Information Fusion: Science and Engineering of Combining information from Multiple Sources

Presented by

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Research supported by the
Mathematics of Complex Networked Systems Program
Office of Advanced Scientific Computing
Department of Energy's Office of Science

Information Fusion at ORNL

- ORNL Instrumental in formulating and fostering this multi-disciplinary area
  - First DOE-sponsored workshop in 1996
  - Foundational analytical and applied work - originally funded by DOE BES Engineering Research Program
  - Statistical foundations for measurement data – also funded by ASCR Statistics Program
  - Cyber-physical networks – ASCR Applied Math Program 2009 - present
- Foundational work at ORNL:
  - Showed tractability of generic information fusion problem using measurements
  - Developed isolation and projective fusion methods
- Applications:
  - Fusion of embrittlement predictors of light-water reactors
  - Fusion of ultrasonic and infra-red sensors for robotics applications
  - Localization of low-level radiation sources by fusing network measurement
- Area of Increasing Importance
  - Applications to cyber-security, cyber-physical systems and sensor networks

First Workshop on Information Fusion - 1996

Department of Energy lead sponsor

Brought together scientists from:

Engineering, Computer Science, Mathematics,
Econometrics, Bioinformatics, and Statistics

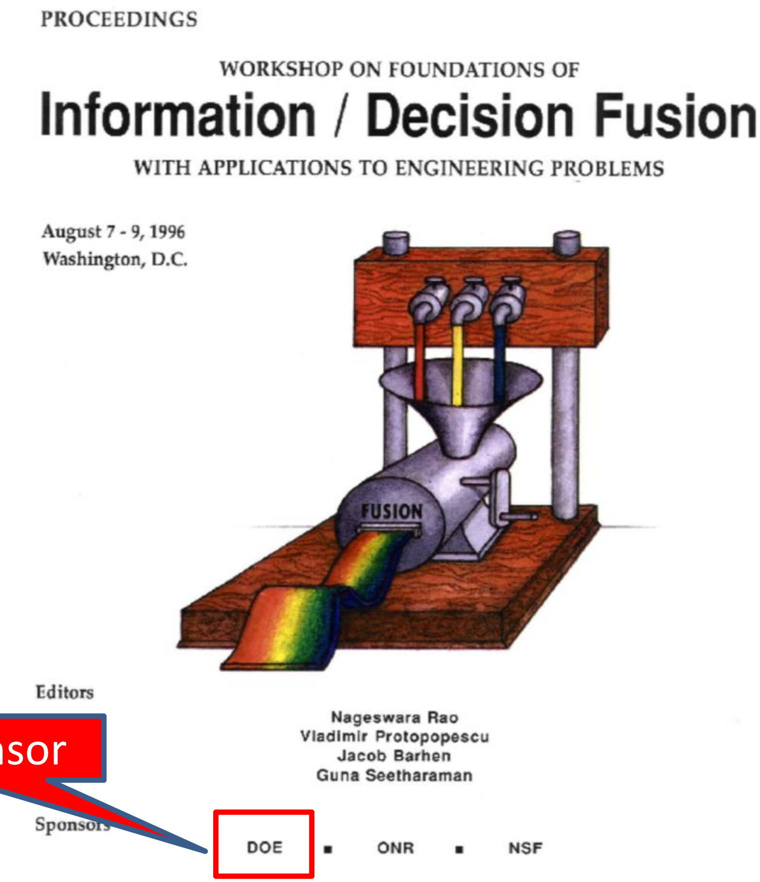
This workshop launched the field of Information Fusion

Now, Integral part of disciplines including:

- Distributed Sensor Networks
- Cyber Data Mining
- Cyber-Physical Networks

Journals:

- *Information Fusion* (2000)
- *Advances in Information Fusion* (2006)



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Dedicated International Conferences:

- International Conf. on Information Fusion
- International Conf. on Multisensor Fusion and Integration
- International Colloquium on Information Fusion

Information Fusion is a very old area! Eighteenth and Nineteenth Centuries

1786, Condorcet Jury Theorem: (224 years ago)
Democracy of N members each with probability *p* of making right decision: decision probability of majority under statistical independence:

$$p_N \begin{cases} > p & if \quad p > 1/2 \\ = 1/2 & if \quad p = 1/2 \\ < p & if \quad p < 1/2 \end{cases}$$

In general, "good" fuser is better than a member but bad fuser could be worse than member – if p is known to be <1/2, take opposite of majority.

