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Signal Processing, Sensor Fusion, and Target Recognition XIX

Ivan Kadar
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Contents

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1 Multisensor Fusion, Multitarget Tracking, and Resource Management I
Kenneth J. Hintz, George Mason University (United States)
Thiagalingam Kirubarajan, McMaster University (Canada)

2 Multisensor Fusion, Multitarget Tracking, and Resource Management II
Kenneth J. Hintz, George Mason University (United States)
Ahmed O. Nasif, George Mason University (United States)

3 Multisensor Fusion Methodologies and Applications I
Ronald P. Mahler, Lockheed Martin Maritime Systems & Sensors (United States)

4 Multisensor Fusion Methodologies and Applications II
Ronald P. Mahler, Lockheed Martin Maritime Systems & Sensors (United States)

5 Invited Panel Discussion: Real-World Issues and Challenges in the Integration of Fusion Functions
Chee-Yee Chong, BAE Systems Advanced Information Technologies (United States)
Frederick E. Daum, Raytheon Company (United States)

6 Multisensor Fusion Methodologies and Applications III
Chee-Yee Chong, BAE Systems Advanced Information Technologies (United States)
Kenneth J. Hintz, George Mason University (United States)
Michael L. Hinman, Air Force Research Laboratory (United States)

7 Multisensor Fusion Methodologies and Applications IV
Michael L. Hinman, Air Force Research Laboratory (United States)
Chee-Yee Chong, BAE Systems Advanced Information Technologies (United States)
Kenneth J. Hintz, George Mason University (United States)

8 Multisensor Fusion Methodologies and Applications V
Michael L. Hinman, Air Force Research Laboratory (United States)
Chee-Yee Chong, BAE Systems Advanced Information Technologies (United States)
Kenneth J. Hintz, George Mason University (United States)

Invited Panel Discussion

Real-World Issues and Challenges in the Integration of Fusion Functions

Organizers

Ivan Kadar, Interlink Systems Sciences, Inc.

Oliver E. Drummond, CyberRnD, Inc. and Consulting Engineer

Thiagalingam Kirubarajan, McMaster University, Cananda

Moderators

Chee-Yee Chong, BAE Systems Advanced Information Technologies

Frederick E. Daum, Raytheon Company

April 5, 2010

SPIE Conference 7697

"Signal Processing, Sensor Fusion and Target Recognition XIX"

Orlando, FL April 5-7, 2010

Invited Panel Discussion

Participants:

Dr. Chee-Yee Chong, BAE Systems Advanced Information Technologies, U.S.A.

Dr. Frederick E. Daum, Raytheon Co., U.S.A.

Dr. Oliver E. Drummond, CyberRnD, Inc.,and Consulting Engineer, U. S. A

*Dr. Ivan Kadar, Interlink Systems Sciences, Inc., U.S.A.

Professor Thiagalingam Kirubarajan, McMaster Univ.(Canada)

Dr. Ronald P. S. Mahler, Lockheed Martin Maritime Systems and Sensors, U.S.A

Dr. Aubrey B. Poore, Numerica Corp., U.S.A.

* Note: Unable to attend

Invited Panel Discussion

Topics

"Paradox in Real-World Sensor Fusion"
Dr. Frederick E. Daum, Raytheon Co.

"Information Exchanged Between Fusion Tracker and Other Fusion Functions"
Dr. Oliver E. Drummond, CyberRnD, Inc., and Consulting Engineer

"Some Issues in MHT Tracking and Resource Management"
Dr. Aubrey B.Poore, Numerica Corporation

"Developing Trust in Fusion Systems"
Dr. Chee-Yee Chong, BAE Systems Advanced Information Technologies

Invited Panel Discussion

Topics

***"Interactions of Real-World Fusion Functions"**
Dr. Ivan Kadar, Interlink Systems Sciences, Inc.

"Unified Statistical Integration of Fusion Functionalities"
Dr. Ronald P. S. Mahler, Lockheed Martin Maritime Systems and Sensors

"Some Research Issues for the Real-World"
Professor Thia Kirubarajan, McMaster Univ. (Canada)

* Note: Unable to attend

Paradox of real World multisensor fusion

Fred Daum

5 April 2010

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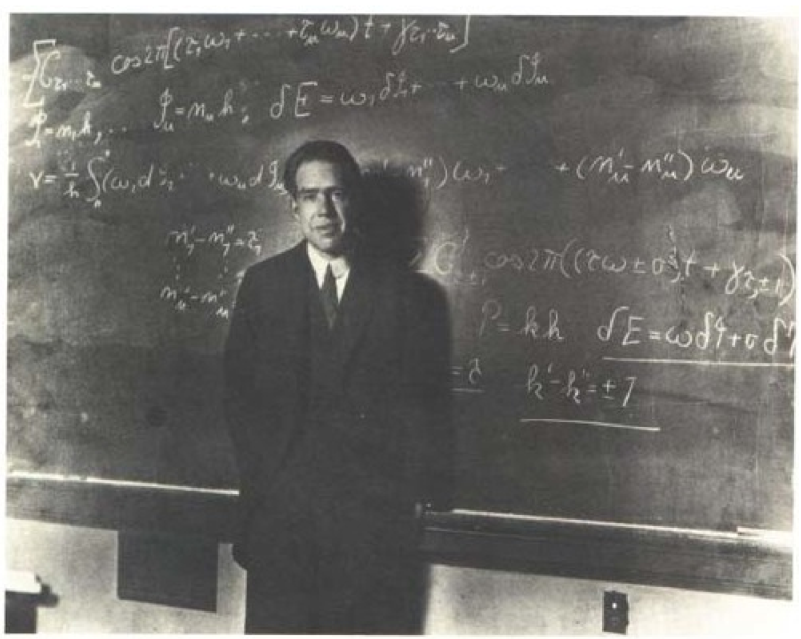
Paradoxes

- Zeno's
- Russell's
- Olber's
- D'Alembert's
- Banach-Tarski's
- Birthday
- Monty Hall

“There is no hope of advance in science without a paradox.”



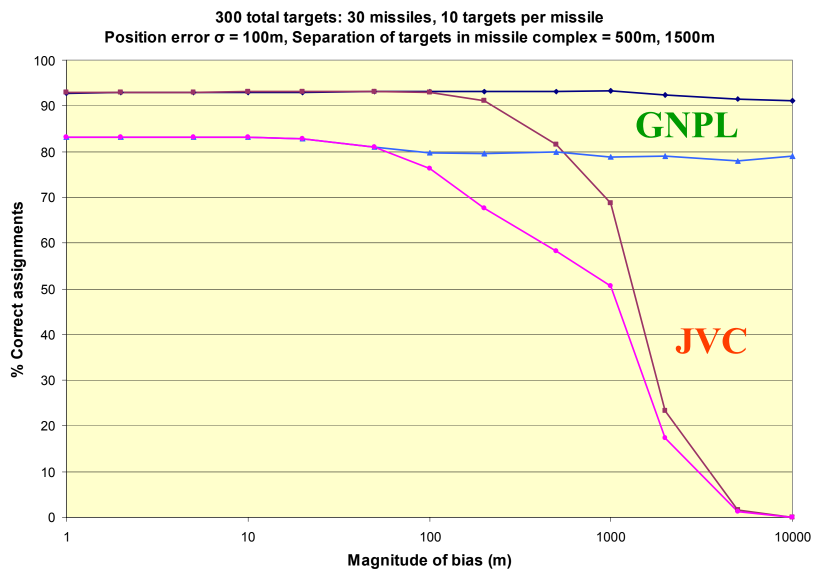
paradox

theory	intuition	real World
More sensors cannot degrade performance (on average), if we use the optimal algorithms.	More sensors should improve estimation & decision accuracy.	More sensors often degrade performance significantly.

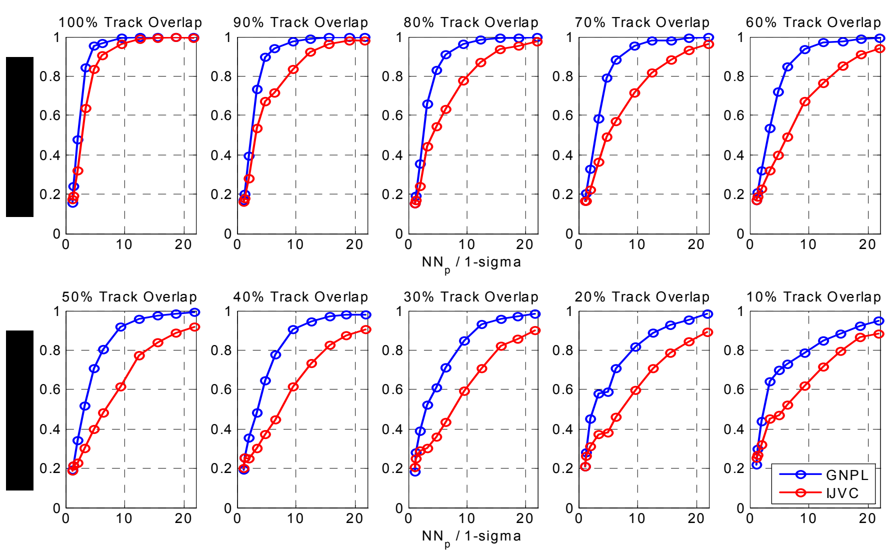
Explanation for paradox:

