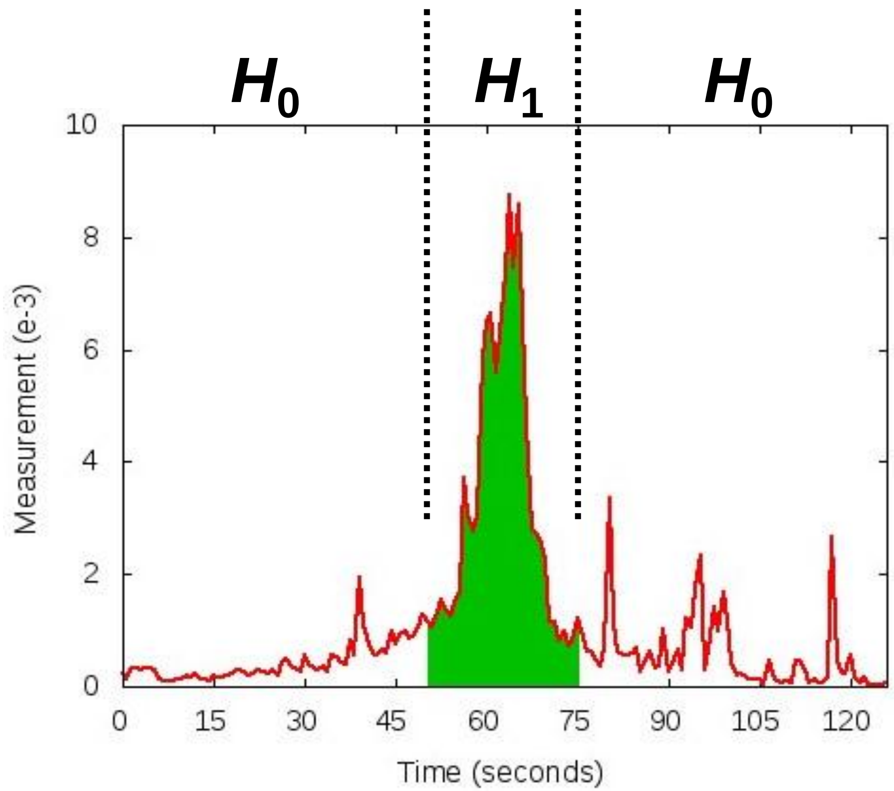
Sensor Measurement Model

- Readings of sensor $\boldsymbol{i}$ when target is absent ($\boldsymbol{H_0}$) and present ($\boldsymbol{H_1}$)

$$\begin{cases} \boldsymbol{H}_0: & \boldsymbol{y}_i = \boldsymbol{n}_i \\ \boldsymbol{H}_1: & \boldsymbol{y}_i = \boldsymbol{s}_i + \boldsymbol{n}_i \end{cases}$$

- Signal energy $\boldsymbol{s_i}$ is unknown
  - Target's source energy
  - Signal path loss
- $\boldsymbol{n_i}$ is Gaussian noise
  - Unknown Gaussian distribution



Readings of a sensor when a vehicle passes by [Duarte 2004]

Data Fusion and Detection Models

- Low-end sensors' decision is made by

$$\begin{cases} \sum_i y_i < T & \Rightarrow \quad \text{decide}\,0 \\ \sum_i y_i \geq T & \Rightarrow \quad \text{decide}\,1 \end{cases}$$

- Average detection cost

$$\sum_{j,k \in \{0,1\}} C_{jk} \cdot P(j \mid H_k) \cdot P(H_k)$$

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  – $C_{00}=C_{11}=0$, $C_{01}=C_{10}=1$, average error rate