1818, Laplace composite method: Certain differential equations are "better" solved by combining a number of "sub-optimal" solutions methods.

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

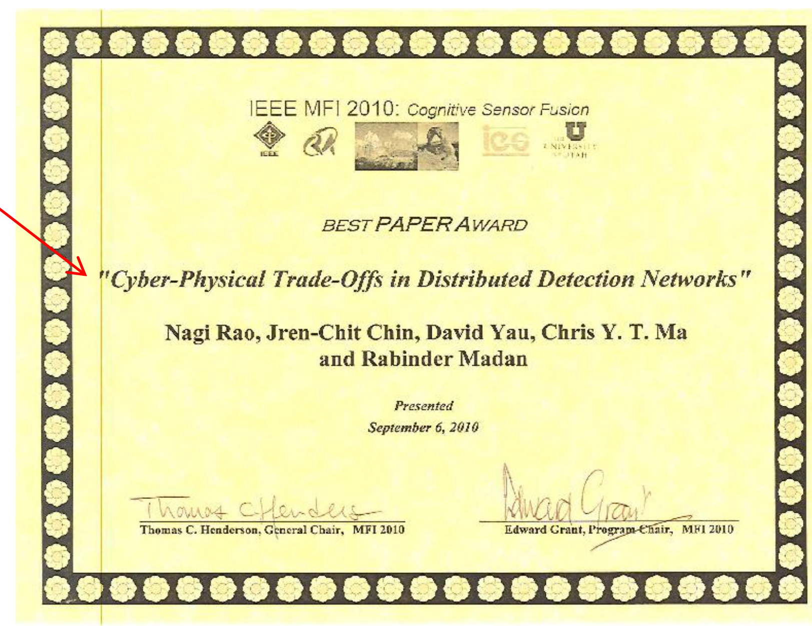
1962, Pattern Recognition: Chow showed optimal Bayesian threshold fuser for multiple independent classifiers.

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

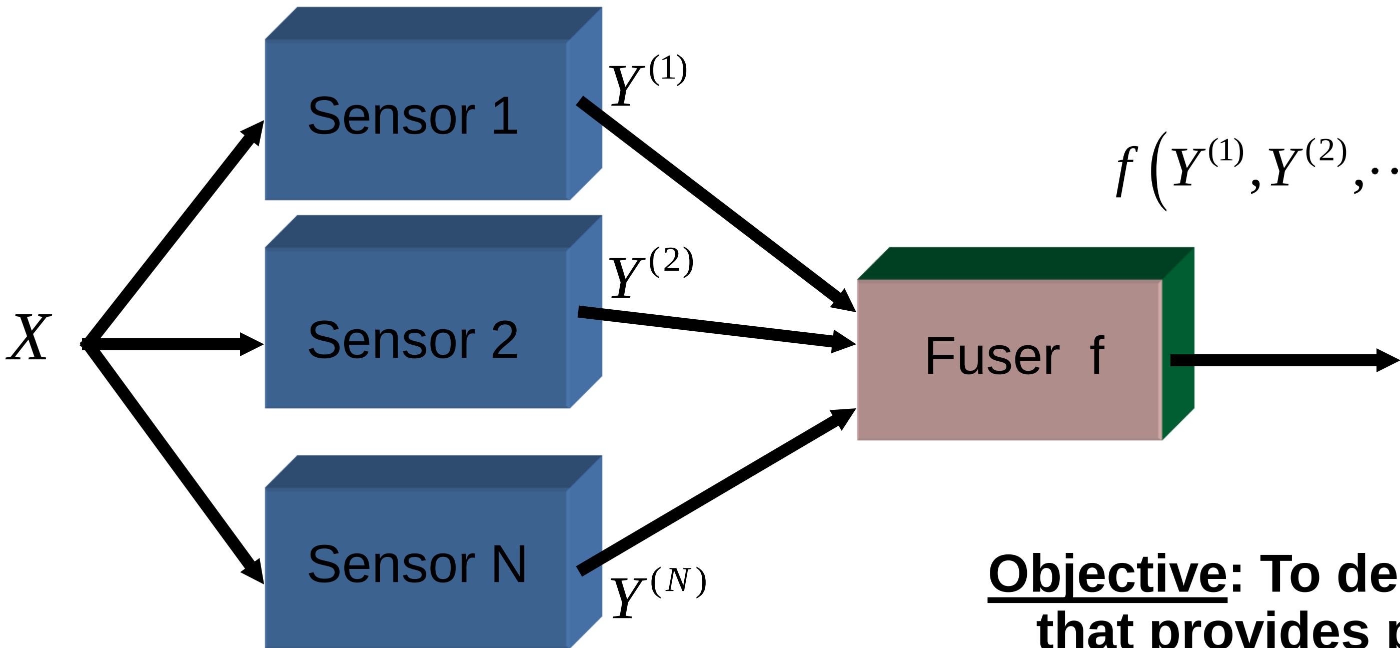
Importance of "fusing" rather than picking the "best" has been demonstrated in a number of disparate disciplines – political economy, applied mathematics, reliability, pattern recognition, forecasting

