Sensor Networking for Detection

From Distributed Detection to Energy Savings, MIMO Radar and Image Fusion

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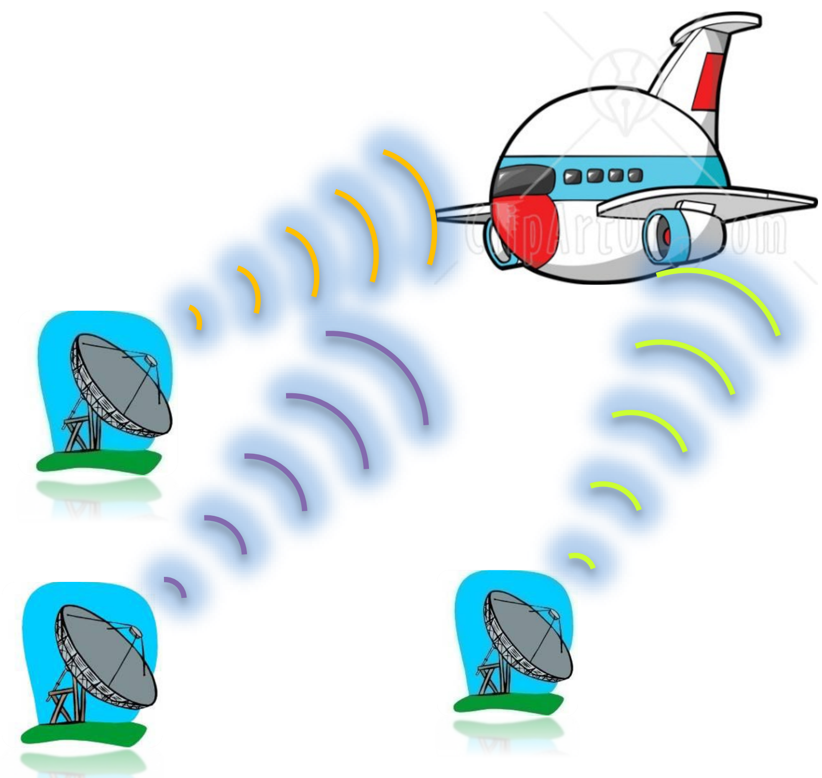


Many collaborators & students contributed to the work discussed, see research papers

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

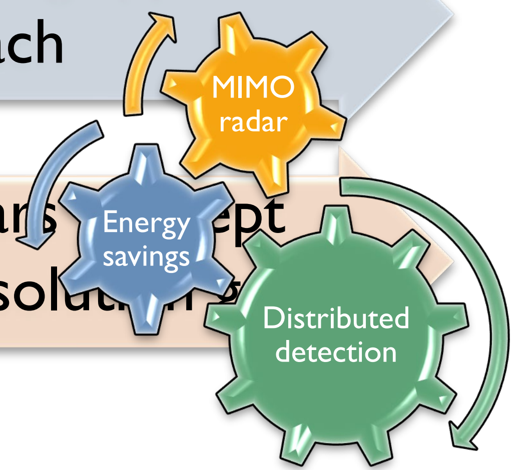
- Problem definition
- Review of some results

Energy Savings

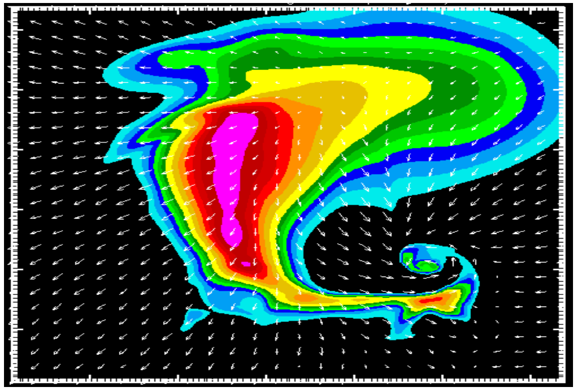
- Goal and censoring approach
- Ordering approach

MIMO Radar

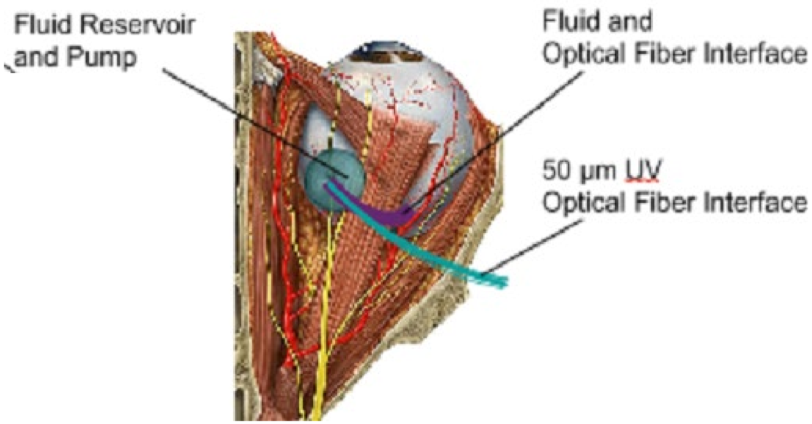
- Network of radar[illegible]ept
- Diversity and resolu[illegible]



Some Non-military Applications



Weather monitoring



Bioimaging, biosciences:
Cell imaging

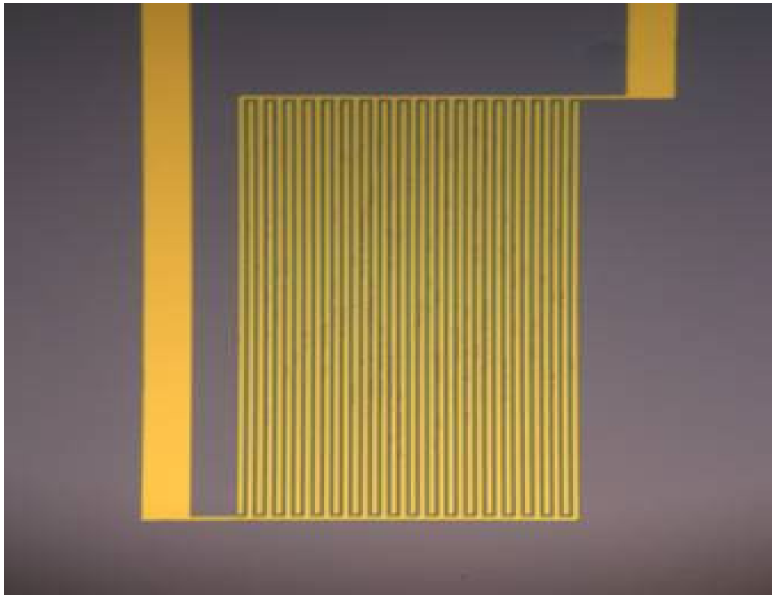
Animal monitoring

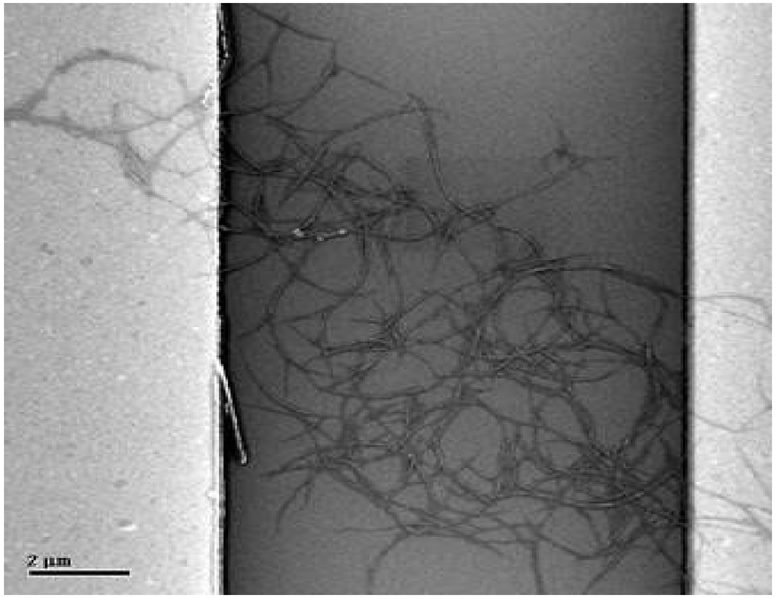
Structure monitoring

UMASS Distributed Radar

Nanotechnology: Small Sensor Trend

- Development of Large array of nanotechnology-based sensors to detect chemical leaks.