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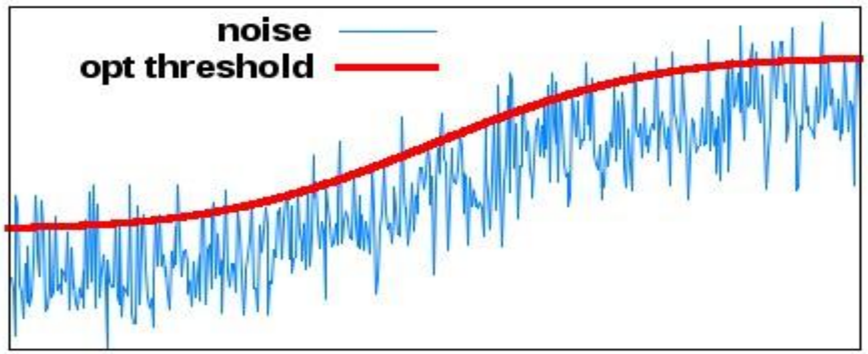
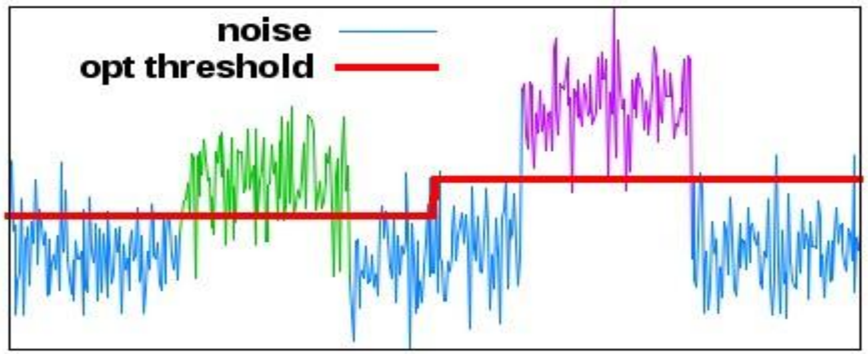
Closed-loop Calibration



Changing noise level



Changing target energy

- Opt threshold that minimizes detection cost depends on
  - Noise profiles: $\sum_{i=1}^{N} E[\boldsymbol{n}_i]$ $\sum_{i=1}^{N} \mathrm{var}[\boldsymbol{n}_i]$
  - Received target signals: $\sum_{i=1}^{N} \boldsymbol{s}_i$

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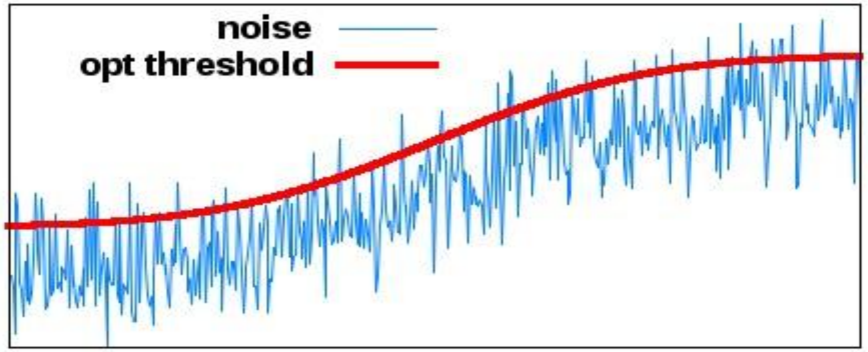

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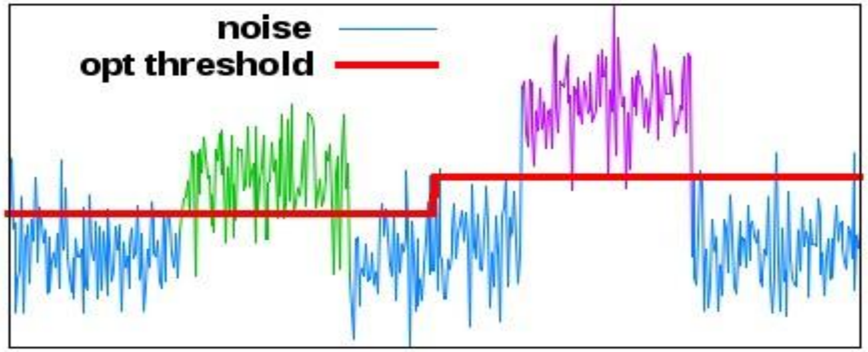