What is new about "recent" 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
- Expanding Application Areas:
  - Cyber Security
  - Cyber-Physical Networks
  - Sensor Networks
  - Data Mining
  - Sensor Fusion
  - Detection and Classification



Generic Sensor Fusion Problem



$$f\left(Y^{(1)}, Y^{(2)}, \cdots, Y^{(N)}\right) = f(Y)$$

Objective: To design a fuser that provides performance guarantees based on measurements.

X and $Y^{(i)}$ are related by an unknown distribution $P_{X,Y^{(i)}}$

Overview of ORNL Solutions: Finite Sample Guarantees

- General Solution
  - Showed that the problem is solvable in principle by empirical risk minimization
  - Under finiteness of scale-sensitive dimension of fuser class finite sample guarantees can be provided
- Specific Fuser Methods
  - Empirical risk minimization
    - Vector space methods
      - Linear fusers
      - Kurkova's neural networks
    - Sigmoid neural networks
  - Non-linear statistical estimators
    - Nadaraya-Watson estimator
    - regressograms
  - We developed finite sample guarantees for the fuser

Empirical Risk Minimization Method

Compute the fuser f from $\mathcal{F}$ to minimize the empirical risk

$$I_{emp}(f) = \frac{1}{l}\sum_{i=1}^{l}\left[X_i - f\left(i_i^{(1)}.Y_i^{(2)},\cdots,Y_i^{(3)}\right)\right]^2$$

Consider expected best fuser $\quad f^*: I_F(f) = \min_{f\in\mathcal{F}} I_F(f)$

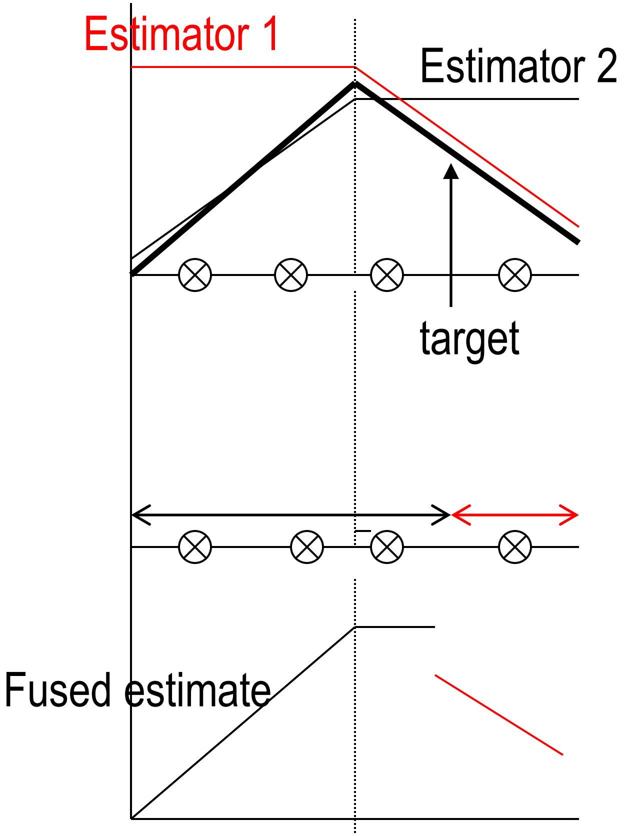
empirical best fuser $\quad \hat{f}: I_{emp}(f) = \min_{f\in\mathcal{F}} I_{emp}(f)$

