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

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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, 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
  - *Advances in Information Fusion* (2006)
- 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! 
18th and 19th 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:
  \[
  p_N = \begin{cases} 
  > p & \text{if } p > 1/2 \\
  = 1/2 & \text{if } p = 1/2 \\
  < p & \text{if } p < 1/2 
  \end{cases}
  \]
- 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 “suboptimal” solution 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 showed “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 economics, 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
Objective: To design a fuser that provides performance guarantees based on measurements.

\[ f(Y^{(1)}, Y^{(2)}, \ldots, Y^{(N)}) = f(Y) \]

\[ X \] 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
  - Nonlinear statistical estimators
    - Nadaraya-Watson estimator
    - Regressograms
  - We developed finite sample guarantees for the fuser
Empirical risk minimization method

Compute the fuser $f$ from $F$ to minimize the empirical risk

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

Consider expected best fuser

$$f^* : I_F(f) = \min_{f \in F} I_F(f)$$

Empirical best fuser

$$\hat{f} : I_{emp}(f) = \min_{f \in F} I_{emp}(f)$$

If $F$ 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 $F$
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 well 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 suboptimal results
  - Backpropagation algorithm is sensitive to starting weights and learning rate

Sigmoid neural networks: different starting weights and learning rates
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

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
  - 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
Our method: Detection by using localization $\Theta_{\hat{S}}$

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

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

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

Sensor 1

Sensor N

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

• Improved detection using measurements at fusion center compared to existing decision fusion methods, using robust localization, under:
  – General nonsmooth conditions: 2010
    • Conditions: Separability of probability ratios
      – Complex analysis and less-intuitive conditions
      + Valid under complex shielding of radiation sources
  – Smooth 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
  1. A network of sensors performs better than single or co-located sensors
  2. Measurement “fusion” performs better than detection fusion
Conclusions

• Information Fusion is a multidisciplinary area
  – In existence for centuries—political economics, 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
  – Two general classes of fusers
    • Isolation – illustrated with classifiers
    • Projective fusers – illustrated with function estimators
  – 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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