Information Fusion and Cognitive Processing

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14. ABSTRACT

In sensor fusion one expects that solutions from individual sensors when combined will lead to a solution that outperforms any one of the individual solutions. Though it is known to be true (Condorcet 1786, Democracy Models) for similar sensors, the story is still unfolding in reality and for dissimilar sensors. In the real world there is a myriad of sensors that are performing similar tasks. They were designed to operate individually and their integration is a current after thought and a compulsion, either to arrive at a better solution or at least a nonconflicting solution. This talk will review the seminal contributions of selected researchers and my involvement in the emergence of the field of data, sensor and information fusion and cognitive processes in sensing.

15. SUBJECT TERMS

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Standard Form 298 (Rev. 8-98)
Prescribed by ANSI Std Z39-18

My Brush with Science

- ONR

- People you may know

- Science and Information Fusion

- Cognitive Radar and Sensor Fusion

Scientists in the Program

- **Moeness Amin**
- **Y. Bar-Shalom**
- **Leon Chua**
- **Petar Djuric**
- **Dan Fuhrman**
- **S. S. Iyengar**
- **Thomas Kailath**
- **Rudy Kalman**
- **R. L. Kashyap**
- **Qilian Liang**
- **S. K. Mitra**
- **Arye Nehorai**
- **Athina Petropulu**
- **Unnikrishna Pillai**
- **Vincent Poor**
- **P. P. Vaidyanathan**
- **N. Vishwanadham**
- **Xiadong Wang**
- **Peter Willet**

Information in Sensor Fusion

- Combining information from two or more sensors

- Combining information from different modes of a single sensor

- Fuse information from different algorithms

Motivations

- Limits of performance for single sensors can be pushed only in small increments

- Multisensor integration MAY LEAD TO improved detection and identification with significantly lower false alarms

- More data - potential for improved information from measurements

Multisensor Integration

- Sensors designed to operate independently: integration is an "after thought"
- Fusion approaches have been system and function specific
- Conventional techniques, models assume identical sensor statistics, equal thresholds, high SNRs, and uncorrelated sensor noise fields - example Radar PDI
- Issues remain in integrating dissimilar sensors collecting data asynchronously and communicating to central processor with different time delays

18th Century Information Fusion

- **1786: Condorcet - Democracy Models:**

  Each individual has probability p of making correct decision:

  What is the probability of democracy making the correct decision ?

<u>Democracy Model</u>

p: individual probability of making correct decision;

n: number of members of democracy

P_n: probability of democracy making correct decision?

  If $p > \frac{1}{2}$ then $P_n > p > \frac{1}{2}$ P_n approaches 1 as n grows

  $p < \frac{1}{2}$ then $P_n < p < \frac{1}{2}$ P_n approaches 0 as n grows

  $p = 1/2$ then $P_n = p = 1/2$

Informally, democracy will do well
if $p > 1/2$ and will do bad if $p < 1/2$

Information Fusion in Twentieth Century

1956, Reliability: Von Neumann showed how to build a reliable system using unreliable components under independent failures.

1962, Pattern Recognition: Chow showed optimal threshold fuser for multiple independent classifiers.

1969, Forecasting: Bates and Granger, "better" forecasts can be made by combining different forecast methods rather than picking one of them

Importance of "fusing" rather than picking the "best" has been demonstrated in a number of disparate disciplines

Information Fusion in Late Twentieth Century

Advances in Computing and Complex Engineering systems posed new challenges:

- Distributed Detection: Bayesian methods for object detection using measurements from different detectors
- Sensor Fusion: Multiple sensors became essential to many engineering systems – fusion is part of the problem specification
- Mixture of Experts: Function and regression estimation can benefit by combining multiple estimators
- Multiple Classifiers: There is no single best classifier but "combined" one is better than its components

Information Fusion began taking roots as a discipline unto itself:

Office of Naval Research sponsored first workshop on Information Fusion in 1996, jointly with National Science Foundation and Department of Energy

First Workshop on Information Fusion

Office of Naval Research was the lead sponsor, together with National Science Foundation and Department of Energy

Brought together scientists from:
Engineering, Computer Science, Mathematics, Econometrics, Bioinformatics, Statistics