If $\mathcal{F}$ satisfies certain properties, we can ensure $P_{X,Y}\left\{I_F(\hat{f}) - I_F(f^*) > \varepsilon\right\} < \delta$ irrespective of sensor distributions

Weakest deterministic characterization available under which this condition can be guaranteed is based on scale-sensitive dimension of $\mathcal{F}$

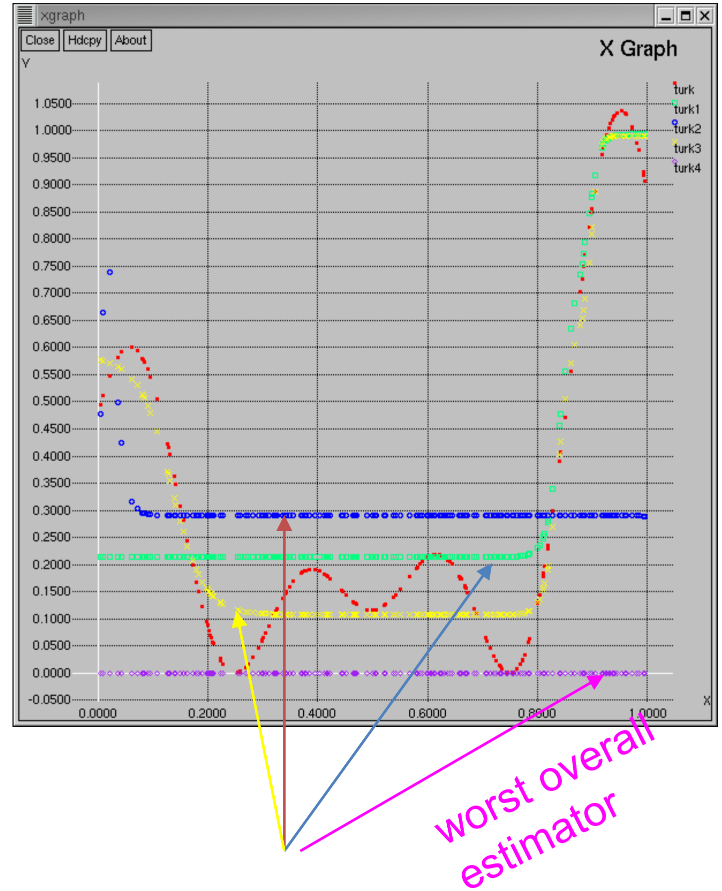
Nearest Neighbor Projective Fuser

- **Basic Idea**
  - Decompose into Voronoi regions of measurements
  - Given a test point
    - Identify Voronoi region that contains it
    - Use the estimator with least error as a predictor
- **Performance**
- **Computational: polynomial-time computable**
- **Finite-sample result: given finite sample, fuser performs almost as good as optimal with a high probability**
  - first finite sample result for projective fusers



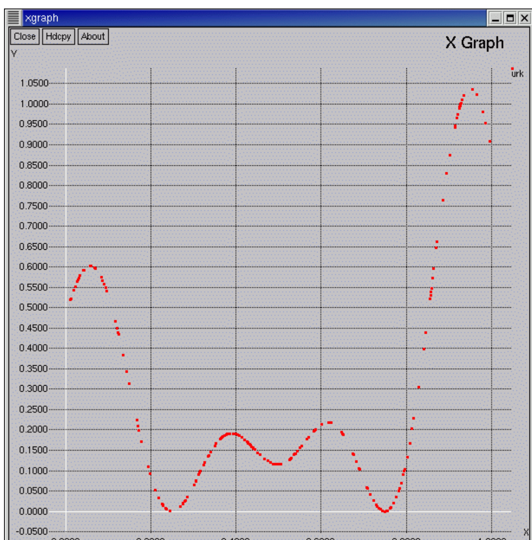
Application: Sigmoid Neural Network Estimators

- Training neural networks: for function estimation
  - Training problem is NP-hard
  - Most training algorithms yield sub optimal results
  - Backpropagation algorithm is sensitive to starting weights and learning rate

