Network Optimization in Cyber-Physical Human Sensing Systems

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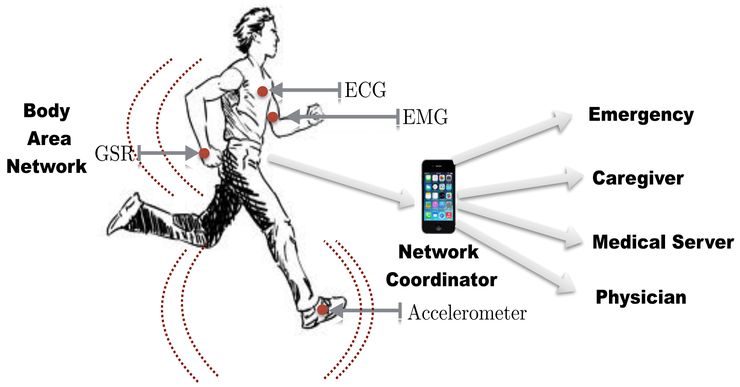


Cyber-Physical System

coupling **bio-sensors** on people and **wireless networks**

Goals

Real-time monitoring health and behavior

Feedback via adaptive and personalized interventions

Design challenges

Sensors & data **heterogeneity**

Sensors & coordinator **energy constraints**

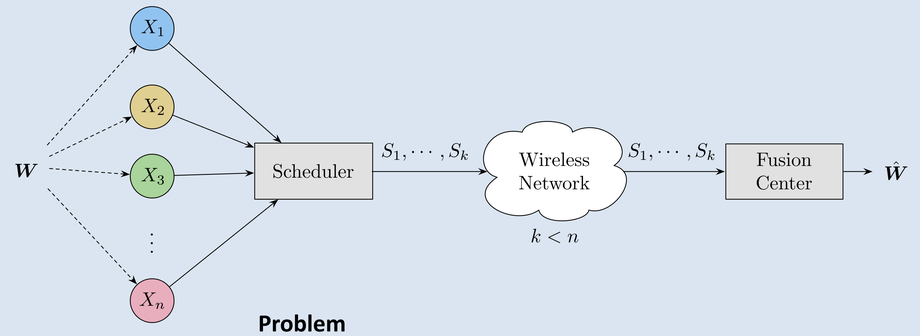
Sensing & communication are **state dependent**

Networked decision systems

New decision-making problems involving

the joint design of **sensing**, **communication** and **control**

Sensor scheduling



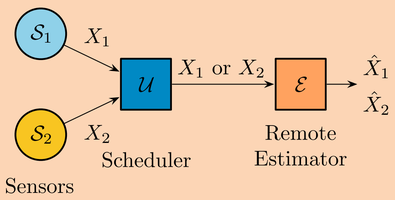
Problem

Choose k out of n sensors such that the expected distortion between $\boldsymbol{W}$ and $\hat{\boldsymbol{W}}$ is minimized

High complexity and signaling effects

Observation-driven scheduling for networked estimation

Observation-driven scheduling: One-shot Problem



$$X_1, X_2 \sim \mathcal{N}(\mathbf{0}, \Sigma)$$

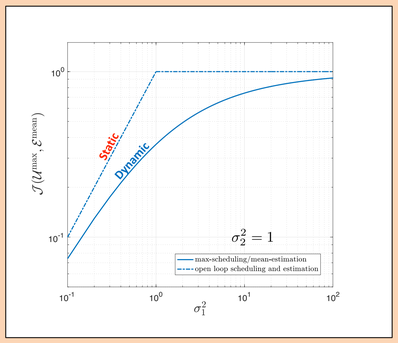
$$\mathcal{J}(\mathcal{U}, \mathcal{E}) = \mathbf{E}\big[(X_1 - \hat{X}_1)^2 + (X_2 - \hat{X}_2)^2\big]$$

Main result[1]

Person-by-person optimality of max-scheduling and simple estimation strategies for independent and symmetrically correlated Gaussian observations

Send the measurement with largest magnitude

Estimate for the unobserved sensor: Conditional mean given the observed sensor value