Signal Detection Sensor Networks

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

  - H_0: $f_X(x_1, \ldots, x_N | H_0)$ is joint pdf of observations at sensors one through N

    versus

    H_1: $f_X(x_1, \ldots, x_N | H_1)$ is joint pdf of observations at sensors one through N

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

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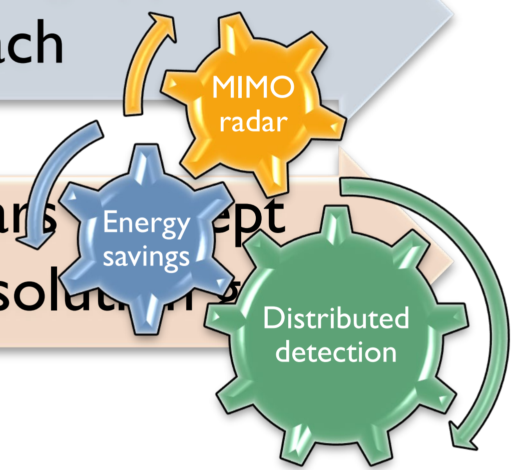
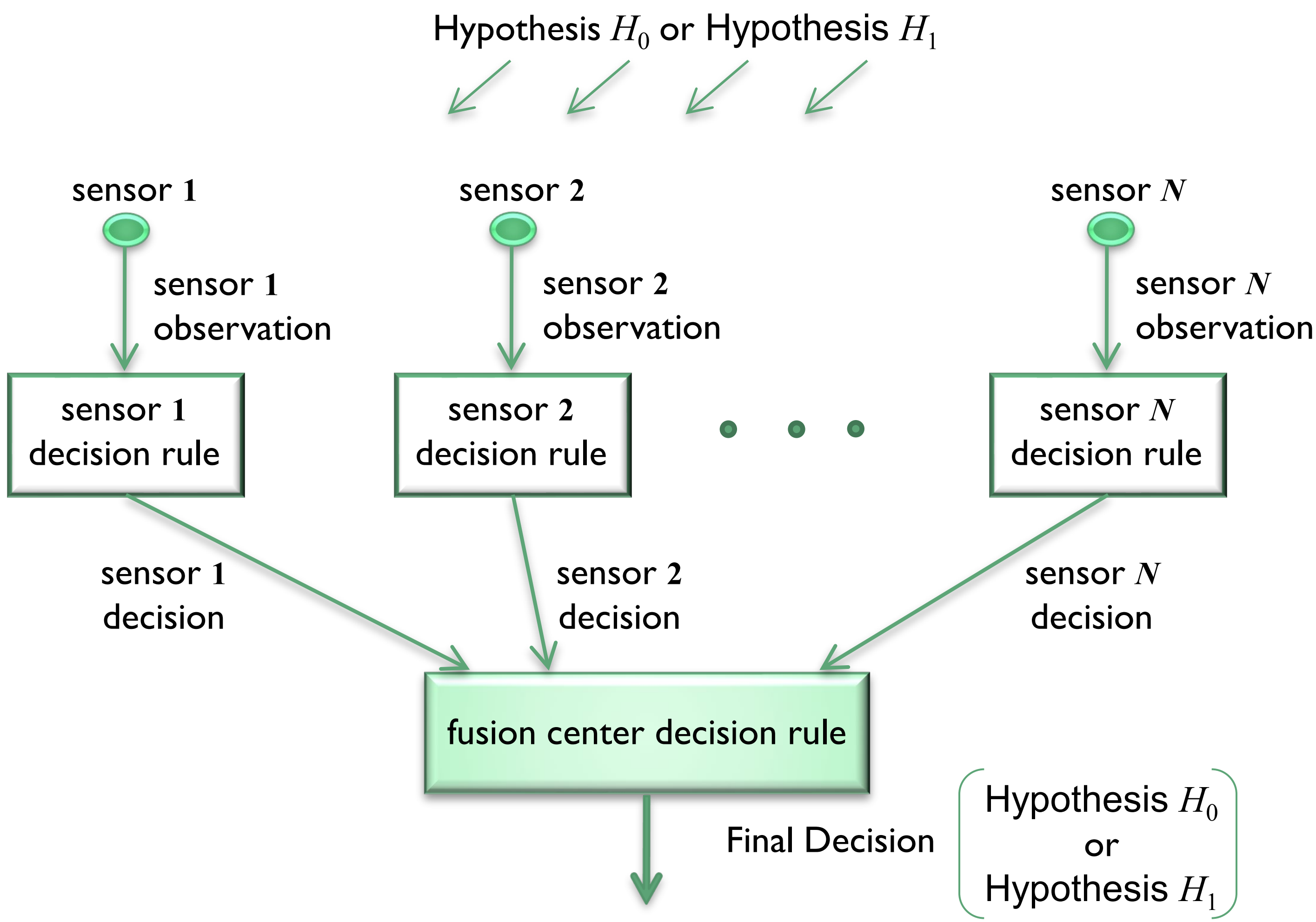


Distributed Signal Detection



Research Groups

Who are working on Distributed Detection ?

Distributed Detection With Multi...
Sensors: Part I—...
RAMANARAYANAN VISWANATH...
Invited Paper
Distributed Detection with Multiple Sensors: Part II—Advanced Topics
RICK S. BLUM, MEMBER, IEEE, SALEEM A. KASSAM, FELLOW, IEEE, AND H. VINCENT POOR, FELLOW, IEEE
Invited Paper
Biao Chen, Lang Tong, and Pramod K. Varshney
Distributed Signal Processing in Sensor Networks
Channel-Aware Distributed Detection in Wireless Sensor Networks
The integration of wireless channel conditions in algorithm design
In a distributed detection (DD) system, multiple sensors/detectors work collaboratively to distinguish between two or more hypotheses, e.g., the absence or presence of a target. While DD can be traced back to the advent of democracy and associated voting schemes, one of its earliest formal treatments can be found in the work of Radner in the early 1960s, [1] who considered the problem of decision making by a team of multiple persons. Each person has access to different information and independently makes his/her decision. The coupling (i.e., the concept of a "team") lies in the fact that the payoff function of the decision-making process depends on all the decisions and the state of situation in an inseparable way.
IEEE SIGNAL PROCESSING MAGAZINE [16] JULY 2006
J. N. Tsistsiklis
Decentralized Detection
Advances in Statistical Signal Processing
Signal Detection
Volume 2
H. V. Poor and J. B. Thomas
Greenwhich, CT: JAI press, 1993.
Pramod K. Varshney
Distributed Detection and Data Fusion
Springer

Distributed Signal Detection

- If observations independent from sensor to sensor under hypothesis

$$f_X(x_1,\ldots,x_N|H_j) = f_X(x_1|H_j)\, f_X(x_2|H_j) \cdots f_X(x_N|H_j), \quad then$$

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

$$L_i = \frac{f_X\left(x_i \mid H_1\right)}{f_X\left(x_i \mid H_0\right)}$$

- This simplifies the task of finding optimum sensors decision rules 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

J. N. Tsitsiklis, ``Decentralized Detection," in Advances in Statistical Signal Processing - Vol. 2: Signal Detection, H.V. Poor and J. B. Thomas, Eds. (JAI Press: Greenwich, CT, 1993)

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 it's 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

R. S. Blum and S.A. Kassam, ``Optimum distributed detection of weak signals in dependent sensors,'' IEEE Transactions on Information Theory, IT-38, pp. 1066-1079, May 1992.

Distributed Signal Detection

- The optimum test at sensor one:

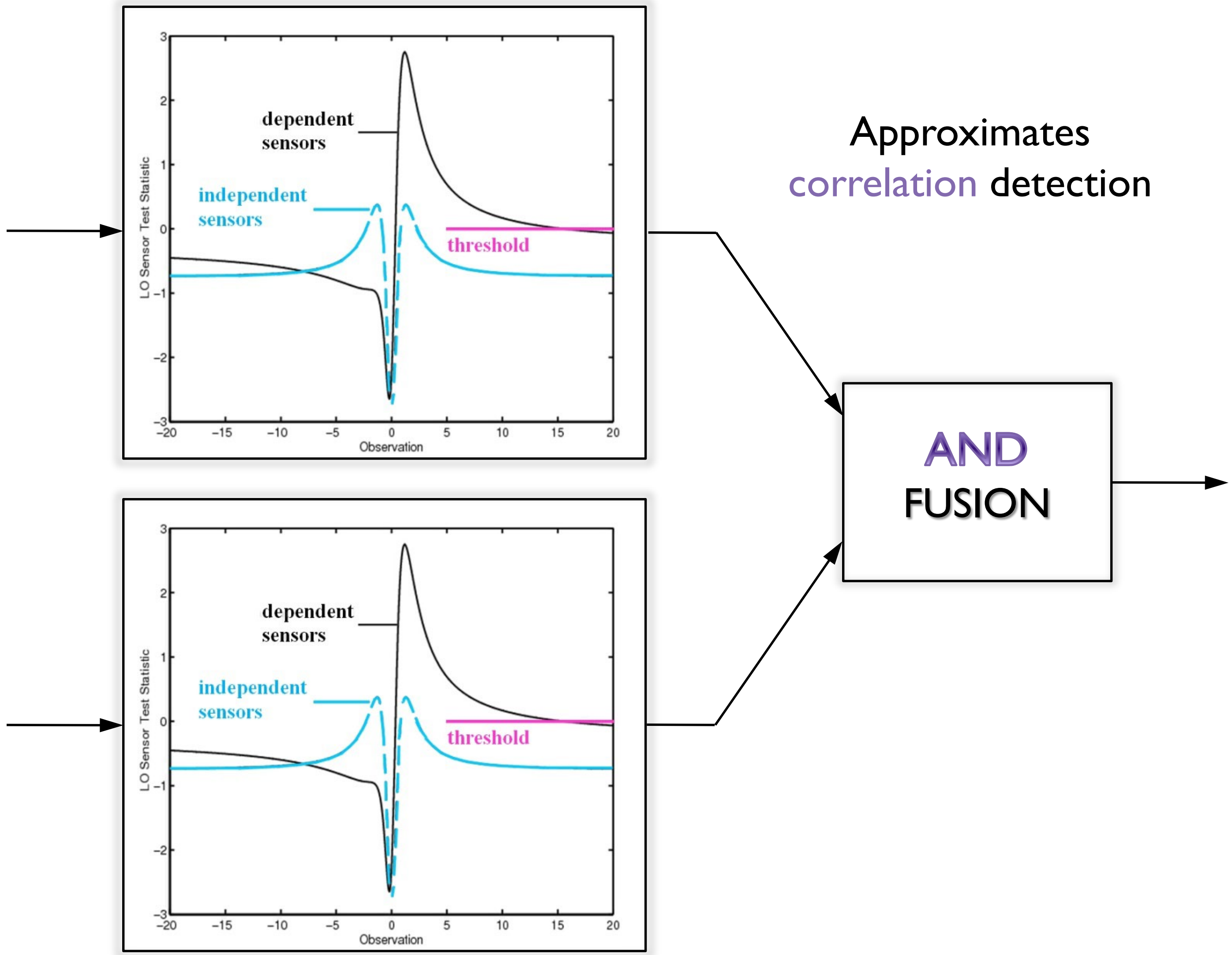
$$\frac{f''(x_1)}{f(x_1)} + a_1 \frac{f'(x_1)}{f(x_1)} > t_1$$

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

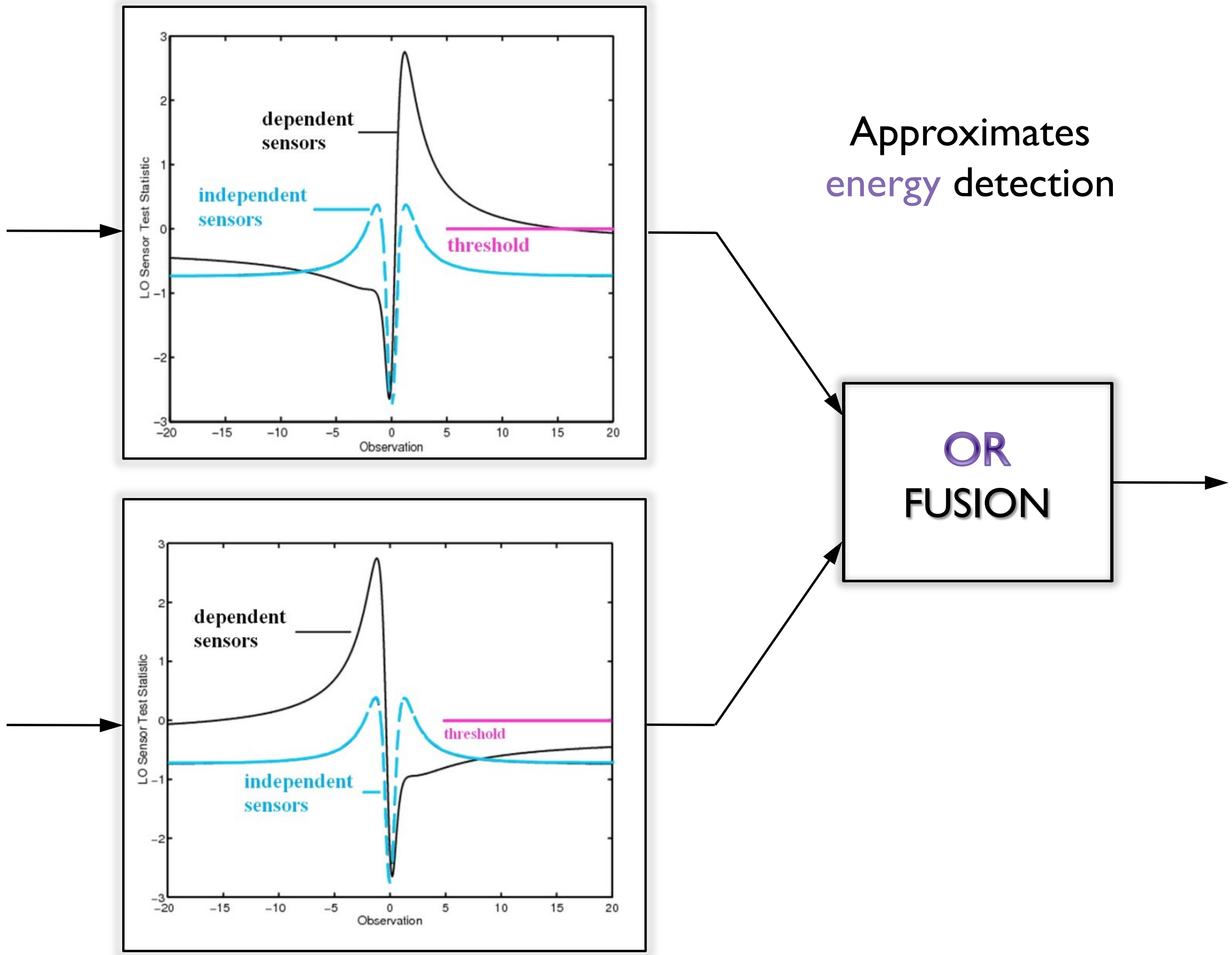
$$\frac{f''(x_1)}{f(x_1)} + 2\frac{f'(x_1)}{f(x_1)}\frac{f'(x_2)}{f(x_2)} + \frac{f''(x_2)}{f(x_2)} > \tau_1$$

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

Distributed Signal Detection



Distributed Signal Detection



Approximates energy detection

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.

P. Willett, P. F. Swaszek and R. S. Blum, ``The good, bad, and ugly: distributed detection of a known signal in dependent Gaussian noise," IEEE Transactions on Signal Processing, pp. 3266-3279, Dec 2000.

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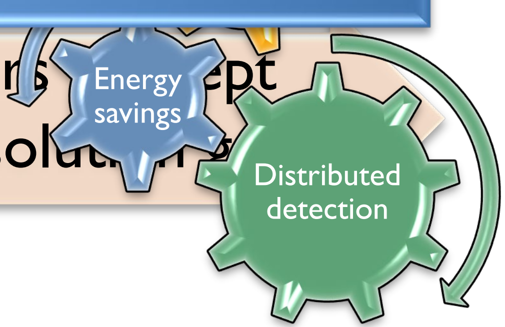


Assumptions/Definitions

- 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

$$\pi_0 = Prob(H_0), \quad \pi_1 = Prob(H_1)$$

- Define sensor likelihood ratio:

$$L_i = \frac{f_X\left(x_i \mid H_1\right)}{f_X\left(x_i \mid H_0\right)}$$

- Optimum N sensor (unconstrained) test compares $\sum_{i=1}^{N} \ln\left(L_i\right)$ 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):

C. Rago, P. Willett, and Y. Bar-Shalom, "Censoring sensors: A low communication-rate scheme for distributed detection," IEEE Transactions on Aerospace and Electronic Systems, vol. 32, pp.554–568, April 1996.

S. Appadwedula, V.V. Veeravalli, and D.L. Jones. "Energy EfficientDetection in Sensor Networks," IEEE Journal on Selected Areas in Communications, Volume 23, Issue 4, pp. 693-702, April 2005.