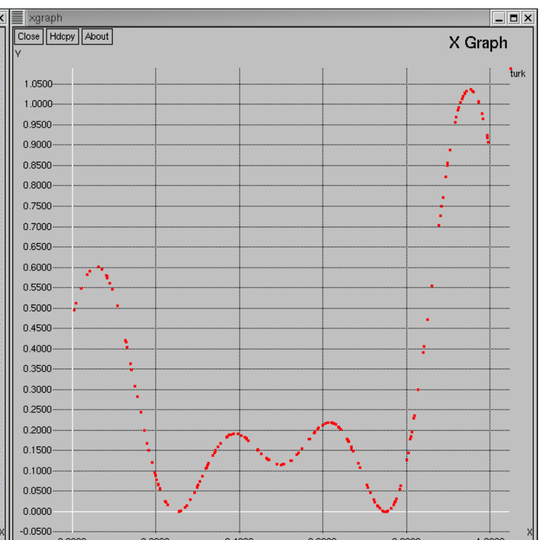


Sigmoid neural networks: different starting weights and learning rates

training data



test data

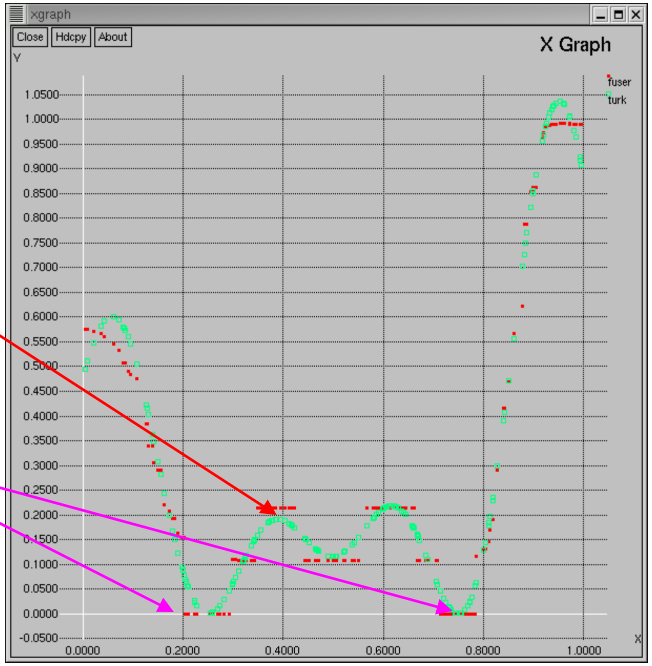


Fused Neural Network Estimators

Nearest neighbor projective fuser

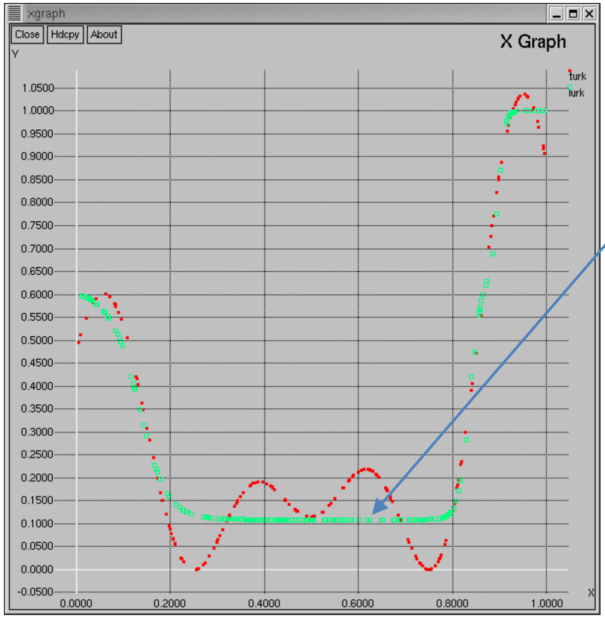
Uses locally best estimators

Note the worst overall estimator is good at certain parts



Linear fuser

Picks a single weight for entire domain



Embrittlement Predictions

- Overall Goal: Predict residual defects in materials due to neutron-induced damage in light-water reactors
- Transition temperature shift – vital indicator of embrittlement level
  - Several predictors available – generic sensor in our case
    - Fluence-based models
    - Eason's models
    - Reg. Guide 1.99 model
    - Feedforward neural network models
    - Nearest-neighbor model
- Fusion Approach: Combine all the predictors
- General Electric boiling water reactor data
    - Isolation Fuser (linear least squares)
      - 56.5% and 32.8% reduction in uncertainty for plate and weld data, respectively, over best model
    - Nearest Neighbor Projective Fuser
      - 67.3% and 52.4% reduction in uncertainty for plate and weld data, respectively, over best model