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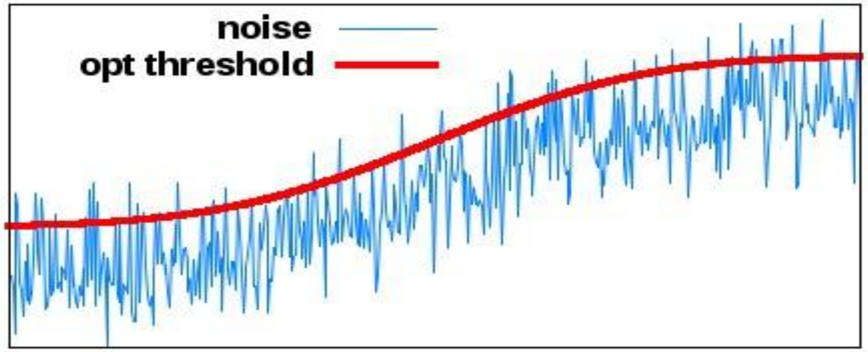

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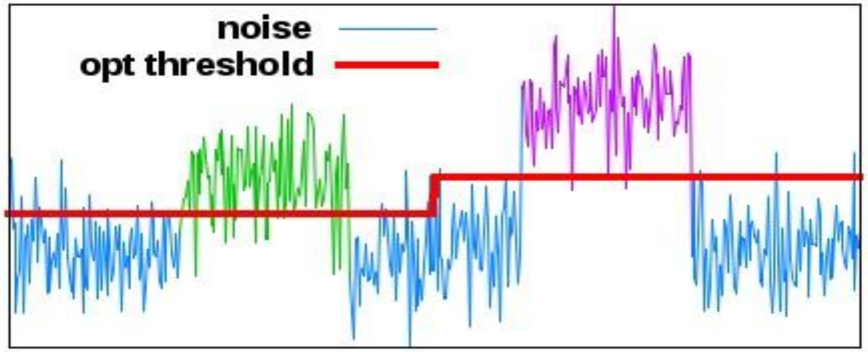

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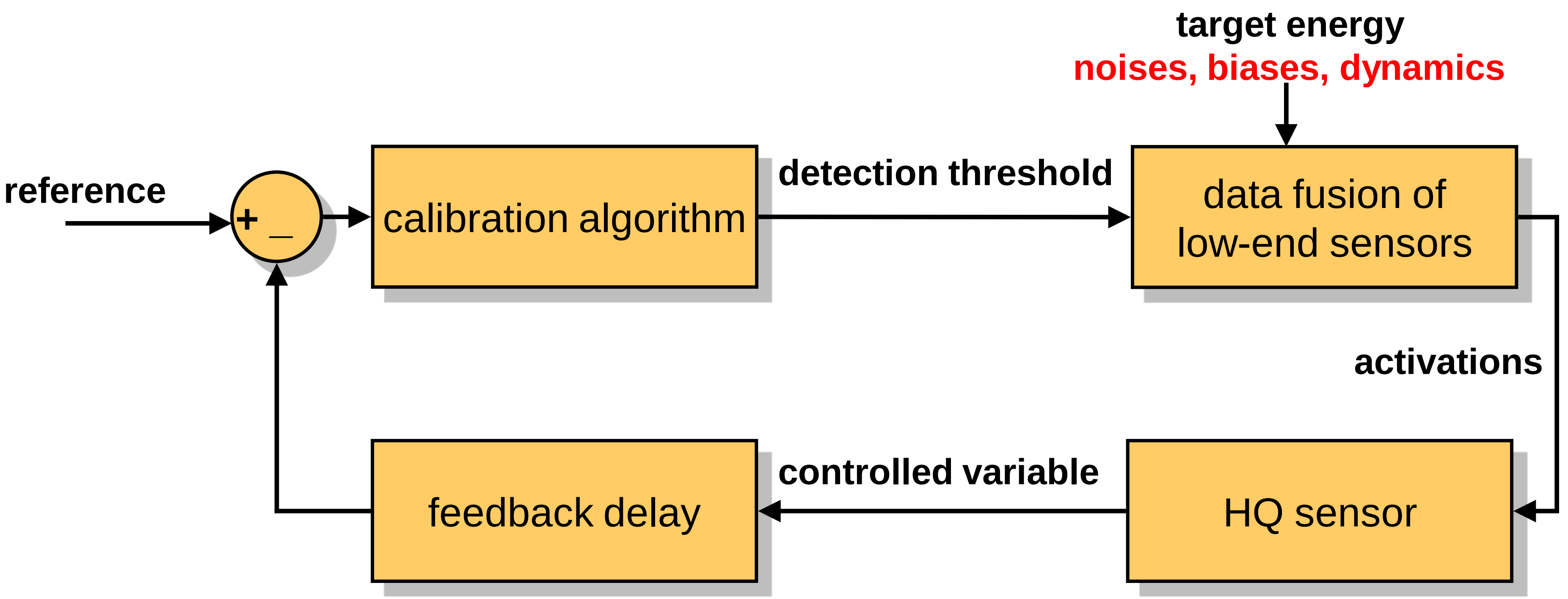
- **Control Problem:** Find a **stable** and **converging** algorithm to calibrate ***T*** based on the feedback of high-quality sensor, **s.t.** detection cost is minimized