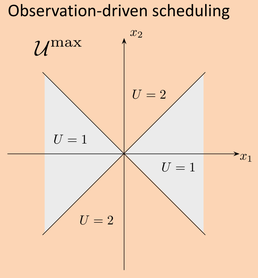
Performance comparison in the independent Gaussian case

$$\bar{\mathcal{J}}(\sigma_1^2, \sigma_2^2) = \min\{\sigma_1^2, \sigma_2^2\}$$

"Open-loop" sensor scheduling

$$\mathcal{J}(\mathcal{U}^{\max}, \mathcal{E}^{\text{mean}}) = \mathbf{E}\Big[\min\big\{X_1^2, X_2^2\big\}\Big]$$

Observation-driven scheduling



Model-free observation-driven scheduling

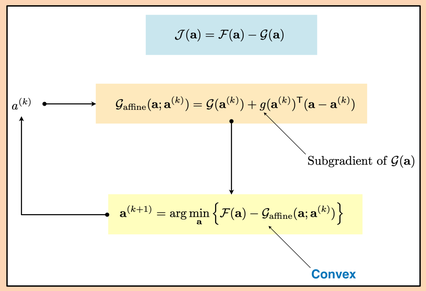
$X_1, X_2 \sim ?$

Unknown distribution

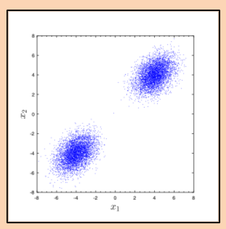
$\Big\{x_1(k), x_2(k)\Big\}_{k=1}^N$

Data

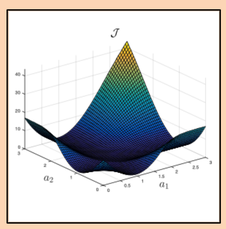
$$\mathcal{J}(\mathbf{a}) = \frac{1}{N}\sum_{k=1}^{N} \min\Big\{\big(x_1(k) - a_1 x_2(k)\big)^2, \big(x_2(k) - a_2 x_1(k)\big)^2\Big\}$$



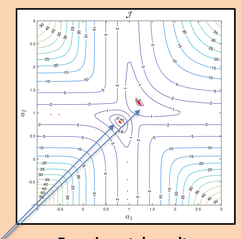
Approximate Convex-Concave Procedure



Data: Gaussian Mixture



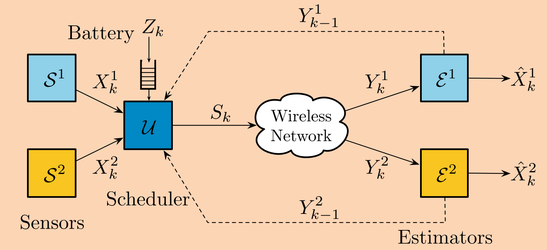
Exact cost function



Experimental results

$\approx 85\%$ are within 50% of the optimal cost

Scheduling with Energy Harvesting: Sequential Problem

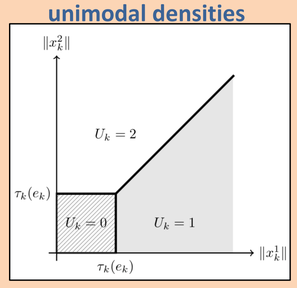


$\Big\{X_k^1, X_k^2\Big\}_{k=1}^N$ i.i.d.

$$E_{k+1} = \min\Big\{E_k - \mathbf{1}\big(U_k \neq 0\big) + Z_k, B\Big\}$$

Main result[2]

Global optimality of max-scheduling with simple estimation strategies for independent observations with symmetric and unimodal densities



[1] Vasconcelos & Mitra "Observation-driven scheduling for remote estimation of two Gaussian RVs" *IEEE Trans. on Control of Network Systems* (under review) 2018

[2] Vasconcelos, Gagrani, Nayyar & Mitra "An optimal sensor scheduling for networked estimation with with energy harvesting" *IEEE Trans. on Control of Network Systems, under review,*2019