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

$$sum\ of\ log\text{-}likelihood\ ratios < t_L\ pick\ H_0,$$
$$sum\ of\ log\text{-}likelihood\ ratios > t_U\ pick\ H_1$$

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

Ordering Approach (cont.)

unconstrained opt. threshold

Last sensor transmission

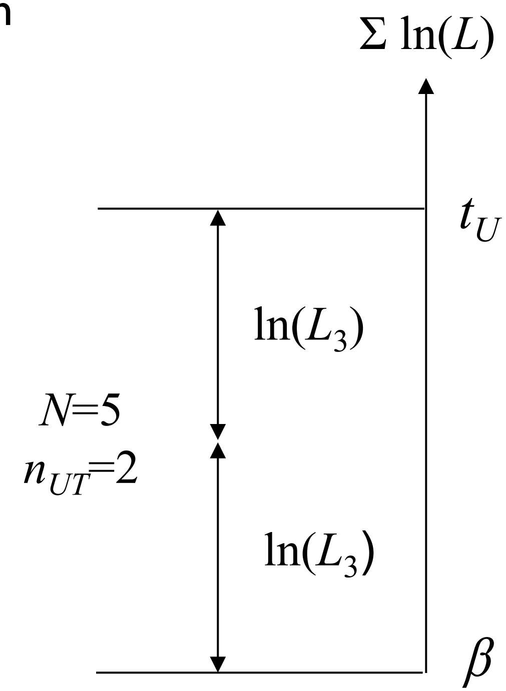
$$t_U = \beta + n_{UT}\,|\ln(L_{N-n_{UT}})|$$
$$t_L = \beta - n_{UT}\,|\ln(L_{N-n_{UT}})|$$

n_{UT} is number of sensors who did not yet transmit

largest possible magnitude contribution from the sum of the sensor LLRs that did not yet transmit

Once sum of LLRs from transmitting sensors is larger than t_U, sum will have to be larger than β, regardless of the data at the sensors that didn't transmit.

Thus even without transmitting further, we can implement the energy unconstrained approach, with fewer transmissions.

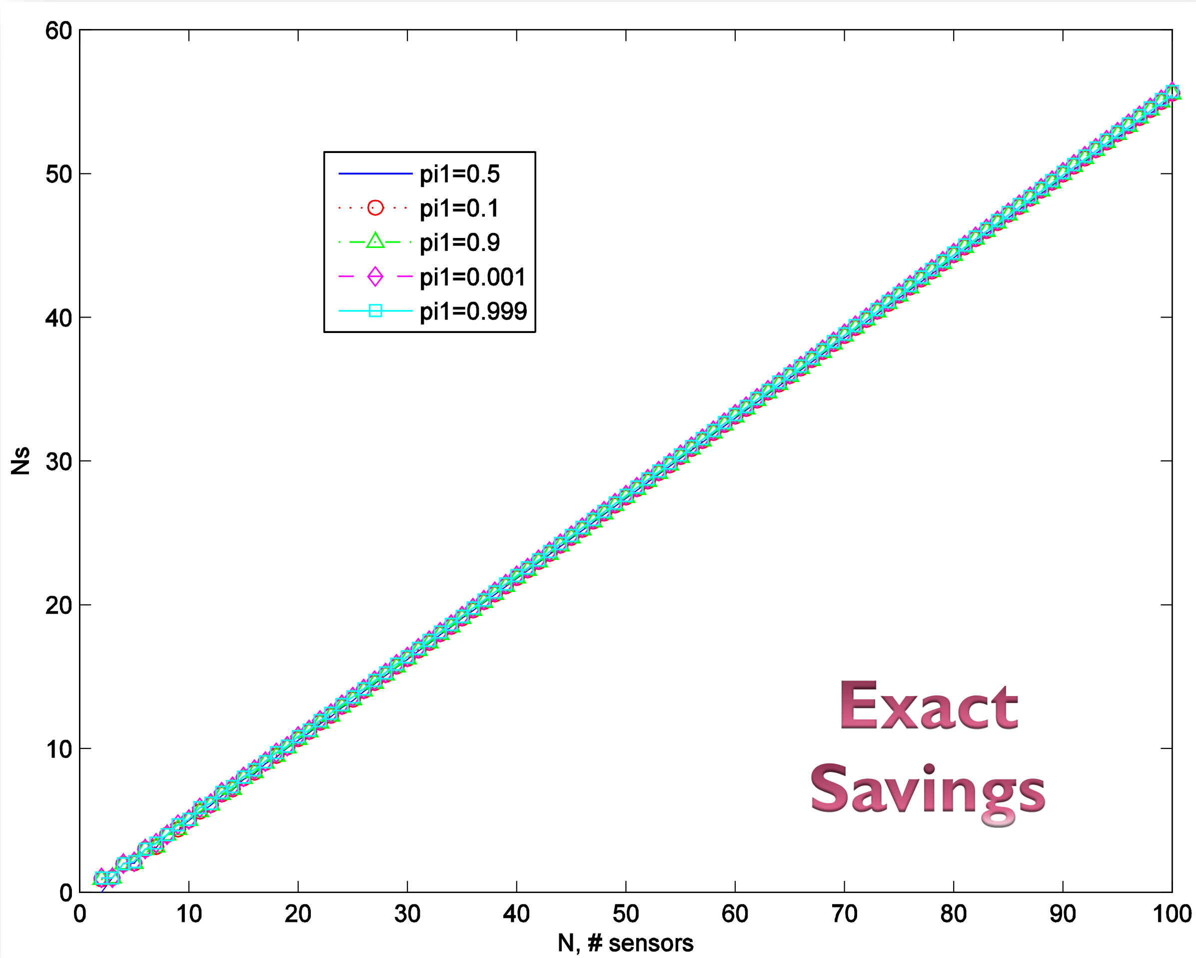


So with Prob one we save energy, but How large are Gains from Ordering?

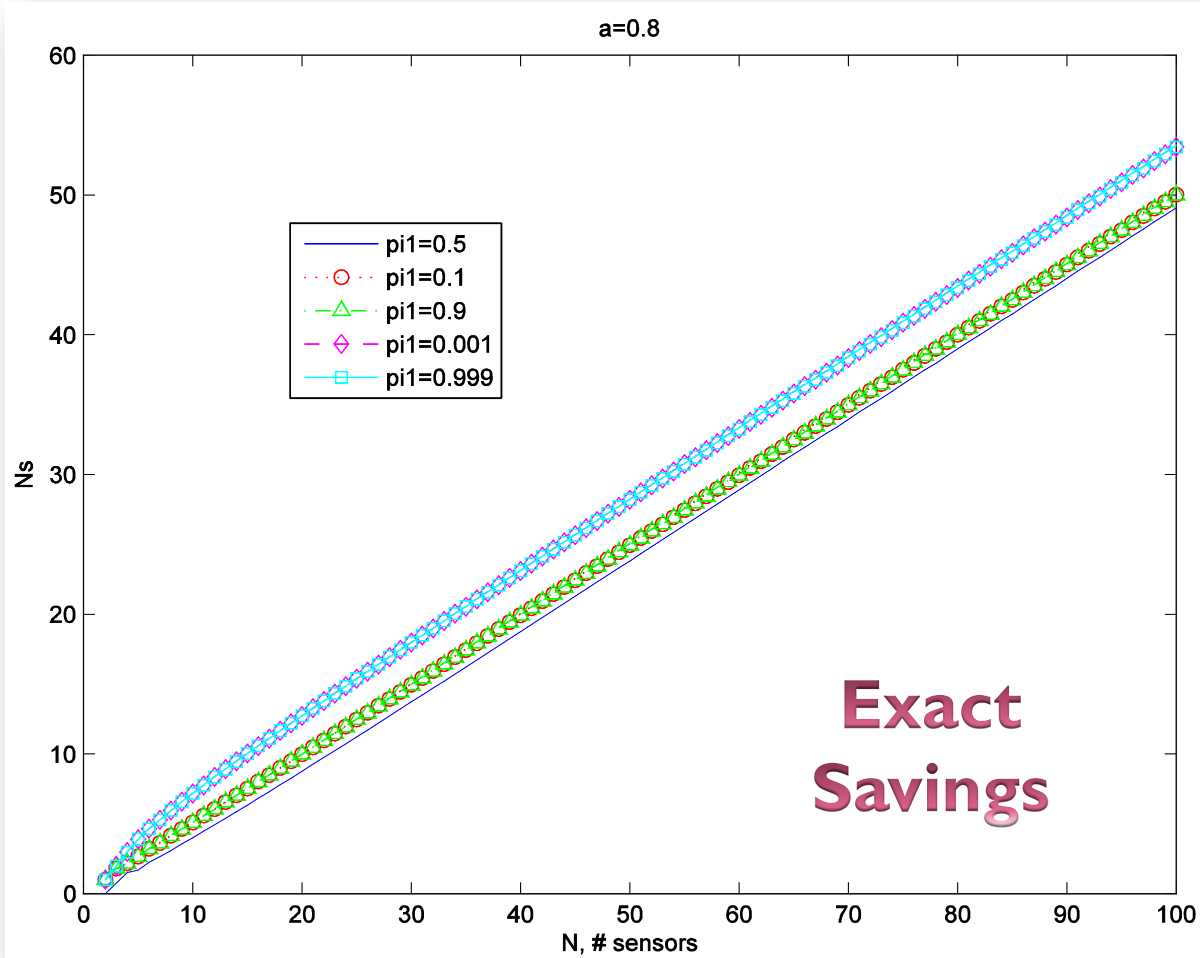
For any reasonable N-sensor binary hypothesis problem problem (P_e decreases with SNR-like quantity s), for sufficiently large s the average number of transmissions saved over the optimum unconstrained energy approach is strictly larger than $N/2$.