- (1) Bugs in the software
- (2) Suboptimal algorithms or bad algorithms
- (3) Data association errors
- (4) Unresolved measurements
- (5) Residual sensor bias & drift errors (tropospheric refraction, ionospheric errors, IMU errors, GPS errors, radome refraction, scan dependent monopulse bias, monopulse error slope, FPA errors, etc.)
- (6) Multipath, ducting & clutter
- (7) Jamming, chaff, flares & other countermeasures
- (8) Ill-conditioning of the covariance matrices or the particle filter probability density
- (9) Nonlinearities in the estimation problem
- (10) Glint (i.e., targets are not points and they rotate)
- (11) Limitations of comm links & format & info. content
- (12) Incorrect or incomplete probability model (e.g., covariance inconsistency or assumption of zero correlation or statistical independence between random variables*)

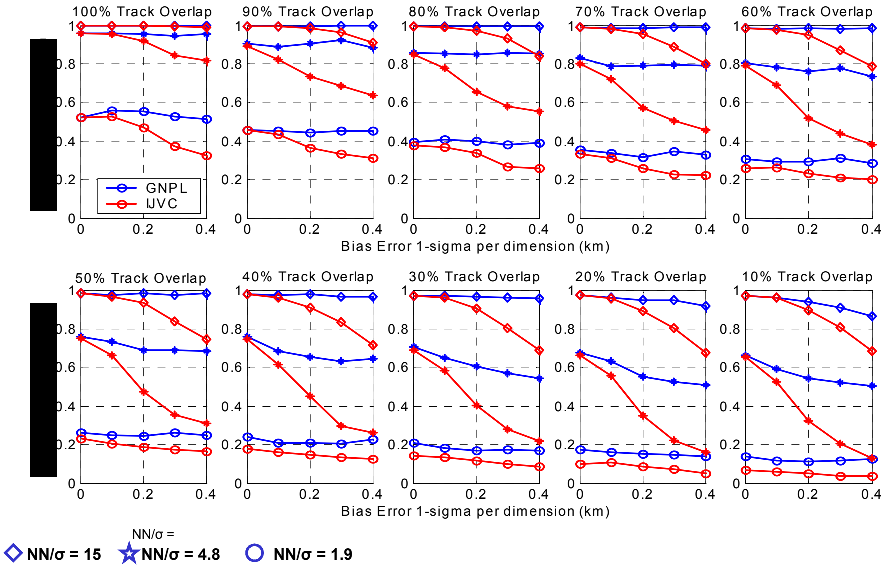
Bias can ruin multi-sensor fusion



GNPL with adaptive gating is much better than Iterative JVC (d = 6 & N = 10 tracks)



GNPL is much more robust to bias than iterative JVC (d = 6 & N = 10 tracks)



Paradox in real world sensor fusion

Fred Daum

In theory and intuitively, one would expect that using more sensors for estimation and decisions would improve performance (on average). Assuming optimal fusion algorithms, this can be proved rigorously under very mild technical assumptions. But in the real world with suboptimal fusion algorithms, we often find that using more sensors actually degrades performance significantly. This is the case for several big expensive important high tech real world applications (which shall remain nameless). Aside from bugs in the software and poor algorithm design, generally there are several reasons for this paradox, including: (a) neglect of data association errors; (b) neglect of unresolved measurements; (c) neglect of residual sensor bias and drift errors (e.g., tropospheric & ionospheric refraction, radome refraction & reflections, IMU & GPS errors, scan dependent monopulse bias for phased array radars, and multipath); (d) ill-conditioned error covariance matrices in the EKF or UKF or batch or ill-conditioned densities in the particle filter (despite double precision floating point arithmetic); (e) nonlinearities in the estimation problem, which render the algorithms highly suboptimal; (f) neglect of some important physical effects in the sensors, environment and targets (e.g., real targets are not points and they generally rotate); (g) latencies and bandwidth constraints and unhelpful protocols in the comm network; etc.

Information Exchanged Between Fusion Tracker and Other Fusion Functions

Panel Discussion on Real-World Issues and Challenges in Integration of Fusion Function

5 April 2010

Excerpts From
Multiple Target Tracking Lecture Notes

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Topics

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- **Part 1: Introduction and Background**
- **Part 2: Information Exchanged Between Fusion Tracker and Other Fusion Functions**
- **Part 3: Conclusions**
- **Part 4: References**

Introduction and Background

A View on Classifying the State-of-the-Art for Tracking or Fusion

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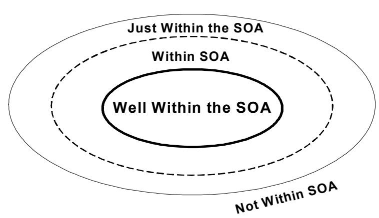
Degrees Within The State of the Art



Degrees Within SOA	
Symbol	**Degree**
+	Well Within
	Within
-	Just Within

Degrees of Maturity	
Symbol	**Test Conditions**
A	Operational System
B	Field Tests or Real Data
C	HiFi Monte Carlo Simulation
D	Feasiability Testing or Conceptual

Types of Targets Tracked
Submarine
Surface
Ground
Air Breather
Ballistic

Example: **Look-Down Single-Sensor MHT Ground Tracking: B-**

Issues of the SOA of Processing

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- **Two Different Aspects of the SOA.**

  Note that the process of interest could be a function (bias estimation), major function (tracker), or system (entire fusion system)
  - **What is the SOA for a specific type of threat and applications?**
  - **How do the requirements, goals, or intent of a specific project/program compare to the current SOA?**

- **When Asked What Is the SOA of a Particular Function, One Engineer Would Reply With One of the Following:**
  - **We developed that processing "X" years ago.**
  - **We are developing that now.**
  - **That is not important.**

On The State-of-the-Art Of Target Tracking and Related Processing (A Personal Opinion)

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- **The State-of-the-Art (SOA) of Target Tracking with Single Sensor Data Under Challenging Conditions:**
  - **Has improved greatly in recent years relative to what is achievable -- is moderately mature**
  - **Improvements are still needed for some specific conditions**
- **Fusion Tracking SOA Lags Far Behind Single-Sensor Tracking**
  - **Fusion introduces opportunities and challenges that do not exist in tracking with single sensor data**
  - **N-sensors offer potential for superior performance relative to tracking with data from a single sensor.**
    - Increased sample rate provides an accuracy increase of at least $\sqrt{N}$
    - Three well located radars provide an accuracy increase of about a factor of 4
    - Offers opportunity for enhanced survivability and graceful degradation
- **Major Trade-Off is Performance Vs Required Resources & Cost**

Some Fusion Considerations

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- There Are No Off-the-Shelf, Universal Fusion Processors; Fusion System Must Be Developed Based on the Requirements and Specific of the Application, Such as Threat Characteristics and Available Hardware.
- The Fusion System Design Depends on:
  - Relative location of the sensors, fusion processors, and users, e.g., physically centralized vs. distributed
  - Communications and processor capacities; threat characteristics
  - System requirements relative to fusion state-of--the art
- Even for a Specific Application, Many Different Types of Sensor Data Fusion Processing Systems Are Possible Each with Different Function Decompositions.
- Fusion Algorithm Architecture and Functional Decomposition Depends on the Specific Fusion System Approach. A Specific Type of Fusion System Has Been Chosen to Simplify This Presentation.

Assumptions for This Presentation

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- To Simplify This Presentation, Assumed a Specific Fusion Problem and Approach (Unless Indicated Otherwise):
  - Multiple platforms; distributed sensors, users, fusion processors
  - IFF, ATR, 2-D, and 3-D data sensors; moderate coverage overlap
  - Limited resolution, moderately close targets, and false signals
  - Moderate Overlap of Coverage by Sensors
  - Air defense (small targets); require SIAP & graceful degradation
  - Requirements: ambitious with challenging conditions (beyond SOA)
  - Moderate communications, processor, and weapons resources
  - Measurement and tracklet (hybrid) fusion for track maintenance
  - Distributed 2-D data assignments with feature/attribute aided tracking
- Address One of the Two Types of Fusion Development Issues
  - Not Addressed: Algorithm development to accommodate multiple sensor data fusion tracking instead of data from a single sensor
  - ***Address explicit interaction between the fusion tracker and other fusion functions and their responses***

Information Exchanged Between Fusion Tracker and Other Fusion Functions

Fusion Functions With Inputs to or Outputs From Tracker (Table 1)

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		Function-Tracker Interface	
	System Major Function	To Tracker	From Tracker
1	Display		X
2	Human Override	X	
3	Implement Commanders Guidance	X	X
4	Manage Processing	X	X
5	Data Base Management	X	X
6	Classification / ATR / Discrimination	X	X
7	CID	X	X
8	Threat/Situation Assessment	X	X
9	Kill Assessment	X	X
10	Target-Weapon Assignment	X	X
11	Data Distribution	X	X
12	Sensor Resource Management	X	X
13	System Damage Control	X	X

Processing That Fusion Trackers Share With Most Other Functions

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- **All Functions Employ Separate Processing of Classified Information. Tracker Marks Security of a Track When It First Employs Classified Measurements That Makes the Track Classified.**
- **Most Functions Need to Know If And When a Track Switch Is Identified and the Appropriate Tracks Are Marked Accordingly.**
- **Most Functions:**
  - **Contribute to setting the value of the track's "potential value added" (or "priority") by evaluating the importance of updating the track using the potentially available information.**
  - **Each function shows preference in processing based on the track's potential value added.**