Motivating Scenario: Detection of Low-level Radiation Sources

Sources of low-level radiation

- **Unexploded dirty bombs during storage and transportation**
- **Slow leakage or controlled injection**
- **Combined with conventional explosions**

It is becoming easier to procure radioactive material

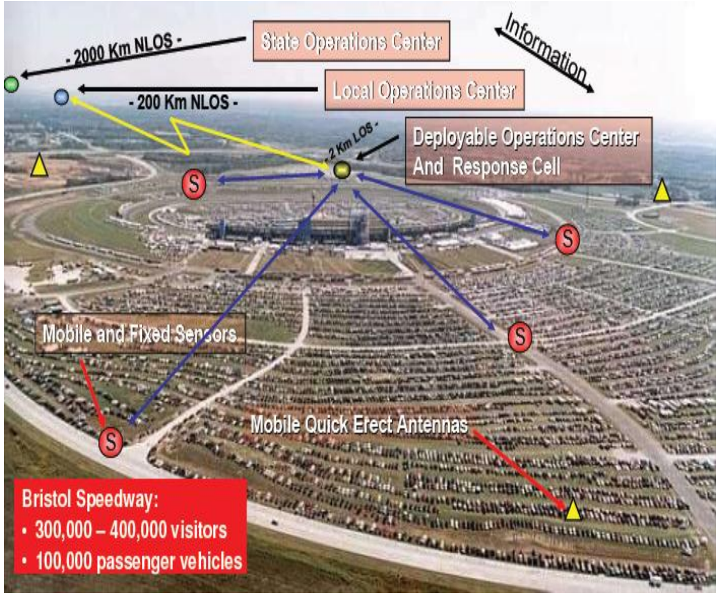
<u>Task:</u>

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**
- **Varied Background: Depends on local natural and man-made sources and may vary from area to area**
- **Probabilistic Measurements: Radiation measurements are inherently random due to underlying physical process – gamma radiation measurements follow Poisson Process**
- **Several solutions are based on thresholding sensor measurements**

Well-Studied Problem: Has been studied for decades using single or co-located sensors: analytical, experimental and

- sensor networks offer "newer" solutions but also questions

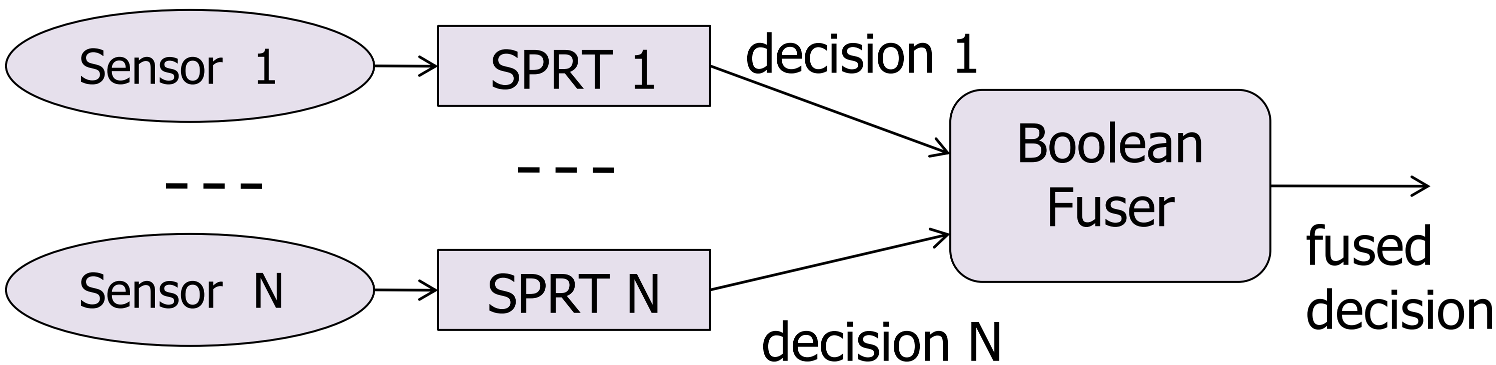
Recent Results (2010):

ORNL developed mathematical quantification for a network of sensors to achieve better performance than single-sensor detectors

Detection of Sources Amidst Background

A Traditional Detection Fusion Method:

1. Sequential Probability Ratio Test (SPRT) to infer detection (yes/no) from measurements at sensors;
2. Fuse the Boolean decisions at fusion center.