This workshop launched the field of Information Fusion
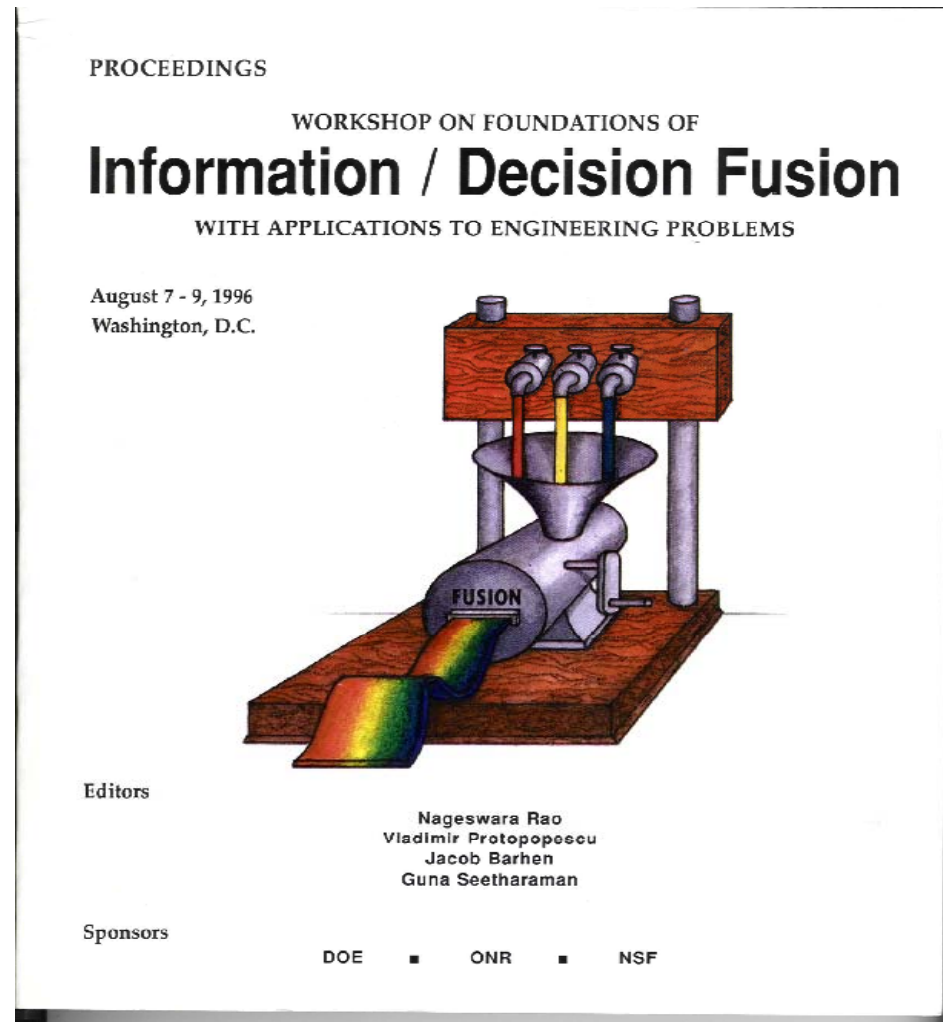
Information Fusion Area Today

Integral part of newer disciplines including:

- Distributed Sensor Networks
- Cyber Data Mining
- Cognitive sensor Fusion

Dedicated International Conferences:

1. International Conference on Information Fusion (13th in Edinburgh, 2010)
2. International Conference on Multisensor Fusion and Integration (Salt Lake City, UT, 2010)

Journals:

Information Fusion (2000)

International Journal of Distributed Sensor Networks (2005)

Journal of Advances in Information Fusion (2006)

Information Fusion area – last decade or two?

- Rich Information Sources
  - Sophisticated sensors – visual, hyperspectral, radiation, chemical, biological, and others
  - Information sensors – web crawlers, information servers, sophisticated databases
- Advances in Computation
  - Fusion problems have become complex
  - Powerful computer hardware and algorithms have been developed
- Advances in Networking
  - Made access to computing and data resource easier
  - Wireless networking made *ad hoc* deployments possible
  - High-performance networks made it possible to support large data transport and remote control possible

NEW in September 2010

IEEE 2010 INTERNATIONAL CONFERENCE ON MULTISENSOR FUSION AND INTEGRATION FOR INTELLIGENT SYSTEMS (IEEE MFI 2010), SEPTEMBER 5-7, 2010

The theme of IEEE MFI 2010 was   Cognitive Sensor Fusion

 Here the goal of multi-sensor fusion systems is to achieve human-like performance in terms of perception, knowledge extraction, and situation assessment, exploiting symbolic and/or dynamical systems approaches.