Feedback Control Loop



- Detection threshold is calibrated for each cycle
- A typical discrete-time control problem

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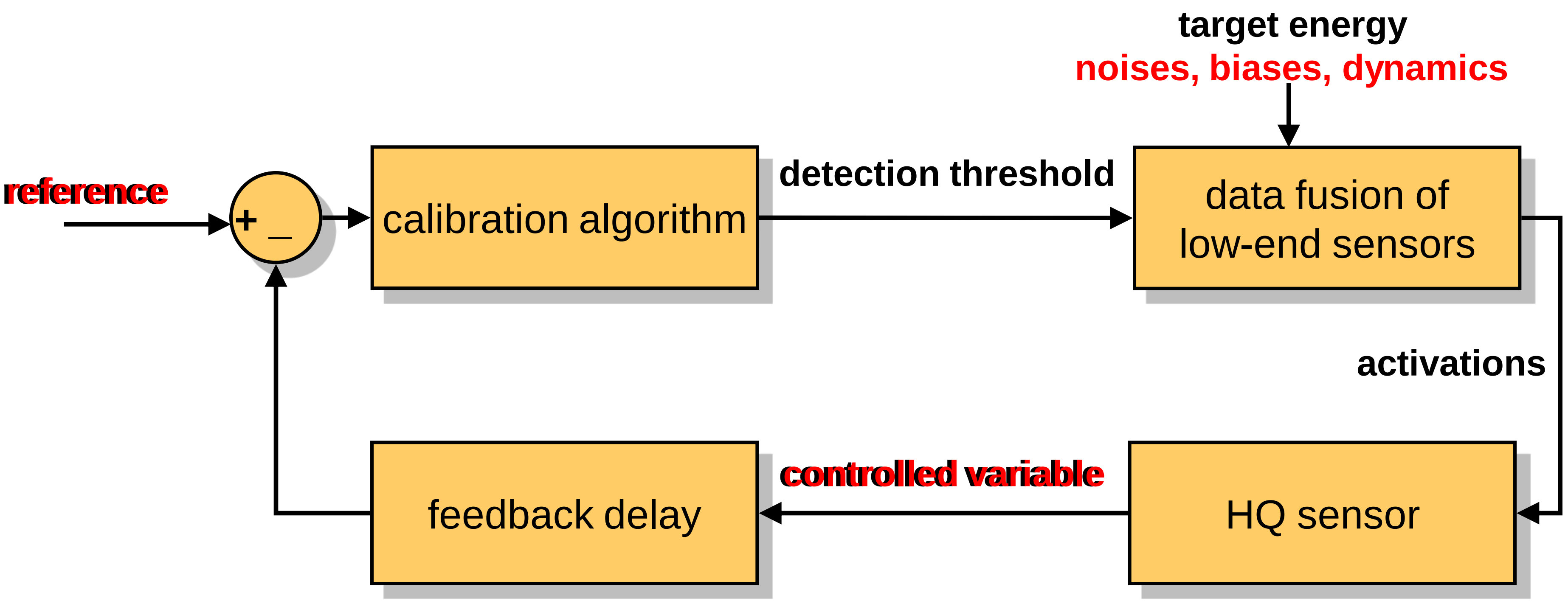

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Condition for Min Detection Cost

- Average detection cost is minimized **iff**

$$\boldsymbol{Q}^{-1}(\boldsymbol{P_F})^2 - \boldsymbol{Q}^{-1}(\boldsymbol{P_M})^2 = \delta$$