Sp10_OEDPanelPrestFn.ppt 11

Covariance Consistency Is More Important in Fusion Systems

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- ***Covariance Consistency* Measures How Realistically the Tracker Computed Covariances Reflects the Actual Innovation or Estimation Error Covariance. Currently, Many Fusion Tracks Exhibit Degraded Consistency.**
- **Primary Source of Inconsistency is Tracker Model Errors in the Structure and Parameters. Causes Can Include:**
  - **Inadequate Compensation of Residual Biases of Measurements and Their Time Tags; of Sensor Location and Orientation; and Inconsistency of their Covariances.**
  - **Misrepresented Covariance Matrix of the Input Data**
  - **Errors in Dynamic State Transition Model or Parameters**
  - **Missing (or Incorrect) Compensation for Possible Misassociation**
  - **Linearization of Non-linearities, e.g., Coordinate Transformations**
  - **Round-off Errors or Simplified (or Incorrect) Algorithm Design**
  - **Hardware or Software Implementation Errors or Damage**

Sp10_OEDPanelPrestFn.ppt 12

Many Functions Expected to Depend on Reasonable Covariance Consistency

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- **Functions Expected to Depend on Reasonable Covariance Consistency of Fusion Tracker Estimated Kinematic, Features, or Attribute States:**
  - **Human Override**
  - **Manage Processing**
  - **Classification / ATR / Discrimination**
  - **CID**
  - **Threat/Situation Assessment**
  - **Kill Assessment**
  - **Weapons Manager**
  - **Data Communications Manager**
  - **Sensor Resource Manager**
  - **System Damage Control**

Challenging Interactions Between Fusion Tracker and Processor Manager

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- **Advanced Systems Should Require Graceful Degradation**
  - **In Spite of Unexpected Regions of Dense Targets and Large Number of Targets Plus Damaged/Degraded Hardware.**
    - Tracker needs to provide estimates of processing load prior to processing a frame of data (or provide the information so Processor Manager can compute it).
    - Tracker needs to be able to adjust processing parameters to stay within processing load budget provided by Processor Manager for the current frame of data.
- **Both Functions Contribute to Deciding for Which Tracks to Distribute Tracklets.**
- **Tracker Assists in Identifying Processing Inconsistencies or Errors and Identifying Potential Sources of the Problem.**

Major Interactions Between Fusion Tracker and Sensor Resource Manager

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- **Tracker Provides Sufficient Information (Potential Value Added) for Sensor Resource Manager to Identify Which Sensor Regions Would Provide the Most Useful Information for Improved Accuracy and Consistency of Tracker Estimated Kinematic, Feature, and Attribute States.**
- **Both Functions Contribute to Deciding From Which Target Tracks to Distribute Tracklets.**
- **Tracker Requests Measurements From Specific Sensor Regions Needed to Update Bias Estimates and Their Covariance Consistency.**
- **Tracker Requests Measurements From Specific Sensor Regions Needed to Update Adaptive Estimates of Tracker Processing Parameters and Their Covariance Consistency.**

Sp10_OEDPanelPrestFn.ppt 15

Interactions Between Fusion Tracker and Other Fusion Functions (1 of 3)

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- **Tracker Provides Sufficient Information to *Data Base Manager* for It to Maintain a Relational Data Based That Also Supports Geographical Queries.**
  - **The goal is to let the operator (Human Override) simplify what is on the display and manage by exception**
  - **The goal is to provide operator ready access to more information on demand including relational queries,**
  - **Note that the assumption that all data is stored in the on-board database including track data. A fusion function obtains track information from the Data Base Manager not from the Tracker.**

Sp10_OEDPanelPrestFn.ppt 16

Interactions Between Fusion Tracker and Other Fusion Functions (2 of 2)

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- The *Weapons Manager* Provides the Fusion Tracker (by Way of the Data Base) When a Weapon Engages a Target and the Weapons Nominal Trajectory So It Can Be Easily Tracked (If Applicable).
- The Fusion Tracker Needs to Be Able to Change Track Data in Response to Changes Directed by the *Human Override*.
- Tracker Provides Sufficient Information for the *Data Communications Manager* to Identify (If Any)
  - Which measurements received from other platforms not to process on-board (screen out, discard)
  - .Which on-board measurements not to distribute to other platforms.

Interactions Between Fusion Tracker and Other Fusion Functions (3 of 3)

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- The *Kill Assessment Function* Provides the Fusion Tracker (by Way of the Data Base) the Status of Each Target Engaged and If It Still Exists but Is Harmless or It Was Destroyed and the Track Can Be Terminated.
- Tracker Provides Sufficient Information to the *System Damage Control* to Identify Inconsistent Processed Data (Such Degraded SIAP) or Faulty Fusion Processing or Hardware Anywhere in the Fusion System So That the System Can Be Reconfigured.

Conclusions
(A Personal Opinion)

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- **The "Hi Fi Sim" SOA of Basic Fusion Kinematic Tracking Is Moderately Mature ("Within" That SOA).**
- **The SOA of the Entire Fusion Processing System Is Far Less Mature Than Basic Fusion Tracking.**
  - **Tracker Algorithm Development Is Needed to Take Advantage of the Opportunities for Substantial Improvement of Functional Performance of Both Tracking and Target Classification by More Effectively Fusing the Data From Multiple Sensors**
  - **The System Battle Management Performance Would Benefit Greatly From Further Development of the All the Fusion Processing Functions With Special Attention to the Interactions Between Functions**
  - **Additional Algorithm Development Is Needed for the More Challenging Conditions and for Graceful Degradation**

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Information Exchanged Between Fusion Tracker and Other Fusion Functions

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Abstract

Multiple-sensor data fusion offers the opportunity for substantial improvement in functional performance compared to single sensor processing. Data fusion processing, however, is typically substantially more complex than processing with data from a single sensor. Consequently, data fusion processing typically involves more processing functions than processing with data from a single sensor. Accordingly, the fusion tracker function may be required to provide more and better information to the other fusion-level (network-level) functions. The fusion track function may also be required to receive and act on more information from the other fusion functions than the information typically received by a single sensor tracker. The types of information that the fusion tracker function is expected to provide to the other fusion functions as well as the types of information provided by the other fusion functions that the fusion tracking function is expected to utilize are the subject of this presentation.

Keywords: Sensor Data Fusion, Target Tracking, Fusion Tracker, Data Fusion Functions, Measurement Fusion, Covariance Compensation, Network Centric Tracking, and Hybrid Fusion.

Presentation Summary

Fusion target tracking and classification problems can be broadly categorized into four generic types [1], as follows:

1. Sensor tracking of a single (bright) target
2. Tracking of large targets
3. Tracking of medium sized targets
4. Tracking of small targets.

Note that the size indicated in this list is in terms of the number of resolution elements or pixels of a target. Typically, a small target is less than 12 pixels (resolution elements) in width. The algorithms used in the signal, image, and track processing for each of these types of problems differ substantially. Since each type of tracking problem poses different algorithm development issues, this paper and the accompanying Power Point presentation concentrate on only one type, namely, fusion tracking of small targets using multiple target tracking methods. Multiple target tracking is a relatively new field. The first book dedicated exclusively to multiple target tracking was published in 1986 [2] and a number of recent books are available, such as [3, 4].

Target tracking exhibits properties and unexpected results that are not common to most statistical estimation tasks. One of the major causes of unexpected results is that tracking involves random variables from both continuous sample space and discrete sample space. Accordingly, using a high fidelity simulation is a vital step in algorithm development [1]. These issues need to be considered when developing a fusion system and addressing the exchange of information between the fusion tracker and the other fusion functions.

A data-fusion processing system could be fairly simple or sophisticated and complex or anywhere in between depending on the specifics of application and the fusion system requirements. The fusion processing design depends on the requirements; the characteristics, limitations, and locations of the sensors, processors, threat, communications, and operating conditions; the location of the users; and the state of the art of fusion processing. Thus the type of algorithm architecture and functional decomposition of a data fusion processing system for one application could be very different from another application and thus, the exchange of information between the fusion tracker function and other fusion functions could be very different. These issues are summarized as background for the discussion of the specifics of the type of information exchanged between the fusion tracker function and the other fusion functions. The introduction also describes the type of fusion system assumed so that the presentation can be simplified. Note also that the fusion tracker function could be simply a single tracker if the fusion processing is centralized and could involve multiple trackers if fusion processing is distributed. Since the term *state-of-the-art* is used in the presentation, a clarification of what is meant here by the state-of-the-art is included in the Introduction, see [5].

Sensor data fusion (and especially network centric processing) is accompanied by a variety of fusion-level functions. Most of those fusion-level functions interface with the fusion tracker either directly or indirectly, e.g., by way of the database that stores the target tracks and related data. Thus, the fusion tracker needs to accept inputs from these other functions and provide information for their use, as needed. Table 1 lists thirteen other fusion-level major functions that might interact with the fusion tracker. Note in the table that the interaction between the fusion tracker and most of the other fusion-level major functions is two ways, i.e., both to the tracker and from the tracker.

As an example of the envisioned interaction from and to the fusion tracker, consider the exchange of information between the Fusion Tracker and the Manage Processing function [5]. When the fusion tracker receives a frame of data, it might provide the Manage Processing function (Function 4 of Table 1) on the local platform with the amount of computer resources <u>desired</u> to process that frame of data; the other fusion-level functions could do so also. Based on all these estimates, the Manage Processing function would compare the processing resources desired to the resources available and then provide a processing resource budget to each of the fusion-level functions. The fusion tracker would then select algorithms and parameters that will permit its processing of the frame of data within the computer resource budget. This approach assumes one of the fusion trackers goals or requirements is graceful degradation and could be used in the event of processor faults or a damaged processor. A separate slide addresses covariance consistency [6] because the performance of most fusion functions would be degraded by inconsistent covariances. Another example, is the request by the Tracking Function to the Sensor Resource Manager to obtain measurements from specific sensor regions (or with specific characteristics) to facilitate sensor bias estimation or adaptive tracking [7].