Example: Known signal in additive noise with symmetric unimodal noise pdf

$$x_j = \theta + n_j \qquad \begin{cases} \theta = 0 & \text{under} \quad H_0 \\ \theta = s > 0 & \text{under} \quad H_1 \end{cases}$$



- Average number of transmissions saved over the optimum unconstrained energy approach for signal strength $s=5$, various number of sensors and prior probabilities $pi1 = Prob(H1)$, and a known signal in $N(0,1)$ Gaussian noise.



- Average number of transmissions saved over the optimum unconstrained energy approach for signal strength $s=0.8$ and various number of sensors for a known signal in $N(0,1)$ Gaussian noise.

Ordering for Signal Detection

- R. S. Blum and B. M. Sadler, "Energy Efficient Signal Detection in Sensor Networks using Ordered Transmissions," IEEE Transactions on Signal Processing, Volume 56, Issue 7, Part 2, pp. 3229-3235, July 2008.

- R. S. Blum and Brian Sadler, "A New Approach to Energy Efficient Signal Detection," CISS 2007.

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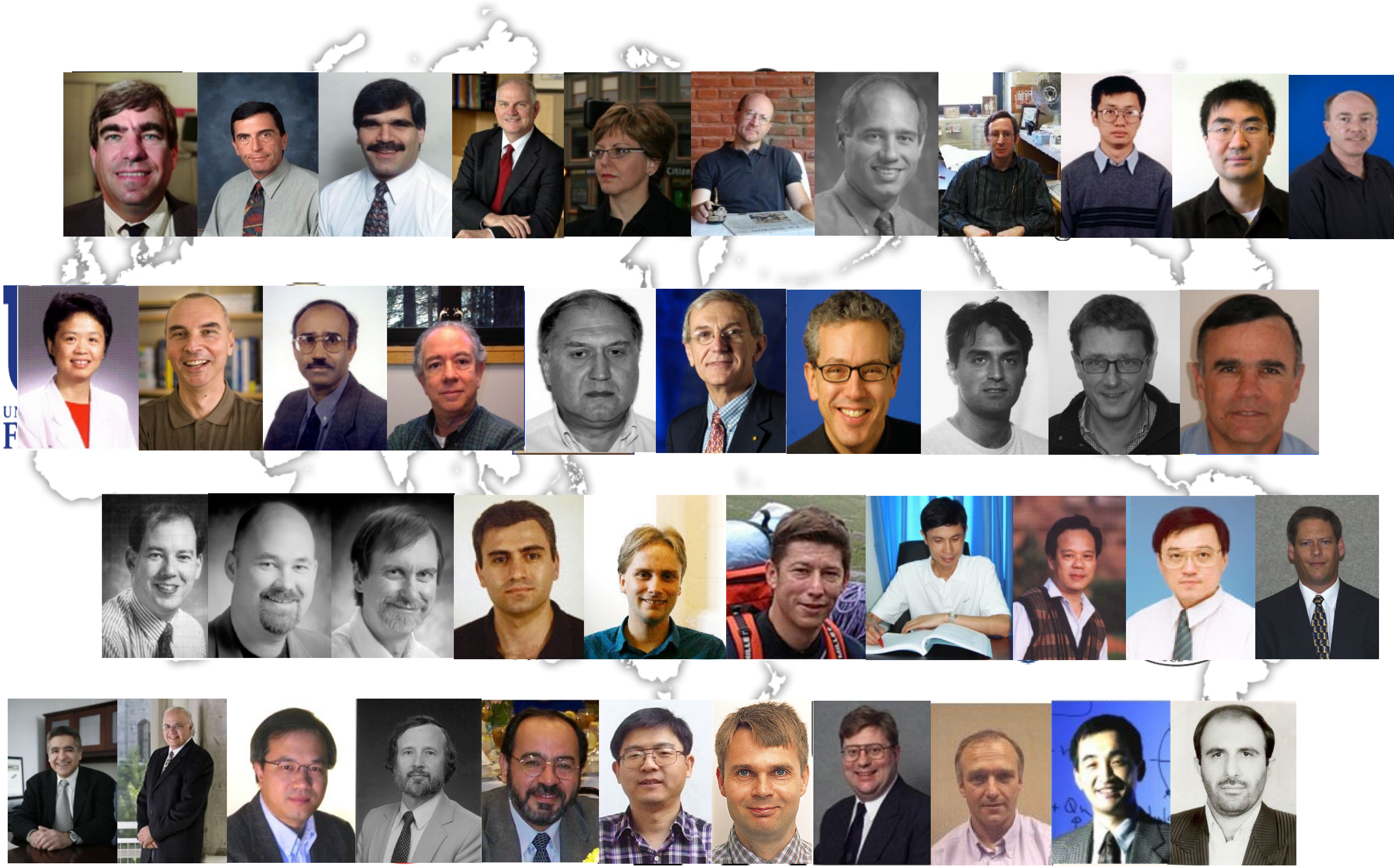
MIMO Radar

- Network of radars concept
- Diversity and resolution gains

MIMO Radar is Attracting Attention

- Research groups from all over the world

People working on MIMO Radar



MIMO Radar Special Issue -2009

Call for Papers
IEEE Signal Processing Society
IEEE Journal of Selected Topics in Signal Processing

Special Issue on MIMO Radar and Its Applications

-input and multiple-output) radar has been receiving increasing attentio
, practitioners, and funding agencies. MIMO radar is characterized b
nnas to simultaneously transmit multiple (possibly linearly independent
ceiving antennas to receive the reflected signals. Like MIMO commu
paradigm for signal processing research. MIMO radar possesses signific
, resolution enhancement, and interference and jamming suppression.
an result in much improved target detection and recognition performance.

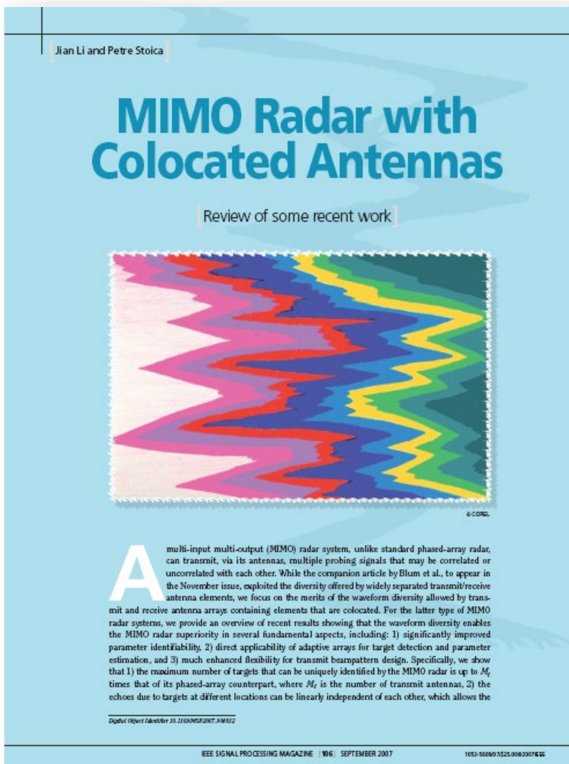
this special issue is to introduce recent developments on MIMO radar,
, and applications on the topic, and to foster further crossfertilization of i

previously unpublished and not currently under review by another journal
The scope of this special issue includes, but is not limited to:

MIMO radar.
ern analysis and optimization for MIMO radar.
ed MIMO radar.

Two types of MIMO Radar

- Classified by antenna configurations



[Jian Li and Petre Stoica]

MIMO Radar with Colocated Antennas

[Review of some recent work]

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A multi-input multi-output (MIMO) radar system, unlike standard phased-array radar, can transmit, via its antennas, multiple probing signals that may be correlated or uncorrelated with each other. While the companion article by Blum et al., to appear in the November issue, exploited the diversity offered by widely separated transmit/receive antenna elements, we focus on the merits of the waveform diversity allowed by transmit and receive antenna arrays containing elements that are colocated. For the latter type of MIMO radar systems, we provide an overview of recent results showing that the waveform diversity enables the MIMO radar superiority in several fundamental aspects, including: 1) significantly improved parameter identifiability, 2) direct applicability of adaptive arrays for target detection and parameter estimation, and 3) much enhanced flexibility for transmit beampattern design. Specifically, we show that 1) the maximum number of targets that can be uniquely identified by the MIMO radar is up to M_t times that of its phased-array counterpart, where M_t is the number of transmit antennas, 2) the echoes due to targets at different locations can be linearly independent of each other, which allows the

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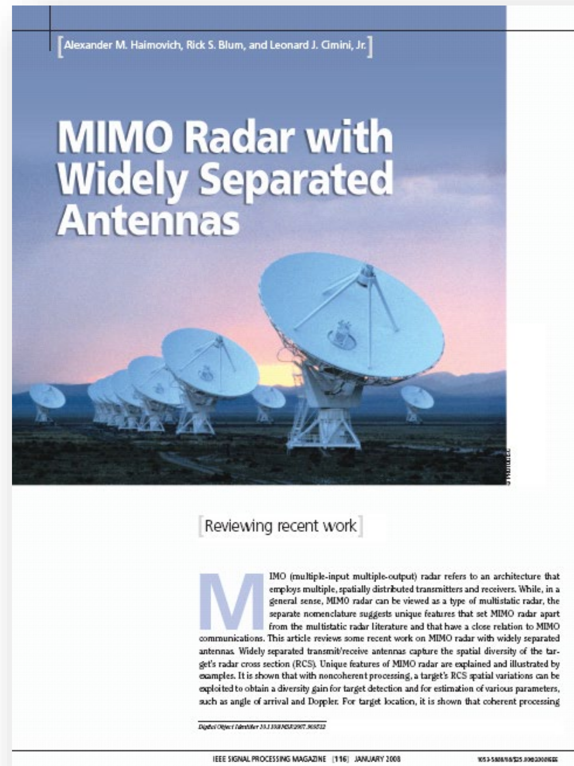


[Alexander M. Haimovich, Rick S. Blum, and Leonard J. Cimini, Jr.]