  - $\boldsymbol{P_F}$ and $\boldsymbol{P_M}$: false alarm rate and missing probability of low-end sensors
  - $\boldsymbol{Q^{-1}(x)}$: the inverse Q-function of $\boldsymbol{N(0,1)}$
  - $\boldsymbol{\delta}$**:** a known constant

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controlled variable

reference

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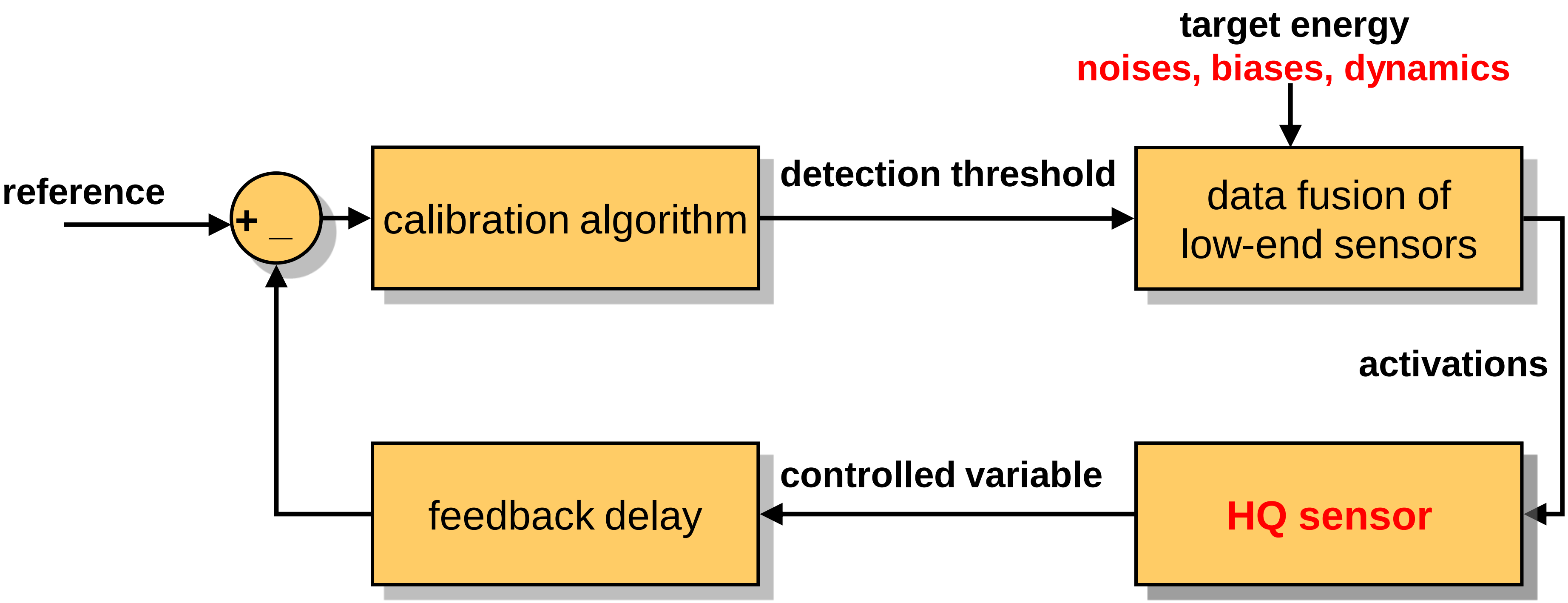

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Feedback of HQ Sensor

- Estimate $\boldsymbol{P_F}$ and $\boldsymbol{P_M}$ from HQ sensor's results
  - 100 detections in a cycle, target appearance prob. is 20%
  - 8 triggers are classified as false alarms

$$\boldsymbol{P_F} = \frac{8}{100 - 100 \times 20\%} = 10\%$$

  - 19 triggers are confirmed as correct detections

$$\boldsymbol{P_M} = \frac{100 \times 20\% - 19}{100 \times 20\%} = 5\%$$

- We account for the inaccuracy of HQ sensor and target appearance prob.