The exchange of information between the fusion tracker and the other functions are also discussed. There are no doubt additional efforts needed beyond this list to ensure that the fusion tracker effectively interacts with the other major functions of the fusion-level. Furthermore, different systems will have specific needs that should be addressed based on the unique character of their operating conditions, sensors, and targets.

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Some Issues in Multiple Target Tracking and Resource Management

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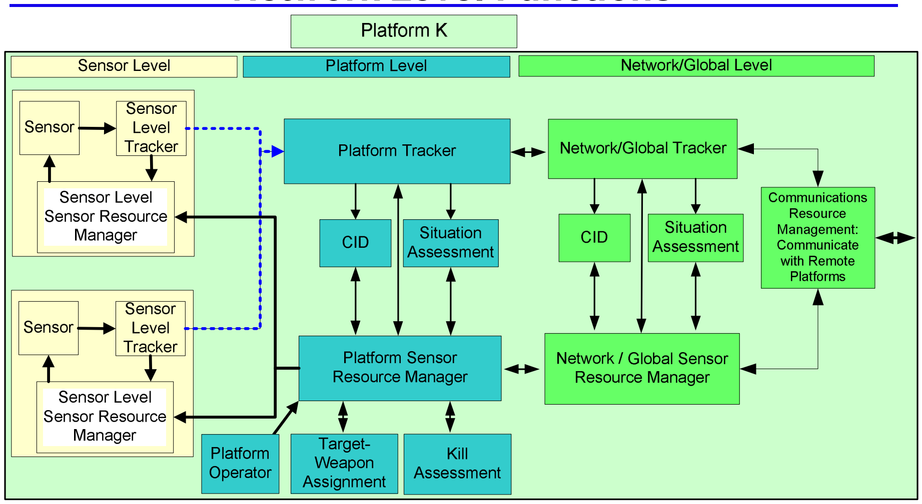
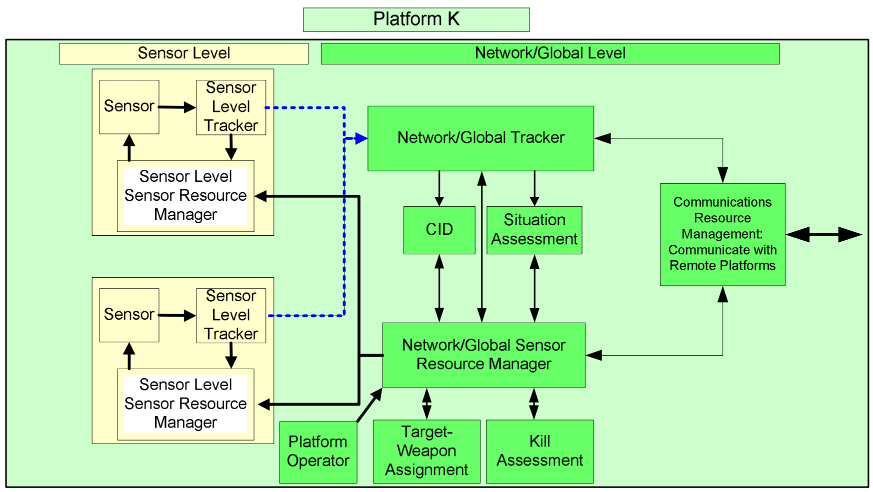
Sensor, Platform, and Network Level Functions



Higher level tasks are distilled from the network level, through the platform level, to the individual sensors.

Sensor and Network Level Functions Without a Platform Tracker



Some Interactions

- **Platform/Network Tracker**
  - **Platform/Network Resource Manager**
  - **Communications Resource Manager**
  - **CID/Discrimination**
  - **Situation Assessment/Awareness**
- **Resource Manager**
  - **Weapon-Target Assignment (Battle Management)**
  - **Kill Assessment**
  - **CID/Discrimination**
  - **Situation Assessment/Awareness**
  - **Sensor vs. Platform vs. Network**
  - **Operator in the Loop**
- **Network Tracker and Resource Manager also interact with remote platforms.**

- **This presentation addresses some aspects of the Tracker and Communications/Resource Manager**

Outline

- Ambiguity Assessment in Support of Fusion
- Distributed Resource Management

AMBIGUITY ASSESSMENT IN SUPPORT OF FUSION

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State Estimate Uncertainty and Association Ambiguity in MTT

- **Most Tracking System Produce a State and Estimate of the Error (uncertainty) in the Form of a Covariance Matrix.**
  - **Uncertainty of the state is required for fusion and association as well as other system functions such as CID, discrimination, weapon-to-target assignment, resource management, maneuver and anomaly detection.**
  - **An accurate characterization of the uncertainty, e.g., covariance consistency, is essential.**
- **New Requirement: Modern Tracking Systems should also produce an estimate of ambiguity, i.e., association uncertainty, in terms of the Probability of Association or some other measure.**
  - **For track-to-track (e.g., MSI), the decision to fuse or select source tracks to produce system/global depends on the ambiguity in the association process (and consistency of the covariances).**
  - **For measurement based tracking (e.g., CT), the requirement is to identify relatively pure track segments or to provide an estimate of the Probability of the Association to downstream processing.**
- **Uncertainty and ambiguity in tracking should be**
  - **Assessed and managed and**
  - **Supplied to other system components or computed jointly with other system components.**

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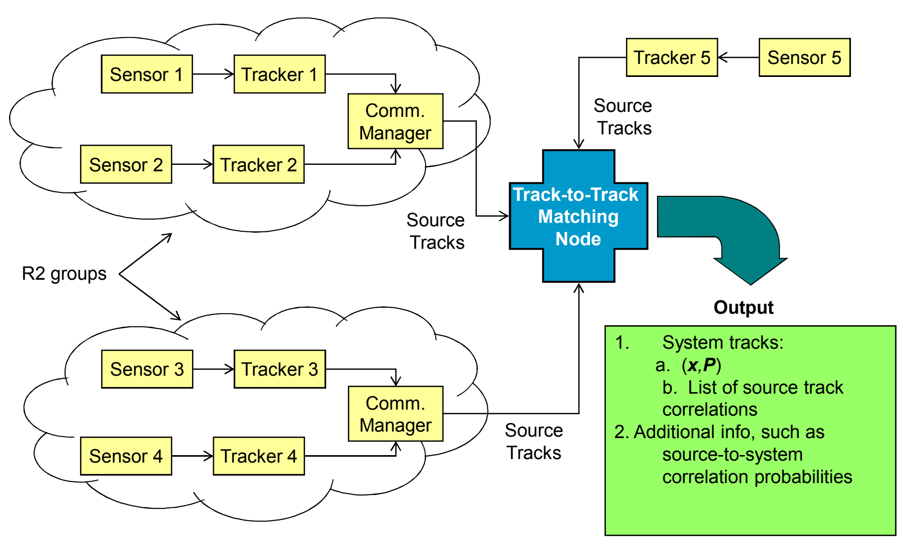
Example of a Track Matching System

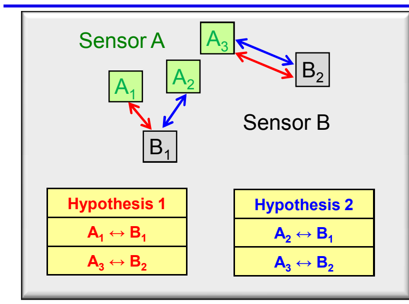


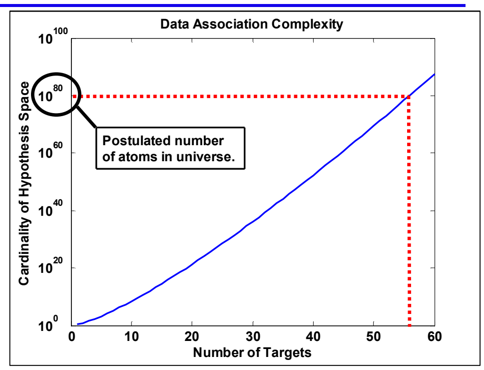
Challenges of Track Matching Systems

- **Challenges related to fusion (i.e., state estimation):**
  - **Statistical correlation of source-level track updates**
    - *Common process noise*
    - *Common prior*
  - **Out-of-order measurements due to communication delays and to different processing requirements on different platforms.**
  - **Standard Kalman filter-related difficulties**
    - *Nonlinear, non-Gaussian environments*
    - *Target maneuvers*

- **Challenges related to correlation (i.e., track-to-track data association):**
  - **Bandwidth constraints on communication**
    - *Low update rates*
    - *Missing or partial covariance matrices*
    - *R2 conventions (platforms only report some of their tracks)*
  - **Matching a few objects to many objects**
    - *Sensors of Different Resolution*
    - *Coverage Gaps*
  - **Sensor Biases**

Ambiguity Assessment





- For a challenging scenario, there can be many data association hypotheses with similar likelihoods:
  - In these cases, there may be many "good" association hypotheses.
  - Ambiguity assessment provides information on certainty of individual association decisions.