ORNL Results (2010):
Developed methods that out-perform this established method of fusing decisions.

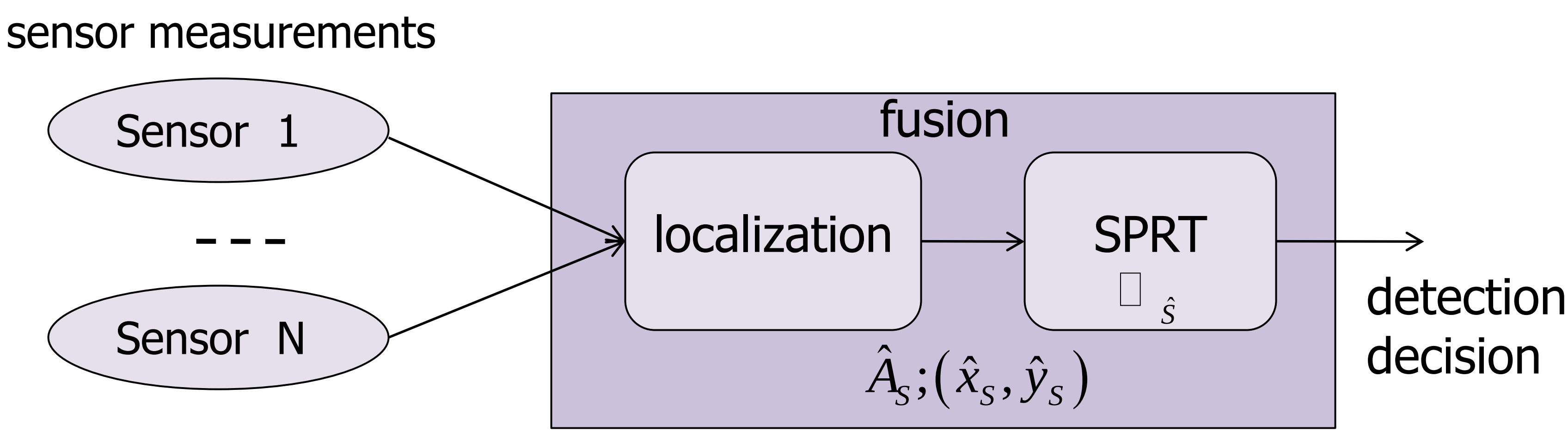
Localization-Based Fusers

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 $\Theta_{\hat{S}}$ at the fusion center

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

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



DOD Radar Fusion Framework: Localization is performed after detection, but our results do the opposite as in computer vision applications

Summary: Improved Detection through Localization

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

- Network Communications Losses: 2011
  - Conditions: Communication losses
    - + under bounded losses, improved detection is still achieved
    - - under severe losses, network under-performs detectors
- General non-smooth conditions: 2010
  - Conditions: Separability of probability ratios
    - - complex analysis and less intuitive conditions
    - + valid under complex shielding of radiation sources
- Smoothness conditions: 2009
  - 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:
  - a network of sensors performs better than single or co-located sensors
  - measurement “fusion” performs better than detection fusion

To Network or Not to Network ?