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Calibration Algorithm

- The system to be controlled is a 0-order system
  - 1st-order controller:

$$G_c(z) = \frac{a}{1 - b \cdot z^{-1}}$$

transfer function of the calibration algorithm

- The system is stable and converging if

$$0 < a < \frac{\sum_{i=1}^{N} \mathrm{var}[n_i]}{\sum_{i=1}^{N} s_i}, \; b = 1$$

noise variance of sensor *i*

signal received by sensor *i*

- The upper bound on ***a*** is unknown and dynamic
  - Can be coarsely estimated
  - Conservative setting of ***a***

Impact of Communication

- Stochastic packet loss
  - The stability condition may change significantly
  - The impact on stability can be mitigated by deploying more low-end sensors

- Optimal route ***R*** that minimizes impact of packet loss:

$$\boldsymbol{R} = \arg\min_{\boldsymbol{R}} \sum_{\boldsymbol{h} \in \boldsymbol{R}} -\log \boldsymbol{PRR}(\boldsymbol{h})$$

PRR – Packet reception ratio

- Feedback delay
  - Comm. delay and sleeping delay of low duty-cycle sensors
  - Has little impact when the delay is up to 10 cycles

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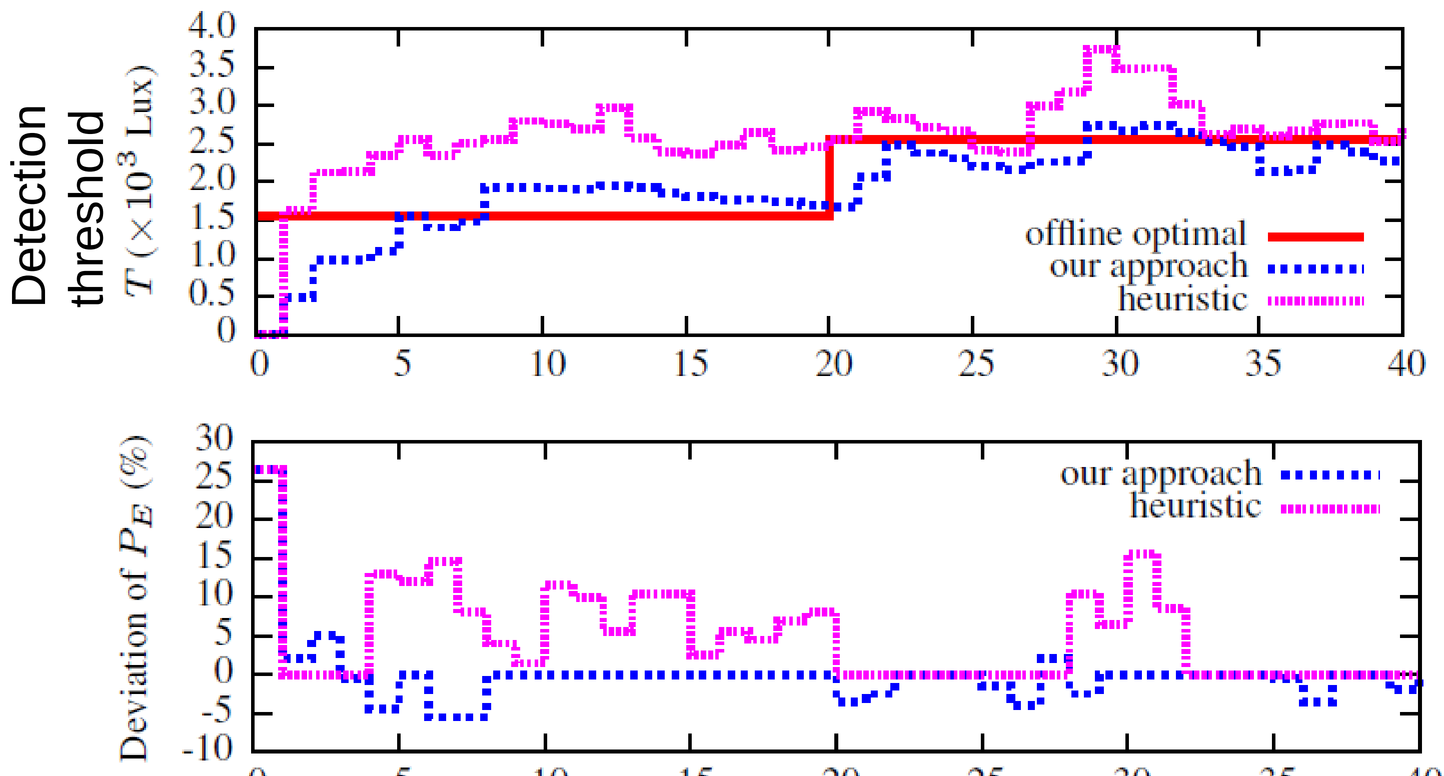
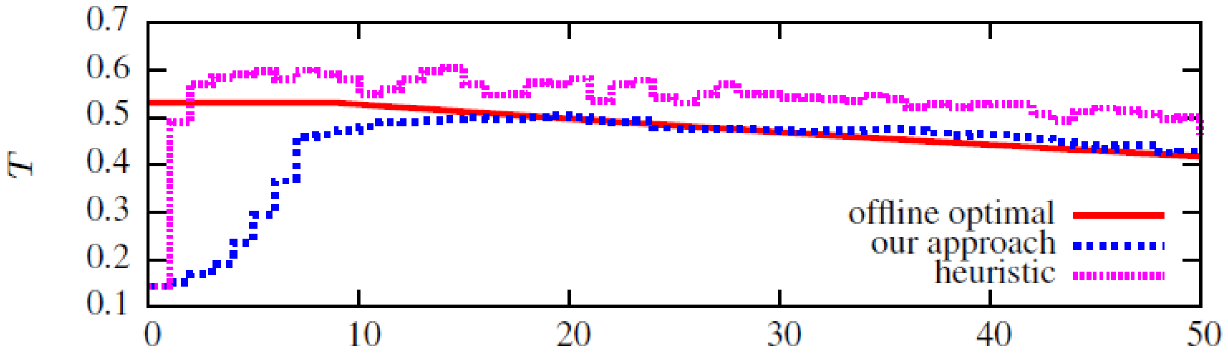
Testbed Experiments