MIMO Radar with Widely Separated Antennas

[Reviewing recent work]

MIMO (multiple-input multiple-output) radar refers to an architecture that employs multiple, spatially distributed transmitters and receivers. While, in a general sense, MIMO radar can be viewed as a type of multistatic radar, the separate nomenclature suggests unique features that set MIMO radar apart from the multistatic radar literature and that have a close relation to MIMO communications. This article reviews some recent work on MIMO radar with widely separated antennas. Widely separated transmit/receive antennas capture the spatial diversity of the target's radar cross section (RCS). Unique features of MIMO radar are explained and illustrated by examples. It is shown that with noncoherent processing, a target's RCS spatial variations can be exploited to obtain a diversity gain for target detection and for estimation of various parameters, such as angle of arrival and Doppler. For target location, it is shown that coherent processing

IEEE SIGNAL PROCESSING MAGAZINE [116] JANUARY 2008

Widely Separated MIMO Radar

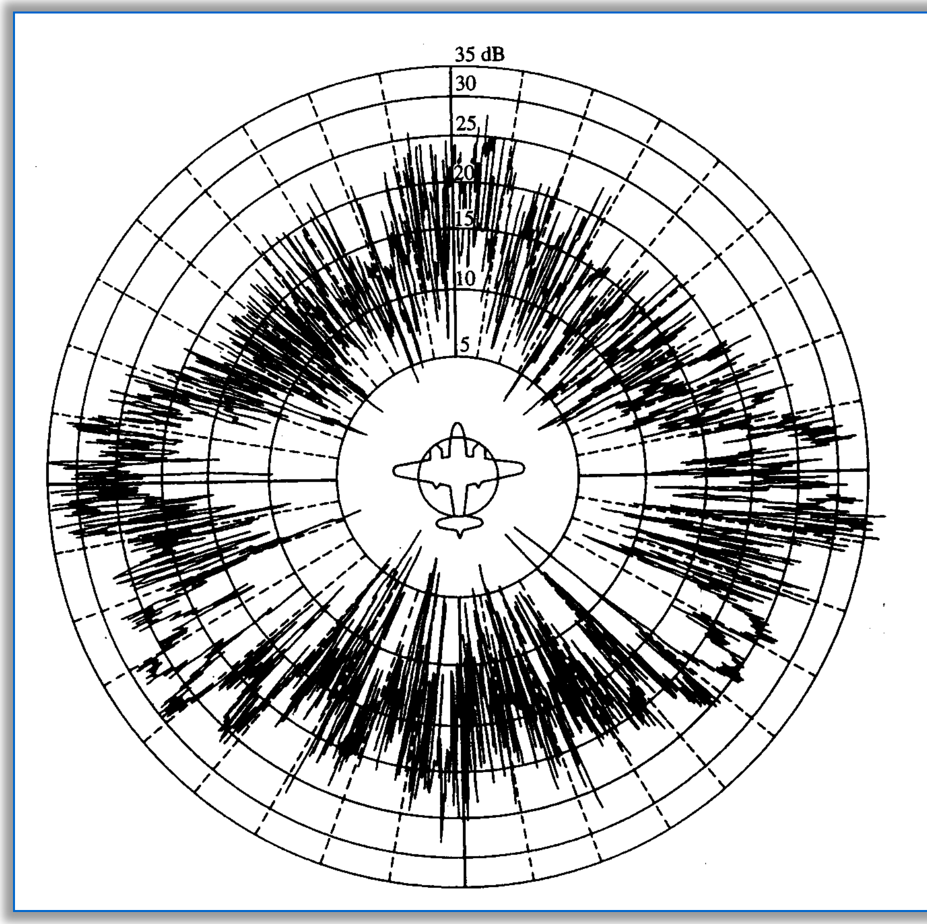
- With MIMO radar, many "independent" radars collaborate to average out target fluctuations, while maintaining the ability to detect target (measure range, AOA).

- MIMO radar offers the potential for significant gains:
  - Detection/estimation performance through diversity gain
  - Resolution performance through spatial resolution gain (create bandwidth)

- A first step to a cooperative radar network.

Motivation

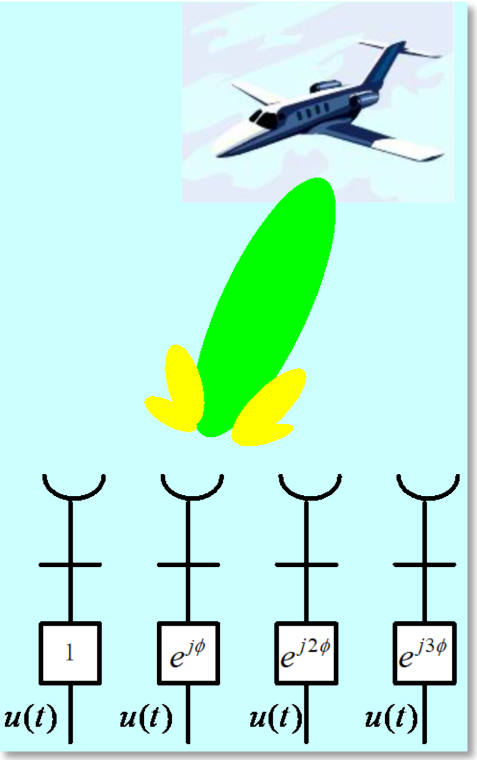
- Conventional radars experience target fluctuations of 5-35 dB
- Slow RCS fluctuations (Swerling I model) cause long fades in target RCS, degrading radar performance.
- MIMO radar exploits the angular spread of the target backscatter in a variety of ways to extend the radar's performance envelope.



Backscatter as a function of azimuth angle, 10-cm wavelength [Skolnik 2003].

Traditional Beamformer

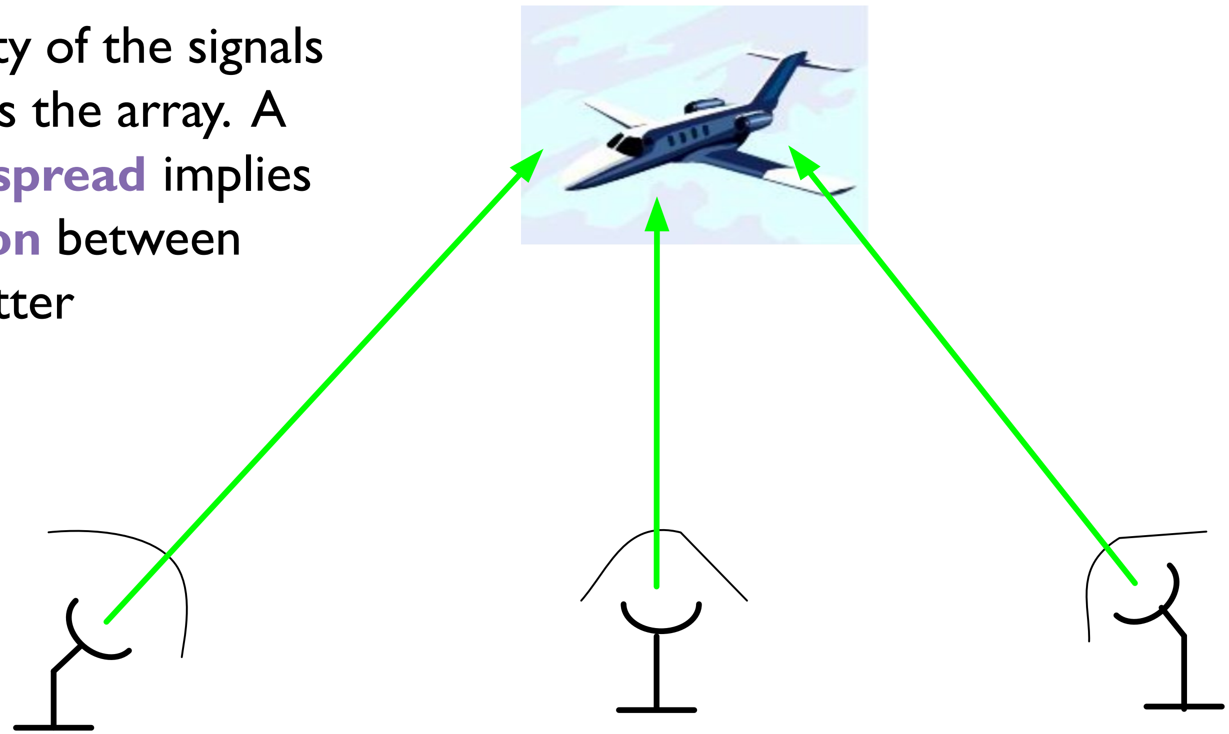
- A typical array radar is composed of many closely spaced antennas.
  - The performance of radar systems is limited by target RCS fluctuations, which are considered as unavoidable loss.
  - The common belief is that radar systems should maximize the received signal energy. This is made possible by the high correlation between the signals at the array elements.



