Sensor Networking

- Military systems frequently employ sensors connected by communication networks.

- Becoming more popular in commercial applications.

- Trend towards simple, less expensive, sensor nodes carrying their own power connected by wireless networks.
Outline

What do we mean by “Sensor Networking for Detection”?  
- Example applications

Distributed Detection  
- Problem definition  
- Review of some results

Energy Savings  
- Goal and censoring approach  
- New ordering approach

MIMO Radar  
- Network of radars concept  
- Diversity and resolution gains

Outline

What do we mean by “Sensor Networking for Detection”?  
- Example applications
Numerous Other Non-military Applications

Weather monitoring

Bioimaging, biosciences: Cell imaging

Animal monitoring

Structure monitoring
UMASS Distributed Radar

Nanotechnology: Small Sensor Trend

- Development of signal processing for large array of nanotechnology-based sensors to detect chemical leaks.

Interdigitated electrode structure for chemical sensors.
Signal Detection Sensor Networks

- All these applications (and many others) attempt to solve a hypothesis testing problem

  - $H_0$: $f_{X}(x_1, ..., x_N|H_0)$ is joint pdf of observations at sensors one through $N$

  - versus

  - $H_1$: $f_{X}(x_1, ..., x_N|H_1)$ is joint pdf of observations at sensors one through $N$

  - Probability of error = $\text{Prob(we choose wrong)} = P_e$

Outline

Distributed Detection

- Problem definition
- Review of some results
Who are working on Distributed Detection?
Distributed Signal Detection

- If observations independent from sensor to sensor under hypothesis

\[ f_{X}(x_{1},...,x_{N}|H_{j}) = f_{X}(x_{1}|H_{j})f_{X}(x_{2}|H_{j})\cdots f_{X}(x_{N}|H_{j}), \]

then optimum sensor tests quantize the likelihood ratio (LR) — Tsitsiklis, Willet, Reibman, Viswanathan

- This simplifies the task of finding optimum sensors from a functional optimization to that of finding a few unknown scalars, the sensor thresholds.

Distributed Signal Detection

- If the observations are statistically dependent from sensor to sensor under a given hypothesis, then the problem is hard in general.

- If observations are dependent from sensor to sensor, can show that the task of finding optimum sensor rules is NP-complete in general — Tsitsiklis

Distributed Signal Detection

- For the special case of weak signals (LO) in additive noise with general pdf \( f \), we can again simplify the problem to finding a set of scalar unknowns.

- Let \( f'' \) and \( f' \) be derivatives of the noise pdf with respect to its argument. Optimum sensor decisions for random signals (\( x_1 \), the observation) made using

\[
\frac{f''(x_1)}{f(x_1)} + a_1 \frac{f'(x_1)}{f(x_1)} > t_1
\]

Need to find \( a_1 \) and threshold \( t_1 \)


Distributed Signal Detection

- The optimum test at sensor one:

\[
\frac{f''(x_1)}{f(x_1)} + a_1 \frac{f'(x_1)}{f(x_1)} > t_1
\]

can be seen as an attempt to approximate the optimum centralized weak signal (LO) test

\[
\frac{f''(x_1)}{f(x_1)} + 2 \frac{f''(x_1)}{f(x_1)} \frac{f'(x_2)}{f(x_2)} + \frac{f''(x_2)}{f(x_2)} > t_1
\]

where \( a_1 \) involves an expected value of \( \frac{f'(x_2)}{f(x_2)} \) given a decision for \( H_1 \)

Here we assumed \( E\{S_1^2\} = E\{S_2^2\} = E\{S_1 S_2\} \)
Distributed Signal Detection

Approximates correlation detection

AND FUSION

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Distributed Signal Detection

Approximates energy detection

OR FUSION

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Distributed Signal Detection

- For cases of nonweak signals, can sometimes find optimum tests analytically.

- For the case of known signals in Gaussian noise, have shown likelihood ratio tests are sometimes optimum at the sensors, sometimes not, and some cases are hard to determine.


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Outline

Energy Savings
- Goal and censoring approach
- New ordering approach
Assumptions/Definitions

- Observations iid across sensors given $H_j, j=0,1$
- Sensors transmit a real valued quantity to a fusion center where final decision is made
- Consider Bayesian formulation with priors
  \[ \pi_0 = \text{Prob}(H_0), \quad \pi_1 = \text{Prob}(H_1) \]
- Define sensor likelihood ratio:
  \[ L_i = \frac{f_X(x_i | H_1)}{f_X(x_i | H_0)} \]
- Optimum N sensor (unconstrained) test compares $\sum_{i=1}^{N} \ln(L_i)$ to threshold $\beta = \ln\left(\frac{\pi_0}{\pi_1}\right)$

Popular Energy Efficient Approach: Censoring

- Each sensor transmits only if likelihood ratio sufficiently extreme: $L_i > t_{SU}$ or $L_i < t_{SL}$
- Will reduce transmissions/Energy at cost of loss in $P_e$
- See (for example):
  
  
New Ordering Approach Outlined

- Each sensor decides to transmit on its own, most informative transmit first, stop transmissions when overwhelming evidence for one hypothesis.

- Each sensor transmits $L_i$ after $K/\ln(L_i)$ seconds, $K>0$ arbitrary small, so most informative transmit first

- Stop when sum of log-likelihood ratios of sensor transmitted exceeds $t_L$ or $t_U$

  \[
  \begin{align*}
  \text{sum of log-likelihood ratios} & < t_L \quad \text{pick } H_0, \\
  \text{sum of log-likelihood ratios} & > t_U \quad \text{pick } H_1
  \end{align*}
  \]

Can choose $t_L$ and $t_U$, so that energy is saved while $P_e$ same as optimum unconstrained test.

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