- 6 Tmotes + a web-cam
- Detect light spots that randomly appear on a LCD
- Heuristic baseline approach
  - Estimates noise and signal when the system makes negative and positive decisions, respectively

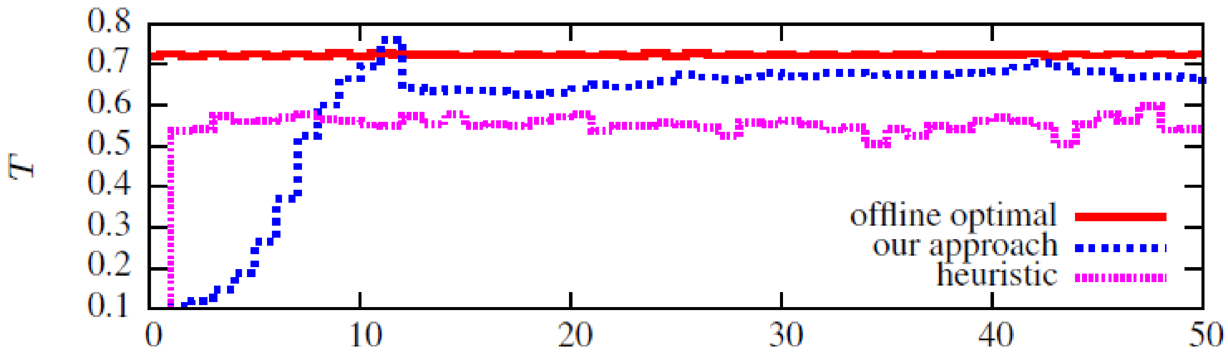


Trace-driven Simulations

- Data traces collected from 75 acoustic sensors in vehicle detection experiments [Duarte 2004]



Static target, decreasing noise level



Moving target

Conclusions

- Propose a system-level adaptive calibration approach
  - Sensor heterogeneity
  - On-demand activation scheme
- Develop a control-theoretical algorithm
  - Ensures provable stability and convergence
  - Accounts for communication performance
- Calibrated network maintains optimal system detection performance in the presence of various dynamics