Beamformer mode:
- Copy waveform

MIMO with Angular Diversity

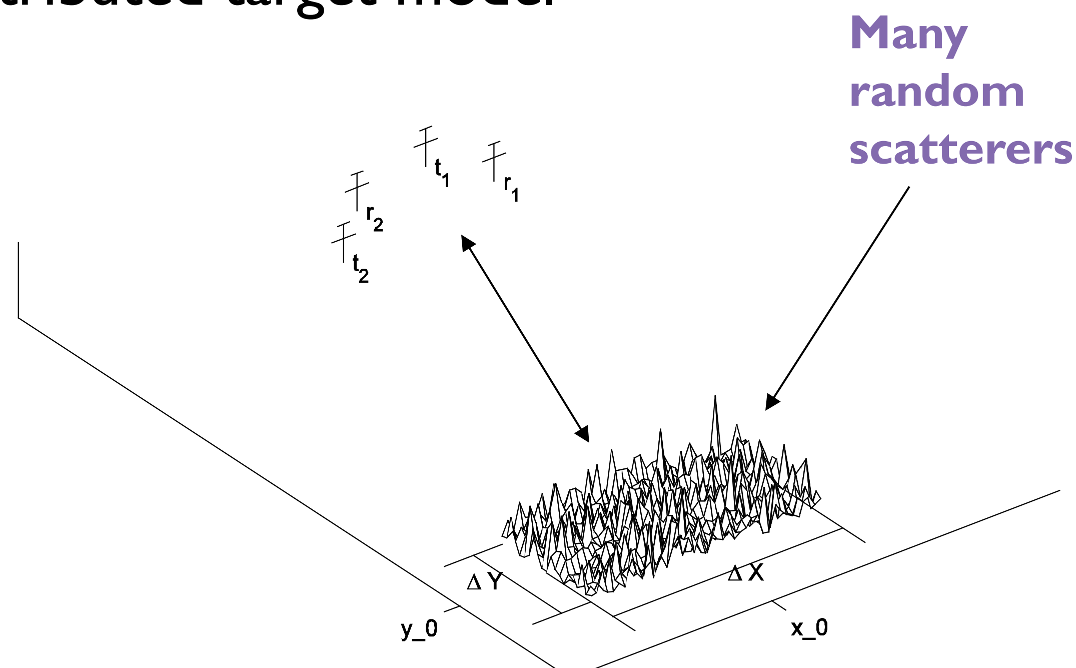
Angular spread - a measure of the variability of the signals received across the array. A **high angular spread** implies **low correlation** between target backscatter



MIMO mode:
- Exploit angular spread
- Orthogonal waveform

Signal Model

- Point source assumption dominates current models used in radar theory.
- This model is not adequate for an array of sensors with large spacing between array elements.
- Distributed target model



Signal Model (Cont.)

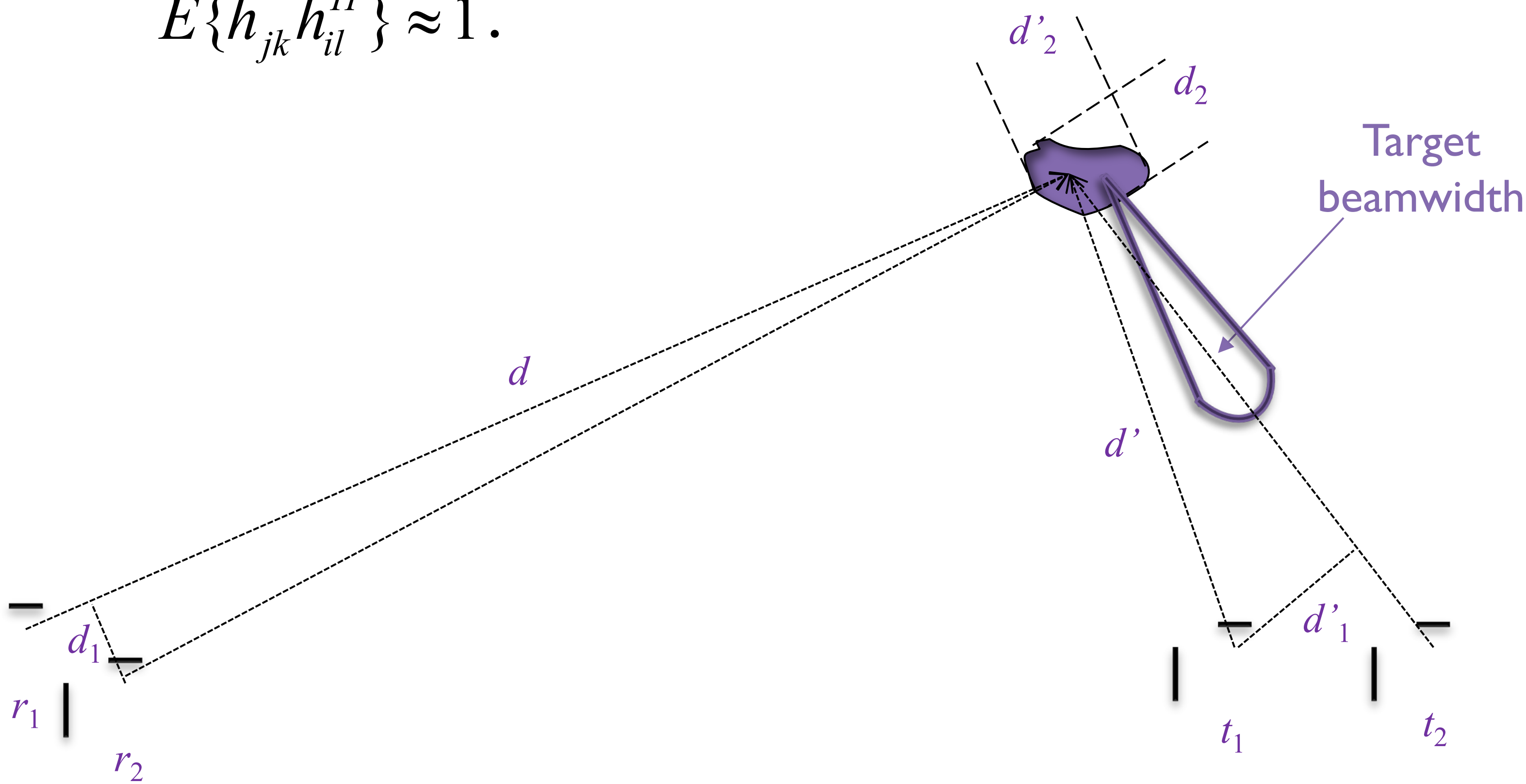
$$\mathbf{r}(t) = \sqrt{\frac{E}{M}}\mathbf{H}\mathbf{s}(t-\tau) + \mathbf{n}(t)$$

- Signal energy: E
- Transmit antennas: M
- Vector of transmitted waveforms: $\mathbf{s}(t)$
- Observation: $\mathbf{r}(t) = [r_1(t), \cdots, r_N(t)]^\dagger$
- Channel matirix: target gain between transmitter k and receiver l: $[\mathbf{H}]_{lk} = h_{lk}$
- Noise: $\mathbf{n}(t) = [n_1(t), \cdots, n_N(t)]^\dagger \sim CN(0, \underset{\uparrow \atop \text{psd}}{\sigma^2})$

E. Fishler, A. Haimovich, R. Blum, D. Chizhik, L. Cimini, R. Valenzuela, "Spatial Diversity in Radars - Models and Detection Performance", IEEE Trans on Signal Processing, 2005.

Distributed Target

- It can be shown that $h_{lk} \sim CN(0,1)$
- Take h_{jk} and h_{il}. We can show that if antenna not in single beamwidth then $E\{h_{jk}h_{il}^H\} \approx 0$, otherwise $E\{h_{jk}h_{il}^H\} \approx 1$.