- Exact computation of association probabilities requires enumeration of entire probability space.
- To be tractable, inexact methods are needed: *Ambiguity assessment.*
- **Ambiguity assessment methods must meet two criteria: accuracy and efficiency.**

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Methods for Ambiguity Assessment

- **Goal: Approximate the Probability of Association of measurement to a track or source track to system track.**
- **Current Methods**
  - **SHT**
    - *K-Best, MCMC, or IS for Two Dimensional Assignment Problem*
    - *Hybrid Methods*
  - **MHT via MDA**
    - *K-Best Solutions of MDA via A*-Search for MHT*
    - *Sequential K-Best/MCMC for Relaxation Procedure*
  - **Other, e.g., local measures.**

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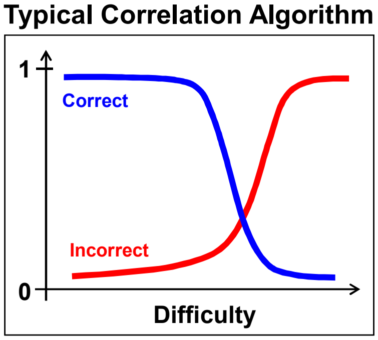
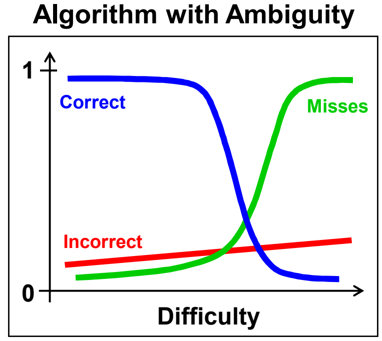
An Important Feature of Ambiguity Assessment

Typical Correlation Algorithm



Algorithm with Ambiguity



Provide a "third outcome" → ambiguous correlations are deferred until uncertainty is resolved and no fusion is performed.

- **Deferred correlations are penalized as *missed* correlations.**
- **The number of incorrect correlations should always be relatively small.**
- **In difficult (i.e., ambiguous) scenarios, missed correlations will increase.**

Applications

- Track-to-Track
  - A system track is represented by fusion or selection depending on ambiguity.
  - Ambiguity should be carried forward to other fusion functions.
- Measurement to Track
  - A goal is often to identify track segments with relatively pure segments.
  - Ambiguity should be carried forward to other fusion functions.

- Many downstream functions such as CID, discrimination, and weapon-target assignment require assessment and management of the uncertainty and ambiguity in the system for better decisions.

- Computing the "best" solution with no assessment of its uncertainty/ambiguity at each function often yields the "wrong" answer.

A Side Comment on MHT Tracking Methods

- Current and Future MHTs Must be Adaptive
  - If association process is unambiguous, use simple association methods (NN, GNN)
  - If association process is ambiguous, delay decisions to resolve ambiguity up to limits of memory and time budgets.
  - Rather than use a sliding window, use ambiguity restricted by the available memory and time budgets.

- Such an MHT requires more efficient determination of ambiguity.

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RESOURCE MANAGEMENT

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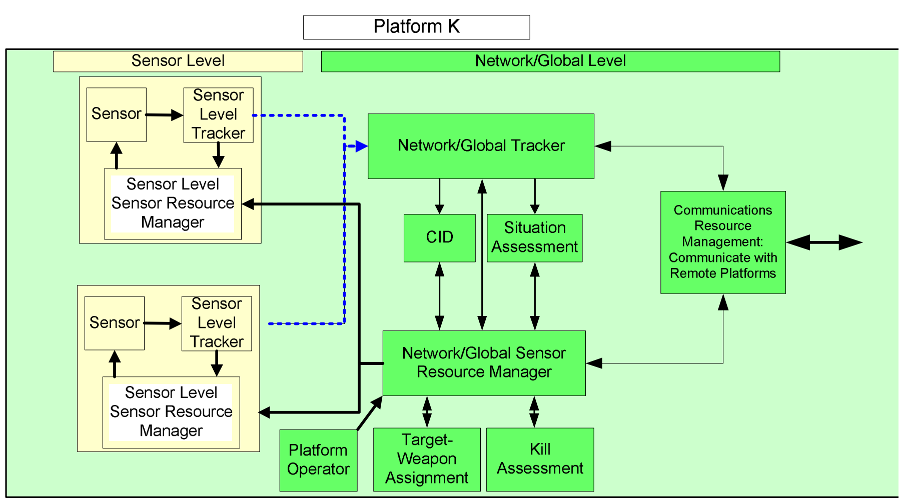
Sensor and Network Level Functions Without a Platform Tracker



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Resource Management in a Decentralized Environment

- Sensor Resource Management
  - Sensor Placement: Where should the sensors or platforms be placed in order to maximize the utility of diversity of information or to provide coverage?
  - Platform Routing: What paths should the platforms pursue in order to maximize the utility of information.
  - Assignment of Sensors to Network Tasks: which sensors should gather what information or perform what tasks for the network of platforms.
  - Uncertainty/ambiguity in tracking and CRM should be utilized in SRM
- Communications Resource Management
  - CRM deals with what information should be sent over a band-limited communications network in order to optimize some utility, value of the information, or reward and addresses the bandwidths.
  - CRM also considers the routing of the information.
  - Uncertainty/ambiguity in tracking and SRM should be utilized in CRM

- Sensor resource management should be considered in conjunction with communications resource management.

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SIAP Across a Network of Platform

- Coordinating these different objectives on a single platform is a technical challenge.
- Coordinating these different objectives on multiple platforms is a technical and political challenge.

- SIAP Across a Network
  - When each platform receives all the data from all other platforms, achieving SIAP is a challenge, especially for MHT tracking.
  - When there is insufficient bandwidth or latency, then SIAP suffers.
    - *We use another fusion function called Shadow tracker to understand the state of tracks based on information common to the network.*
    - *CRM or Data Prioritizer operates on the microsecond level and puts information on the network based on a priority cue, for example.*
    - *Resource Management coordinates which sensor(s) is to perform what tasks over multiple time periods into the future.*
    - *Under extremely heavy network loads in which one can only send 10%-20% of the available data, achieving SIAP can be a challenge.*

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Conclusion

- Assessment and Management of Uncertainty and Ambiguity in Track Managers is essential for performance in various fusion and other components.
- Coordinating information across a network remains a significant technical and political challenge, i.e., much fun remains.

Some Issues in Multiple Target Tracking and Resource Management

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ABSTRACT

The interactions between different fusion systems such as tracking, resource management, combat identification or discrimination, situation assessment, registration, and battle management are complex ones that must be treated at the sensor, platform, and network levels in order to achieve overall system performance. This work and presentation focus on a small subset of these interactions, namely the assessment and management of uncertainty and ambiguity in the tracking component and the interactions with resource management. Most tracking systems produce a state estimate of an object and an uncertainty in the estimate in the form of a covariance matrix. The corresponding uncertainty in the association process is called ambiguity. This is a new requirement for tracking systems and is essential to support downstream processing such as CID or discrimination and situation assessment. This presentation presents some of the salient features of ambiguity and methods for evaluating it. In addition, resource management must coordinate the tasking throughout the system with interactions between between all system components, especially tracking, as well coordination between sensor, platform, and network levels.

Keywords: ambiguity assessment and management, resource management

1. INTRODUCTION

The interactions between different fusion systems such as tracking, resource management, combat identification, situation assessment, and battle management as illustrated in Figure[?] are complex ones that must be treated at the sensor, platform, and network levels in order to achieve overall system performance. This work and presentation focus on a small subset of these interactions, namely the assessment and management of uncertainty and ambiguity in the tracking component and the interactions with resource management. Most tracking systems produce a state estimate of an object and an uncertainty in the estimation process in the form of a covariance matrix. Consistency of this covariance matrix is a key component to ensuring tracking robustness in the system. The corresponding uncertainty in the association process is called ambiguity and can be addressed through the probability of association and is the major topic of the second section. In addition, tracking must interact with resource management including both sensor and communication management. At the network level, both sensor tasking must consider the available bandwidth as well as the individual sensor resources available to the network as outlined in the third section.

2. UNCERTAINTY AND AMBIGUITY ASSESSMENT AND MANAGEMENT.

Fusion is sometimes loosely defined as combining two or more sources of information to arrive at a better understanding of the that which you are trying to understand. For most tracking systems, the goal is to combine multiple sources of information to arrive at an improved state of the object. In addition, most tracking systems produce a state and estimate of the error (uncertainty) in the form of a covariance matrix. Uncertainty of the state is required for fusion and association as well as other many other system functions such as CID, discrimination, weapon-to-target assignment, resource management, maneuver and anomaly detection. An accurate characterization of this uncertainty, normally called covariance consistency, is essential for these functions. Drummond[1] presents both metrics for and causes for a lack of this uncertainty.

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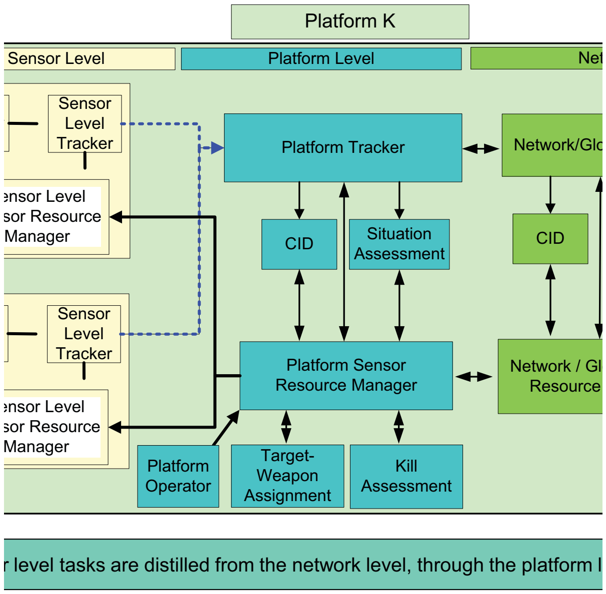

Figure 1. Sensor, Platform, Network Functions

A prerequisite to the fusion function is that of determining what sources go together so that the information can be combined. This step is normally called association or data association. The term "correlation" is often used for track-to-track association. The uncertainty in the association process, called ambiguity, is also critical to many system functions including the decision to select or fuse track states for track matching systems or the identification of pure track segments used by identification or discrimination functions in case of measurement based systems. The new requirement is that tracking systems should also produce an estimate of ambiguity which can be measured by the probability of association. Methods for computing the probability of association can be based on K-Best solutions of a two dimensional assignment problem, Markov chain monte carlo (MCMC), and importance sampling (IS) methods as in earlier work of Gadaleta, Herman, Miller, Obermeyer, Slocumb, Poore, and Levedahl[2] and more recent papers of Kragel and Herman[3,4] for single hypothesis tracking. For MHT, one can generate the K-Best solutions of the NP-hard multidimensional assignment problems using A*-search within a branch and bound, or sequential K-Best within a Lagrangian relaxation procedure. Better approximation schemes are needed for MHT.