Cyber-Physical Trade-Offs in Distributed Detection Networks

Nageswara S. Rao,

Oak Ridge National Laboratory

David K.Y. Yau, J.C. Chin, Chirs Y.T Ma

Purdue University

Rabinder N. Madan

Office of Naval Research

IEEE MFI 2010: Cognitive Sensor Fusion

IEEE

THE UNIVERSITY OF UTAH

BEST PAPER AWARD

"Cyber-Physical Trade-Offs in Distributed Detection Networks"

Nagi Rao, Jren-Chit Chin, David Yau, Chris Y. T. Ma
and Rabinder Madan

Presented
September 6, 2010

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Thomas C. Henderson, General Chair, MFI 2010

_____
Edward Grant, Program Chair, MFI 2010

Motivation
Detection of Low-level Radiation Sources

Task:

- Detect the sources based on
  sensor measurements

Several underlying math problems
related to detection networks are open.
Our work
      -addresses network-based detection
      -provides answers using statistical
      estimation and packing numbers

Difficulty of Detecting Low-level Radiation Sources

The radiation levels are only slightly above the background levels and may appear to be "normal" background variations

- <u>Varied Background</u>: Depends on local natural and man-made sources and may vary from area to area
- <u>Probabilistic Measurements</u>: Radiation measurements are inherently random due to underlying physical process – gamma radiation measurements follow Poisson Process

Several solutions are based on thresholding sensor measurements

<u>Well-Studied Problem</u>: Has been studied for decades using single or co-located sensors: analytical, experimental and
- sensor networks offer "newer" solutions but also questions

<u>Open Mathematical Question</u>: Q1
Is there a mathematical quantification for a network of sensors to achieve better performance than single-sensor detectors?

Detection of Sources amidst Background Noise

A Traditional Method for Detection:

1. SPRT to infer detection from measurements at sensors;
2. Fuse the Boolean decisions at fusion center.
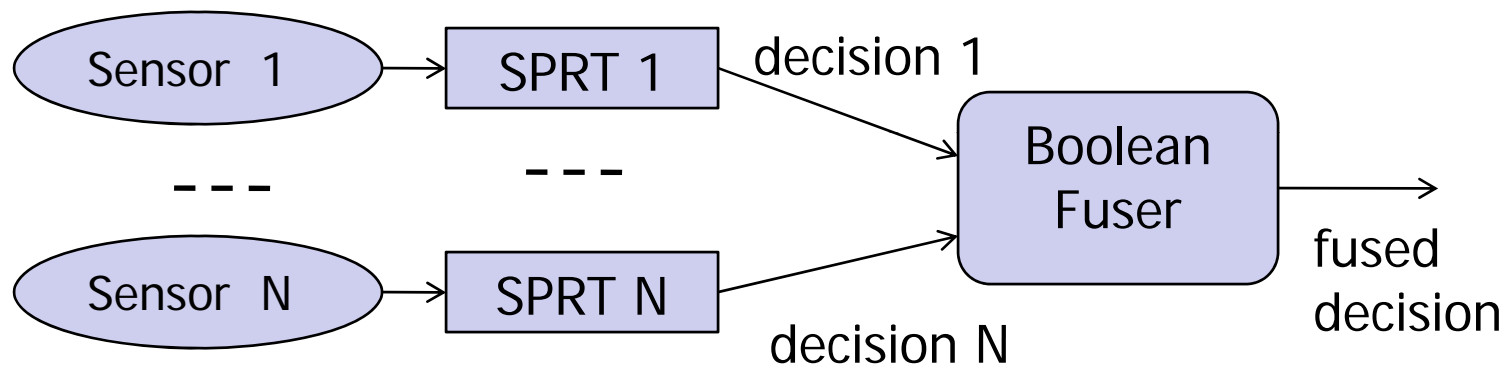
Specific Question: Are there methods that perform better?

Generic Question: Are there classes of detection problems that benefit from "fusing" measurements in place of decisions ?