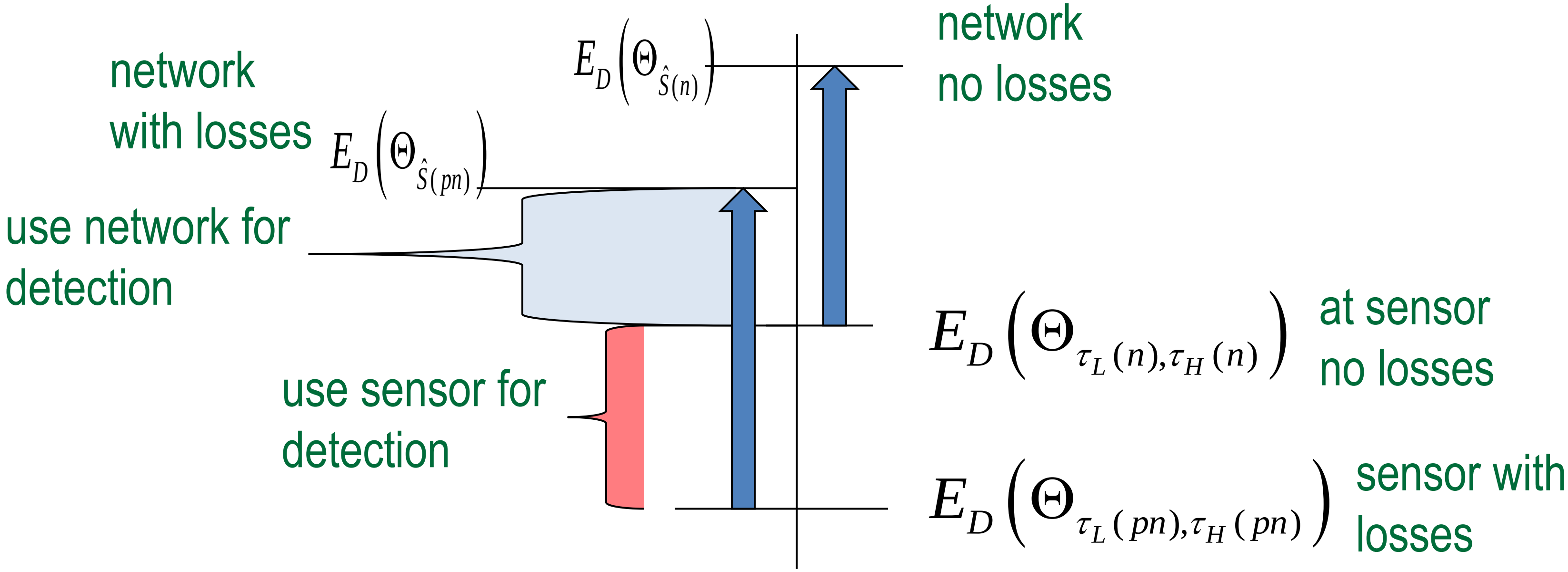
Detection based on *pn* and *n* measurements by network and sensor, respectively

$$E_D\left(\Theta_{\hat{S}(pn)}\right) > E_D\left(\Theta_{\tau_L(n),\tau_H(n)}\right)?$$

Ensured by large enough packing number

$$\mathbf{M}_\infty\left(\mathbf{Z}_L, \in_{pn,D_\mathbf{Z}}, \in_{pm,D_\mathbf{F}}\right) > 1 + \frac{1}{p_{\in_{pn,D_\mathbf{Z}},\in_{pm,D_\mathbf{F}}}}\left[\frac{E_D\left(\Theta_{\tau_L(n),\tau_H(n)}\right)}{\delta\left(\in_{pn,D_\mathbf{Z}}, pn, N\right)} - E_D\left(\Theta_{\tau_L(pn),\tau_H(pn)}\right)\right]$$

Beyond certain loss rate, $E_D\left(\Theta_{\hat{S}(pn)}\right)$ may be degraded below $E_D\left(\Theta_{\tau_L(n),\tau_H(n)}\right)$



Conclusions

- Information fusion is a multi-disciplinary area
  - In existence for centuries – political economy, forecasting, statistics, reliability, pattern recognition
  - New applications and developments – sensor networks, cyber security, data mining, cyber-physical networks
- ORNL developed solutions to generic sensor fusion problems:
  - Solutions based on empirical estimation and statistical estimators
  - Three general classes of fusers
    - Isolation fusers– illustrated with classifiers
    - Projective fusers – illustrated with function estimators
    - Localization-Based fusers – illustrated with radiation source detection
  - Motivated by practical problems: robotics, radiation source detection, embrittlement predictions
- Challenges in Information Fusion
  - Measurements from physically distributed processes exploit physical models and laws
  - Cyber-physical networks combine information from different modalities

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