As an example of uncertainty and ambiguity, consider the case of a track matching system. The challenges related to fusion (i.e., state estimation) include statistical correlation of source-level track updates from common process noise or common priors, out-of-order measurements due to communication delays and to different processing requirements on different platforms, and the standard estimation difficulties including nonlinear and non-Gaussian environments and target maneuvers. Challenges related to correlation (i.e., track-to-track data association) include bandwidth constraints on communications, low update rates, missing or partial covariance matrices, R2 conventions (platforms only report some of their tracks), matching a few objects to many objects due to sensors of different resolutions, coverage gaps and sensor biases.

Ambiguity also provides a method for making MHT more adaptive. If the association process is unambiguous, one should use simple association methods such as global nearest neighbor or even nearest neighbor methods. If the association process is ambiguous, one can delay decisions to resolve ambiguity up to limits of memory and time budgets. Thus, rather than use a sliding window, use ambiguity restricted by the available memory and time budgets. Such an MHT requires more efficient determination of ambiguity.

3. RESOURCE MANAGEMENT

We divide resource management into two components, normally called sensor resource management and communications resource management. The former can occur at several levels, namely network, platform, and sensor levels with each interacting with the other. In particular under the sensor resource management, one can consider several functions such as the following.

- *Sensor Placement:* Where should the sensors or platforms be placed in order to maximize the utility of diversity of information or to provide coverage?
- *Platform Routing:* What paths should the platforms pursue in order to maximize the utility of information.
- *Assignment of Sensors to Tasks:* Which sensors should perform which tasks at the sensor, platform, and network levels?

Communications resource management on the other hand must consider

- What information should be sent over a band-limited communications network in order to optimize some utility, value of the information, or reward and addresses the bandwidths;
- Routing of the information on the network.

Network level sensor and communications resource management should be coordinated. In particular, sensors should not be tasked beyond their resources just because communications bandwidth is available nor should they be asked to perform a task if bandwidth is not available to to transmit the information. While network sensor management[5] plan the sensor to task assignments one (myopic) or several (non-myopic) time periods into the future while taking bandwidth constraints into account. The communications resource manager on the other hand coordinates and routes the transformation over the the network at the micro second level. In both cases, uncertainty and ambiguity in conjunction with that of tracking should be assessed and managed.

4. CONCLUSIONS

Most tracking systems produce a state estimate of the object and a covariance to represent the uncertainty in the state. In addition, uncertainty in the association process, called ambiguity, needs to be part of this uncertainty. Both uncertainty in the state estimate and the ambiguity in the association process needs to be assessed and managed throughout the system to support better fusion and decision making processes.

With respect to resource management, the overall objective at the network level is to operate the platforms in a networked system in an integrated and efficient fashion by managing the resources across the network. The goal is to coordinate in real-time the operation of the sensors in such a way that those best-equipped for certain missions and have the resources to accomplish the mission should perform those missions for the entire network, while other sensors fill in the gaps with their capabilities.

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Developing Trust in Fusion Systems

Chee-Yee Chong
BAE Systems

SPIE Panel on "Real World Issues and Challenges in the Integration of Fusion Functions"
April 5, 2010

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Trust is Important in Building Real Fusion Systems

- Users will only use a fusion system if they can "trust" its output, especially when output is used to make important decisions
- Many research fusion systems are not used because they are not trusted
- Definitions of "trust" depend on specific communities
  - Automation/supervisory control:
    Trust = Predictability + Dependability + Faith + Competence + Responsibility + Reliability
  - Network security:
    Trust = Secure and reliable data communication
  - Human organizations:
    Trust = Belief in future actions of others
- A "trusted" fusion system is one that
  - Does not just produce accurate results from good data
  - Should also assess confidence on results
  - Is honest about its assessment

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Example - Significant Gap Exists Between Research and Practice in GMTI Tracking

Research
- Multiple hypothesis tracking
- Interacting multiple models
- Particle filters
- PHD

Practice
- Single hypothesis
- Simple filters

- Several sophisticated multiple hypothesis GMTI trackers have been developed
- However, most operational GMTI platforms still use fairly simple trackers
- Furthermore, most GMTI analysts do not use sophisticated trackers because they
  - Cannot use trackers effectively – lack of trust from experience/observation
  - Do not have confidence in results – lack of trust from experience/observation
  - Are told that fancy trackers don't work – lack of trust from reputation
- Users need trackers that they can trust

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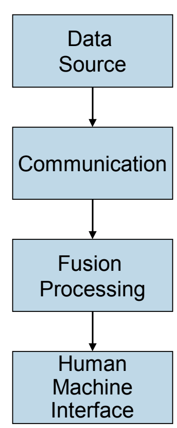
Trust in Fusion System Depends on Trust in Components

- Trusted data source
  - Produces expected data
  - Represents data quality
- Trusted communication
  - Insures timeliness and integrity of data
  - Transmits confidence estimates
- Trusted fusion processing
  - Applies fusion approach suitable for problem
  - Characterizes confidence in results
- Trusted human machine interface
  - Displays results understandable to users
  - Presents confidence in results

Fusion System



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Confidence Assessment is Easier for Physical Sensors Than Human Sources

- Physical sensors
  - Modeling is easier because they are engineered from components
  - Accuracy and reliability can be represented statistically
  - Performance can be verified by tests
- Human sources
  - Perception process varies from person to person
  - Perceptual bias is sensitive to context
  - Performance is affected by training and workload
  - Natural language output is imprecise and subject to different interpretation
  - Modeling and verification is difficult
  - Human sources may intentionally lie

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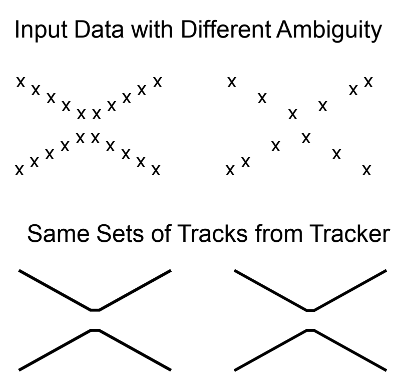
Confidence Assessment for Upstream Trackers Could be Better

- Most trackers now produce error covariances for state estimates - covariance consistency recognized as important problem
- Some trackers produce estimates on uncompensated residual sensor biases
- Few trackers assess data association performance
  - Lack standard association confidence measure similar to error covariance
  - Lack efficient algorithms to compute confidence
- Track fuser does not know how much to trust input tracks when confidence is not represented



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Communication Should Maintain Continuity of Trusted Information

- Information pedigree should be communicated to maintain trust pedigree
  - Source of information
  - Confidence in source
- Information received at processing node should be true copy of what was transmitted by upstream sources
  - Covariances in addition to state estimates – not communicated in some data links
  - Track confidence in addition to tracks – almost never communicated
- Dropped communication should be characterized
  - No report does not affect fusion results
  - Missing report has useful information

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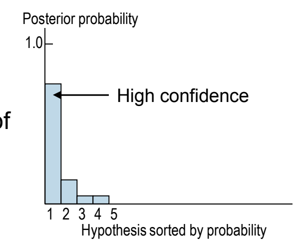
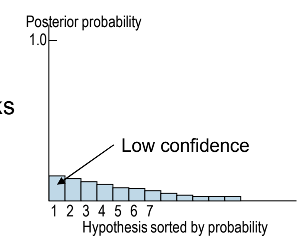
Fusion Processing Should Assess Confidence on Results

- Sophisticated fusion systems generate results even in highly ambiguous situations
  - Best hypothesis from MHT may only be slightly better than other hypotheses with high probability of being wrong
  - Frequent hypothesis hopping
- Trusted fusion processing should only produce results that are credible
  - Don't try too hard to produce good tracks when situation is ambiguous
  - Assess confidence when required to produce tracks
- Trusted fusion system should never let user doubt results





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Fusion Systems Should Only be Used When Assumptions are Valid

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- Fusion system will perform poorly when underlying assumptions are invalid
  - Developers may oversell capability of system
  - Users may not know underlying assumptions
- Fusion system should be explicit about assumptions
  - Data source, e.g., observation errors, false alarm rate, detection probability
  - Targets, e.g., types, dynamics
  - Context, e.g., urban or rural environment,
- Fusion system should have self assessment capability
  - Know when assumptions are violated
  - Qualify results when necessary

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Human Computer Interface Should Display Understandable and High-Confidence Results

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- Understandable results develop trust
  - Single hypothesis results from simple trackers are easier to understand than multiple hypotheses
  - Black box solutions have to generate trust from positive user experience or reputation
  - Drill down capability to examine pedigree of evidence enhances understanding
- Low confidence results destroy trust
  - Should display pure segments (with no association ambiguity) as default
  - Do not display best single hypothesis unless it has high confidence
  - Be conservative about what to display - no result is better than wrong result

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Conclusions

- Trust in fusion system is essential for transition to real world
- Overall trust depends on trust in individual components
  - Data source
  - Communication
  - Fusion processing
  - Human computer interface
- Developing trust in fusion systems requires advances in
  - Representing and assessing confidence in data sources, especially human sources and trackers
  - Communicating confidence over fusion chain
  - Assessing confidence and exposing assumptions in fusion processing
  - Presenting understandable and high confidence results to users

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Developing Trust in Fusion Systems

Position Paper for SPIE Panel on "Real World Issues and Challenges in the Integration of Fusion Functions"

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ABSTRACT

Users will only use a fusion system if they can "trust" its output. In fact, many research fusion systems never get used because they are not trusted. There are many different definitions of "trust" depending on the particular communities, e.g., computer security and social networks. An operational definition of "trust" for a fusion system is its reliability or confidence in its assessment of accuracy. A fusion system discovers and collects data from sources, transforms data to information to knowledge, and disseminates knowledge to provide understanding for users. The trust in the system is composed from trust in the data sources, trust in the process that converts the data to information and knowledge, and trust in dissemination as human understanding.