Our Results: Answer is yes to both questions under
1.   Lipschitz smoothness conditions – limited shielding conditions
2.   Vapnik-Chenvenenkis conditions – discrete intensity drops
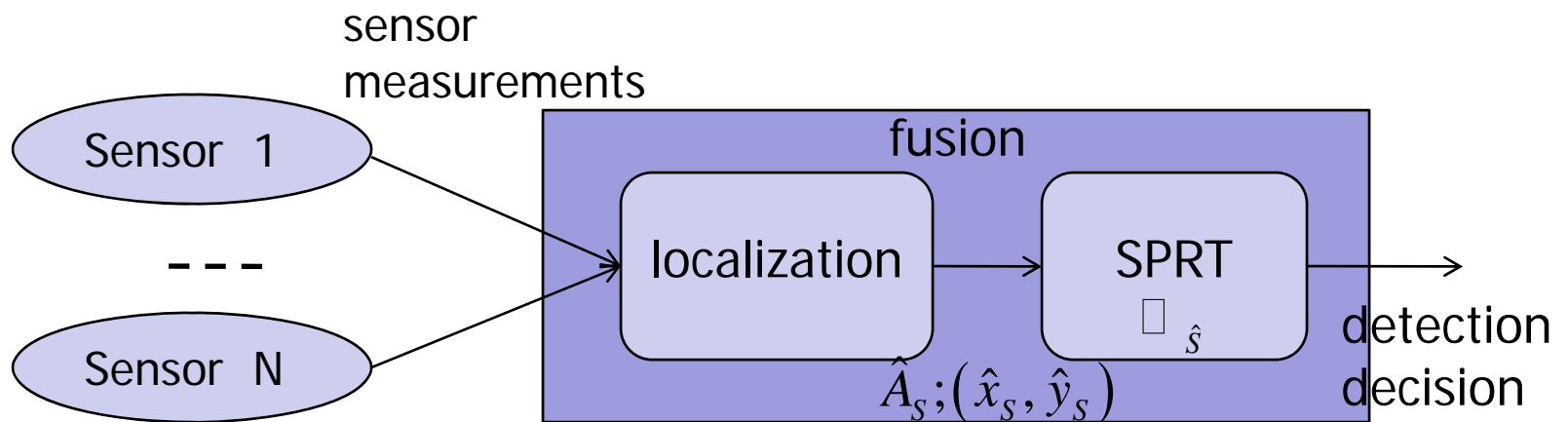3.   * SPRT-sequential probability ratio test

Detection Using Localization $\hat{S}$

Proposed Method for Detection:
1. Estimate the source parameters using measurements - $\hat{A}_S ; (\hat{x}_S, \hat{y}_S)$
2. Utilize likelihood ratio test $\hat{S}$ at the fusion center

$$F_L\left(P_{0,1}, P_{1,0}, \hat{A}_i, B_i, n\right) < \sum_{j=1}^{n} m_{i,j} < F_U\left(P_{0,1}, P_{1,0}, \hat{A}_i, B_i, n\right)$$

where $\hat{A}_i = F_S\left(\hat{A}_S, \hat{x}_S, \hat{y}_S, x_i, y_i\right)$

sensor
measurements

Sensor 1

- - -

Sensor N

fusion

localization → SPRT $\hat{S}$

$\hat{A}_S ; (\hat{x}_S, \hat{y}_S)$

detection
decision

Explanation of Results

A fixed-threshold SPRT detection method optimizes the detection performance within a certain neighborhood of state-space.
- characterized by sets S_{τ_L}, S_{τ_H}

Localization facilitates the adaptation of the threshold to estimated neighborhood of the state-space albeit with a certain error probability.

Our method achieves a trading-off between
- error probability of the localization method in estimating the neighborhood and needed SPRT thresholds; and
- probability of "uncovered" regions of fixed-threshold SPRT

By suitable trade-off one can exceed the performance of the latter.

Summary of Results

Improved detection using measurements at fusion center compared to existing decision fusion methods, using robust localization, under:

    General non-smooth conditions:

        Separability of probability ratios

        - complex analysis and less intuitive conditions

        + valid under complex shielding of radiation sources

    Smoothness conditions:

        Lipschitz separable probability ratios; and

        Lipschitz source intensity

        + intuitive conditions: "bigger" parameter space is better

        - valid typically under open-space environments

First mathematical proofs for this class of problems to show:

i)   a network of sensors performs better than single or co-located sensors

ii)   measurement "fusion" performs better than detection fusion

Performance improvement is characterized by the packing number

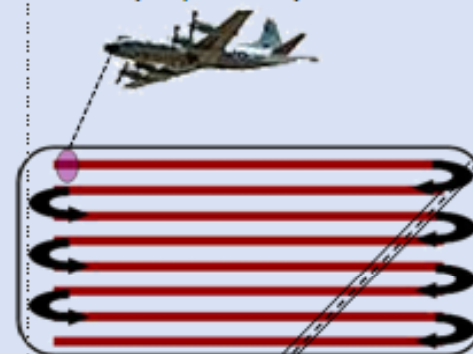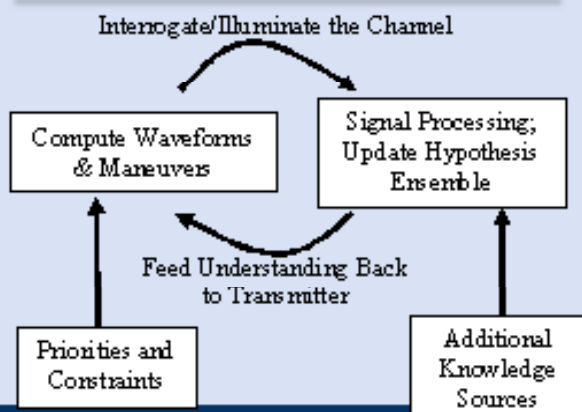   ← single scalar

Summary

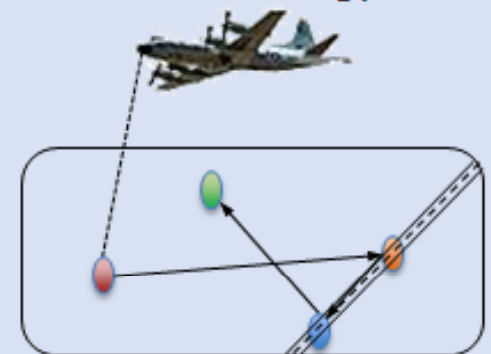We proposed source detection method using a network of sensors:
- utilizes localization followed by SPRT
- out-performs : under both smooth and non-smooth conditions
  any single SPRT method;
  majority and other fusion methods
- For radiation point source detection:
  - performs better than existing decision fusion methods
- Shows cyber-physical trade-off: better detection at higher cyber cost
  - lowest cost: single sensor with SPRT
  - intermediate cost: SPRT at sensors and Boolean fusion
  - highest cyber cost: send measurements and localization-based fusion

Cognitive Radar

- The University of Arizona is developing:
  - Robust Bayesian channel models for target recognition and surveillance
  - Algorithms for waveform optimization derived from the Bayesian models

- Cognitive Radar:
  - An approach to radar that closes the loop between exploitation (signal processing) and control/optimization of the measurements
  - Interrogate the radar environment through smart control of the interrogation properties (i.e., beamsteering, PRF, pulse shape) $\Rightarrow$ optimize available time/energy
  - Adaptive measurement control
    - Where to go, what to transmit, where to aim, who to cooperate with, ...

Interrogate/Illuminate the Channel

Compute Waveforms & Maneuvers

Signal Processing; Update Hypothesis Ensemble

Feed Understanding Back to Transmitter

Priorities and Constraints

Additional Knowledge Sources

Fixed search pattern; Includes areas where target unlikely

Adaptive search pattern; Focus radar on important, but uncertain, areas

Use past observations to enhance future measurements

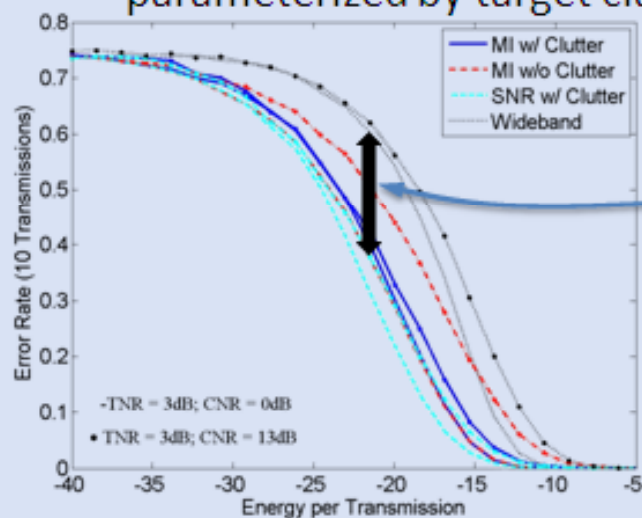THE UNIVERSITY OF ARIZONA®

Sample Results: Two Applications

Target ID

- Characterize targets by transfer function and compute variance over the classes:

$$\sigma_H^2(f) = \sum_{i=1}^{M} P_i \left| H_i(f) \right|^2 - \left| \sum_{i=1}^{M} P_i H_i(f) \right|^2$$
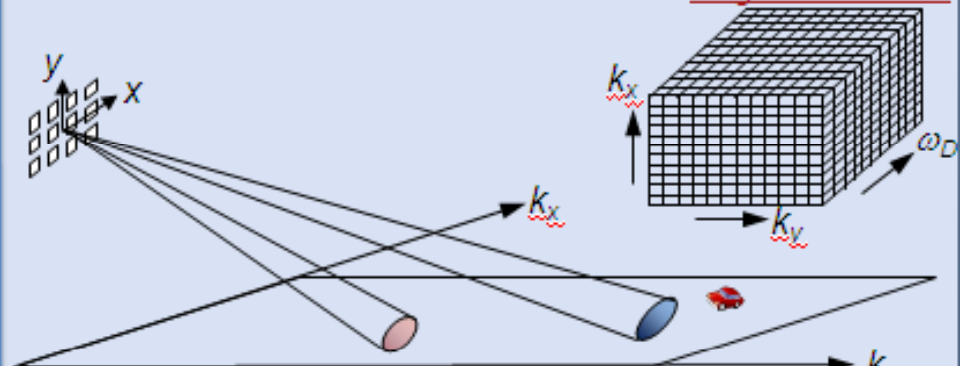
– A measure of entropy vs. frequency parameterized by target classes
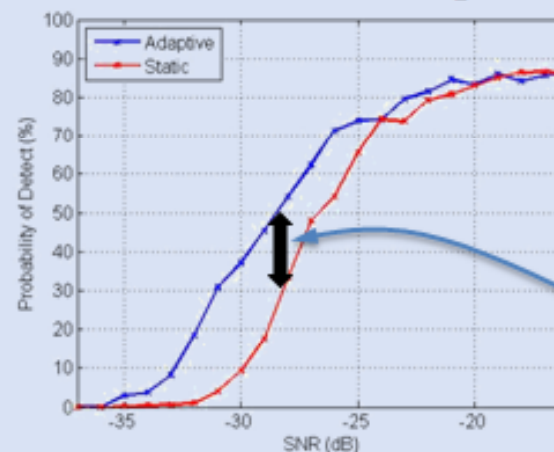

Gain due to adaptive, optimized waveforms

Search & Track

Target Parameters

- Describe target parameter space as a grid of target probabilities

- Convert the probabilistic representation into the best beamsteering location

Probability of detecting a weak target moving through search zone; (500-target test)

Adaptive Control makes more efficient use of time/energy!

Ongoing Work

- At UA:
  - Computationally efficient and robust probability update procedures
    - For example, how do we perform stable updates of the Bayesian probability map when interference/clutter have unknown pdf?
  - Probability updating procedures for multiple platforms (mapping of target parameters to range/Doppler/angle is unique for each platform)
  - Adaptive PRF selection for range-Doppler ambiguity mitigation
  - Practical classification algorithms and waveform constraints (e.g., constant modulus)
- Elsewhere:
  - Dr. Dan Fuhrmann (now at Michigan Tech University)
    - "Active-testing surveillance systems, or playing 20 questions with a radar"; 2003 ASAP workshop
      - Proposes radar measurement optimization via probabilistic representation (closed loop system!)
  - Dr. Simon Haykin, McMaster University
    - "Cognitive Radar: A Way of the Future", *IEEE Signal Processing Magazine*, Jan. 2006.
      - Summarizes philosophy of cognitive radar and feedback from receiver to transmitter
    - Cognitive Tracking Radar; Cognitive Dynamic Systems (http://soma.mcmaster.ca/haykin.php)
  - Dr. Arye Nehorai, Washington University-St. Louis
    - Adaptive waveform parameters and radar flight path (Asilomar 2008)
    - "Adaptive polarized waveform design for target tracking based on sequential Bayesian inference," *IEEE Trans. on Signal Processing*, Mar. 2008.

Signal Processing for Networked Sensing

A majority of performance improvements in Sensors, Networking and Communication connectivity are expected to come from conceptualization of new systems, and through innovations in Signal Processing.

Leverage developments in Signal Processing techniques to bring about improvements in sensing, target resolution, small target detectability, multi-target tracking, and address hard problems in sensor data fusion, track fusion and communications.