Radar Detection Problem

- The radar detection problem:

$$\mathrm{Hyp}_0 \quad : \text{Target does not exist at point in space}$$

$$\mathrm{Hyp}_1 \quad : \text{Target exists at point in space}$$

- Assume that all the parameters are known. The optimal detector is the LRT detector, and it is given by

$$T = \log \frac{p\left(\mathbf{r}(t) \middle| \mathrm{Hyp}_1\right)}{p\left(\mathbf{r}(t) \middle| \mathrm{Hyp}_0\right)} \underset{Hyp_0}{\overset{Hyp_1}{\gtrless}} \delta$$

- The channel matrix $\mathbf{H}$ is unknown, but its distribution is assumed known

$$p\left(\mathbf{r}(t) \middle| \mathrm{Hyp}_1\right) = \int p\left(\mathbf{r}(t) \middle| \mathbf{H}, \mathrm{Hyp}_1\right) p(\mathbf{H}) d\mathbf{H}$$

Detection with MIMO Radar

- It can be shown that the sufficient statistic for the MIMO radar problem with unknown channel is the vector $\mathbf{x}$, the output of a bank of matched filters.

- Orthogonality of waveform is assumed
- The optimal NP detector is

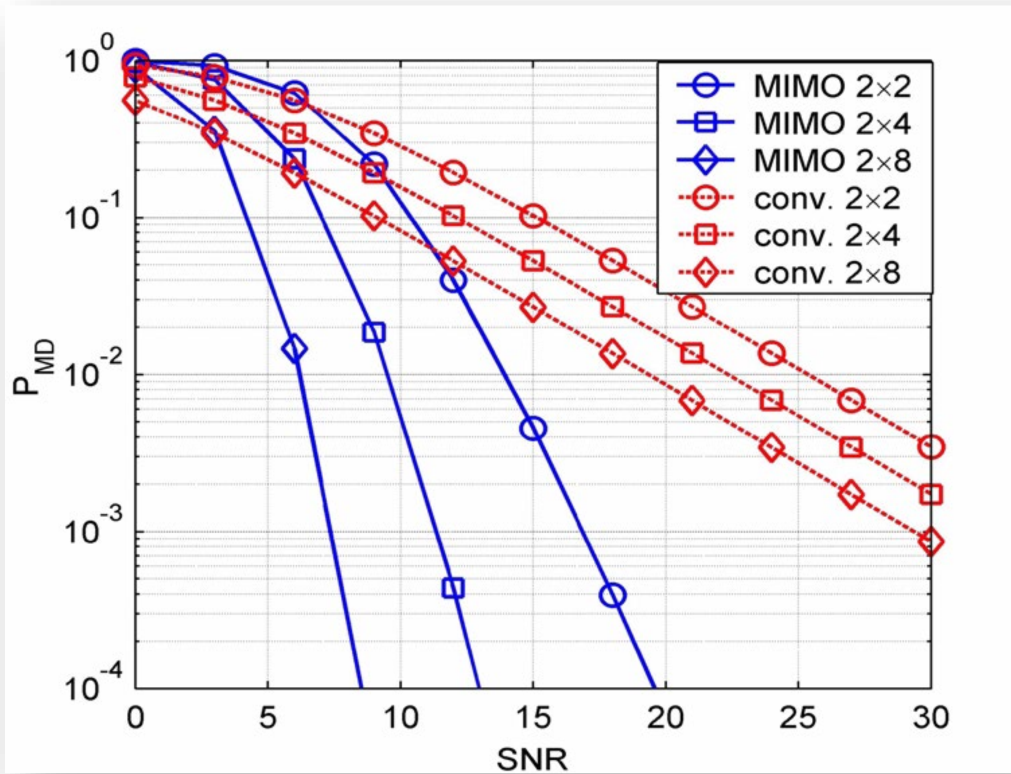
$$T = \left\|\mathbf{x}\right\|^2 \underset{Hyp_0}{\overset{Hyp_1}{\gtrless}} \delta, \quad \text{where} \quad \delta = \frac{\sigma_n^2}{2} F^{-1}_{\chi^2_{2MN}}\left(1 - P_{FA}\right)$$

- Non-coherent processing in a network of MN radars.

UMP Test, invariant extensions…

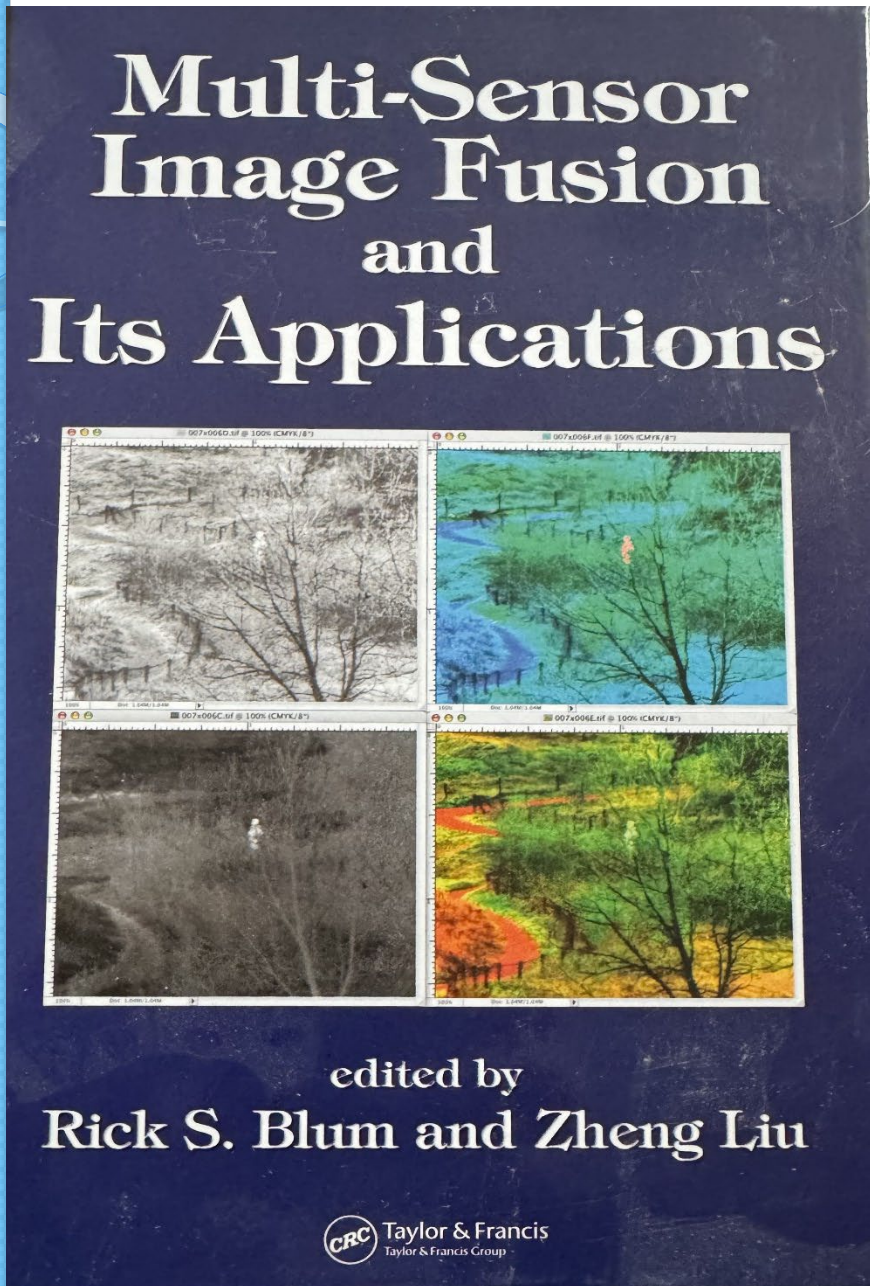
Prob(Miss) to illustrate Diversity Gain

- MIMO diversity (blue)   Beamforming (red)



Miss prob versus SNR (fixed false alarm prob 10^{-6})

Image Fusion



Some of our books/papers:

R. S. Blum and Zheng Liu, ``Multi-Sensor Image Fusion and Its Applications ", CRC Press in the special series on Signal Processing and Communications, 2006.

Z. Zhang and R. S. Blum, " A categorization and study of multiscale-decomposition-based image fusion schemes with a Performance Study for a Digital Camera Application ", Proceedings of the IEEE, Aug. 1999, pp. 1315-1328.

Y. Chen, and R. S. Blum, `` A New Automated Quality Assessment Algorithm for Image Fusion,", Image and Vision Computing, Volume 27, Issue 10, 2 September 2009, Pages 1421-1432 Special Section: Computer Vision Methods for Ambient Intelligence

Questions ?

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http://www.ece.lehigh.edu/SPCRL/

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