Keywords: fusion systems, trust, confidence

1. INTRODUCTION

Trust is important in building real world fusion systems. Users will only use a fusion system if they can "trust" its output, especially when the output is used to make important decisions. Many research fusion systems are not used because they are not trusted. The definitions of "trust" depend on the specific communities. In automation and supervisory control, trust is predictability + dependability + faith + competence + responsibility + reliability [1]. In network security, trust is secure and reliable data communication [2]. In human organizations, trust is belief or faith in future actions of others [3]. For fusion systems, we use the following operational definition. A "trusted" fusion system is one that does not just produce accurate results from good data because that is expected. It should also assess the confidence on the results and is honest about its assessment.

An example of trust or lack of trust in fusion systems can be found in ground moving target indicator (GMTI) tracking. Currently, significant gap exists between research and practice in GMTI tracking. Several sophisticated multiple hypothesis GMTI trackers have been developed over the last decade. However, most operational GMTI platforms still use fairly simple trackers. Furthermore, most GMTI analysts do not use sophisticated trackers. They cannot develop trust from their own experience or observation because the trackers are often too difficult to use or produce results that do not instill confidence. There is also lack of trust from reputation because analysts are often told that fancy trackers do not work.

2. TRUST IN FUSION SYSTEM DEPENDS ON TRUST IN COMPONENTS

At a high level, a fusion system consists of the components shown in Figure 1. Trust in the fusion system depends on trust in the components. A trusted data source produces expected data and represents data quality. Trusted communication insures timeliness and integrity of communicated data and commuincates confidence on the estimates. Trusted fusion processing applies a fusion approach that is suitable for the problem and characterizes its confidence in the results. Trusted human machine interface displays results that are understandable to users and presents confidence in the results.

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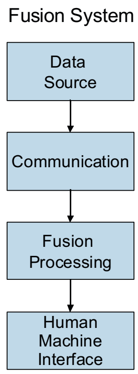

Figure 1: Fusion system components

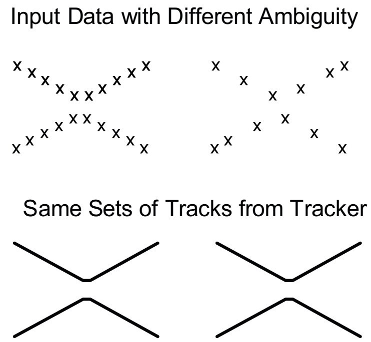

Figure 2: Different inputs result in similar outputs

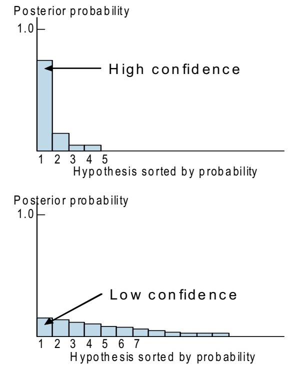

Figure 3: Hypothesis probabilities

Confidence assessment is easier for physical sensors than human sources. Physical sensors are easier to model because they are engineered from components. Their accuracy and reliability can usually be represented statistically and performance can be verified by tests. Human sources are difficult to model because human perception process varies from person to person. Human perceptual bias is sensitive to context and performance is affected by training and workload. Further more, natural language output is imprecise and subject to different interpretation. In addition, human sources may intentionally lie.

Many fusion systems process outputs from trackers. So far, confidence assessment for upstream trackers is not as good as that for sensors. Most trackers now produce error covariances for state estimates and covariance consistency is recognized as an important problem [4]. Some trackers also produce estimates on uncompensated residual sensor biases. However, few trackers assess data association performance [5, 6]. This is important for fusion because it needs to know how much to trust the tracks from the trackers. Figure 2 shows that a tracker will produce similar results even though the tracks from data with high sampling rate should be trusted more than the ones from data with low sampling rate. We lack standard association confidence measure similar to error covariance and efficient algorithms to compute confidence. It is hard for the track fuser to do its job when it does not know how much to trust the input tracks.

Communication should maintain continuity of trusted information. Information pedigree should be communicated to maintain trust pedigree. This should include the source of information and the confidence in the source. The information received at the processing node should be a true copy of what was transmitted by the upstream sources. The covariances should be communicated in addition to state estimates. This is not done in some data links. Track confidence should be communicated in addition to tracks but this is almost never done. Dropped communication should be characterized because a missing report conveys useful information.

Fusion processing should assess its confidence on the results. Sophisticated fusion systems generate results even in highly ambiguous situations. However, the best hypothesis from multiple hypothesis tracking (MHT) may only be slightly better than the other hypotheses. Then the best hypothesis has a high probability of being wrong and frequent hypothesis hopping may result. Trusted fusion processing should only produce results that are credible. It should not try too hard to produce good tracks when the situation is ambiguous. It should assess confidence when required to produce tracks.

Fusion systems should only be used when assumptions are valid. A fusion system will perform poorly when the underlying assumptions are invalid. This may be due to several reasons. Developers may oversell the capability of the system and users may not know the underlying assumptions. Thus, a fusion system should be explicit about its assumptions. These include observation errors, false alarm rate, detection probability, etc. for data sources, types and dynamics for targets, and context such as urban or rural environment. Further more, a fusion system should have self assessment capability. It should know when assumptions are violated and qualify the results when necessary.

Human computer interface should display understandable and high-confidence results because understandable results develop trust. In general, single hypothesis results from simple trackers are easier to understand than multiple hypotheses. Black box solutions have to generate trust from positive user experience or reputation. Drill down capability to examine pedigree of evidence also enhances understanding. Producing low confidence results on a regular basis destroys trust. Thus it is better to display pure segments (with no association ambiguity) as default. The best single hypothesis should not be displayed unless it has high confidence. Finally, it is better to be conservative about what to display because no result is better than wrong result.

3. SUMMARY

Trust in fusion system is essential for transition to the real world. Overall trust depends on the trust in individual components that form the fusion system. Developing trust in fusion systems requires advances in representing and assessing confidence in data sources, especially human sources and trackers, communicating confidence over fusion chain, assessing confidence and exposing assumptions in fusion processing, and presenting understandable and high confidence results to users.

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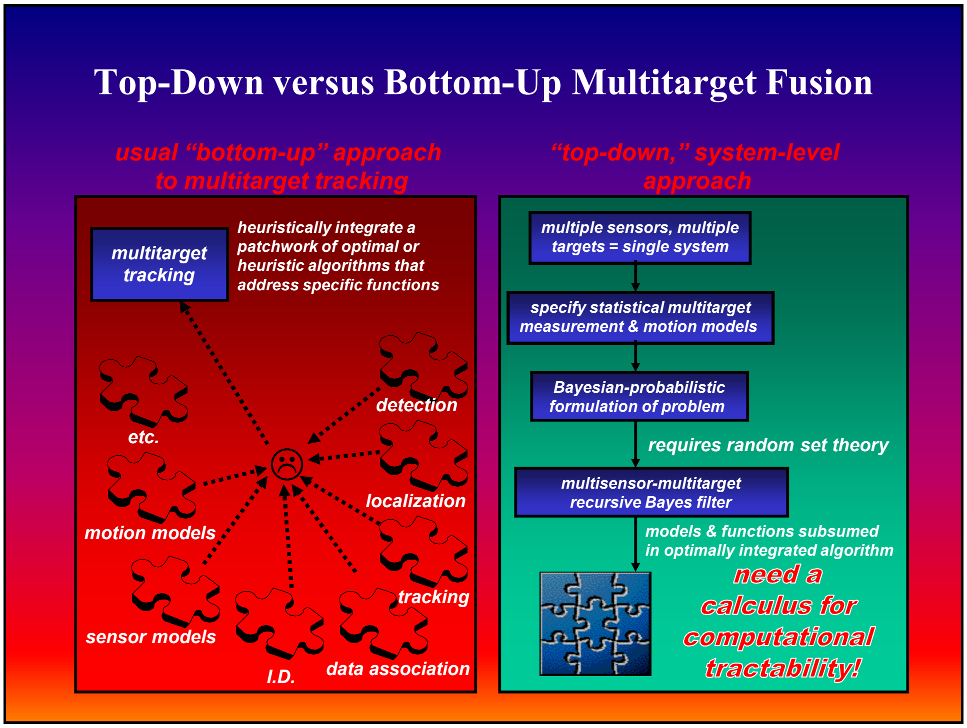
Unified Statistical Integration of Fusion Functions

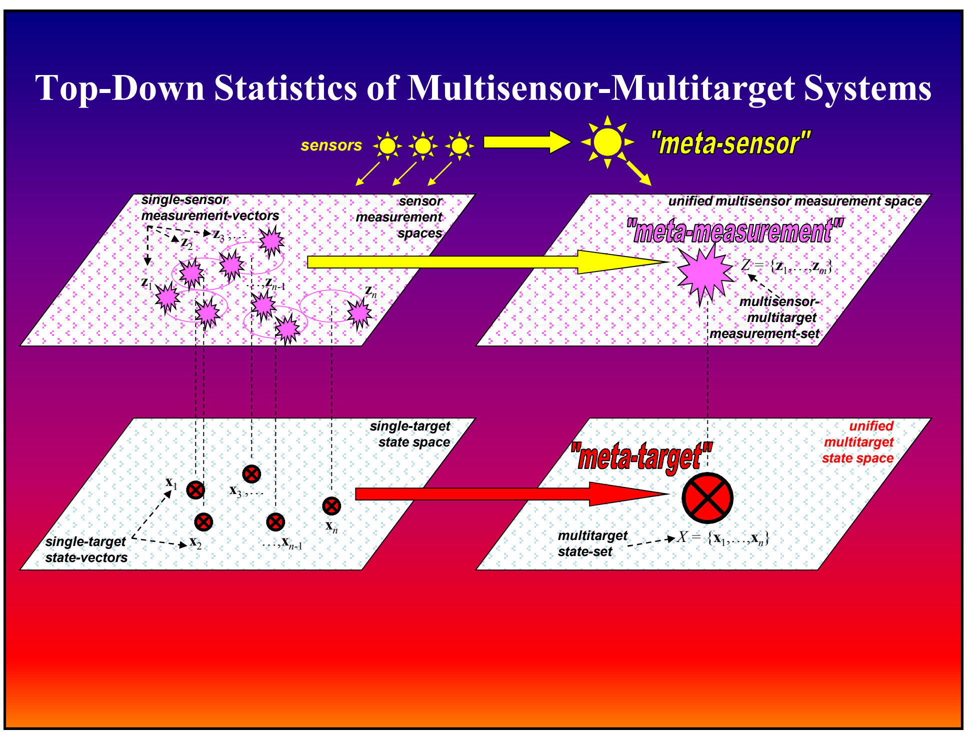
Ronald Mahler

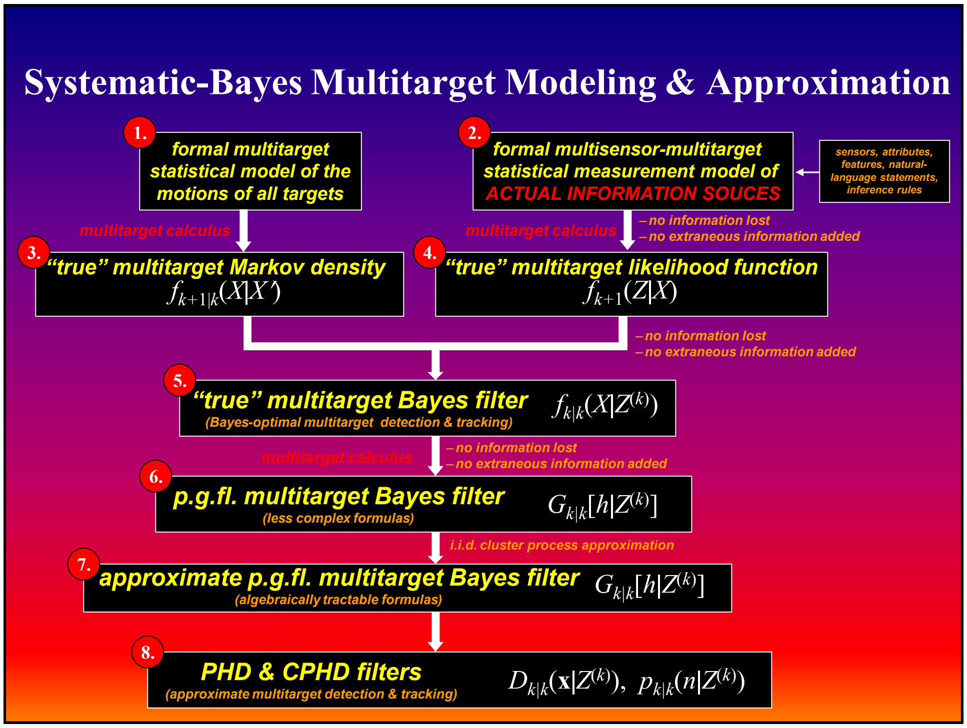
SPIE Defense, Security + Sensing Symposium
April 5, 2010, Orlando

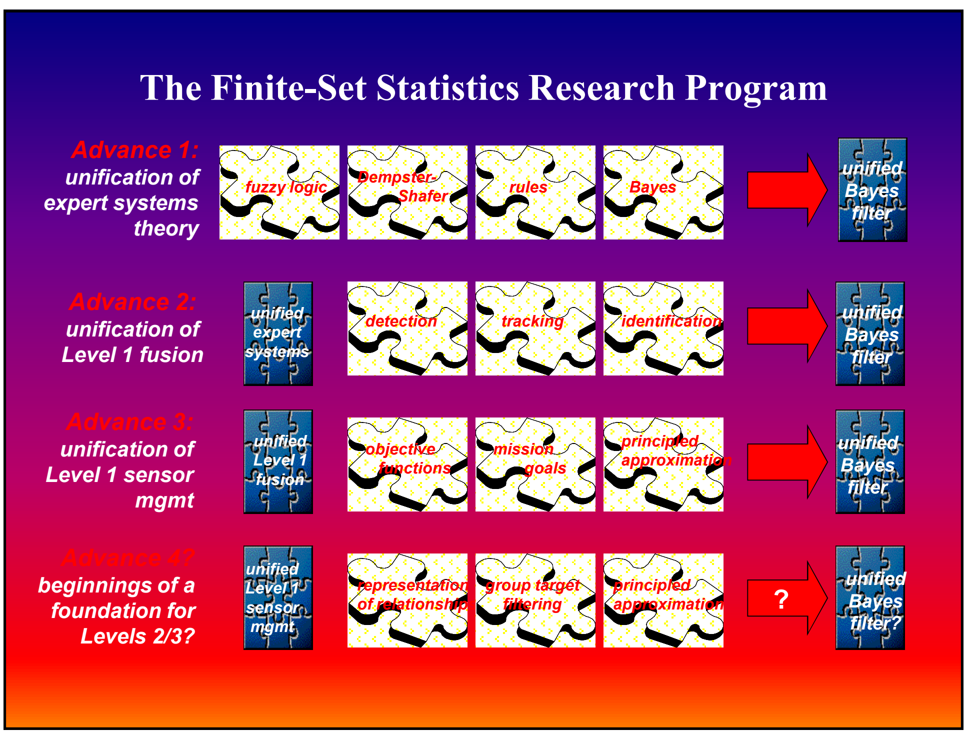
A Non-Exhaustive List of Fusion Functions

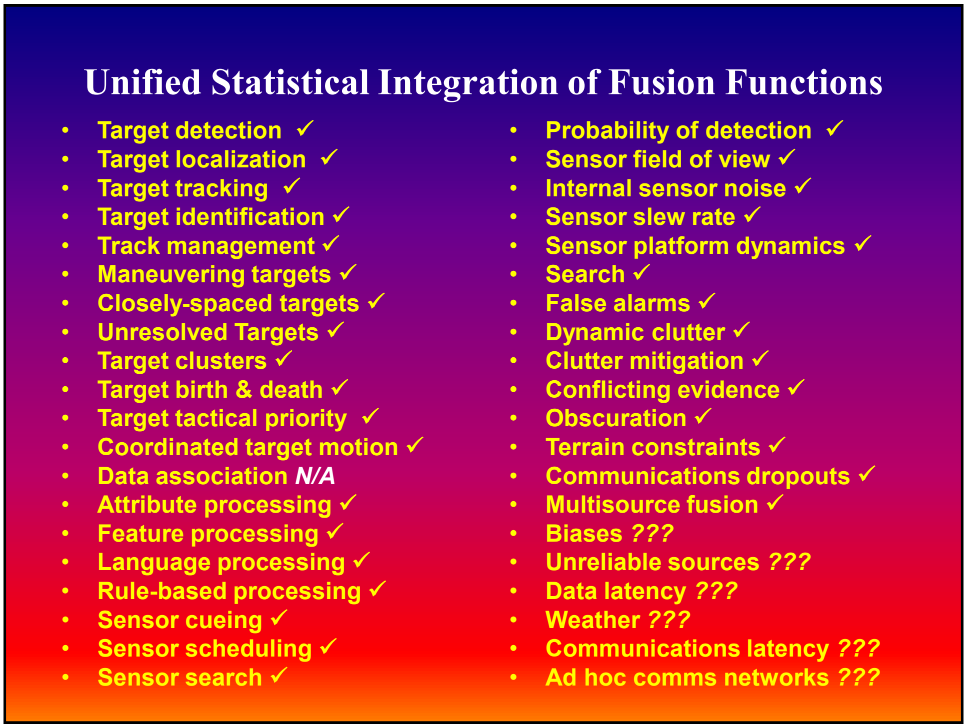
- Target detection
- Target localization
- Target tracking
- Target identification
- Track management
- Maneuvering targets
- Closely-spaced targets
- Unresolved Targets
- Target clusters
- Target birth & death
- Target tactical priority
- Coordinated target motion
- Data association
- Attribute processing
- Feature processing
- Natural-language processing
- Rule-based processing
- Sensor cueing
- Sensor scheduling
- Sensor search
- Probability of detection
- Sensor field of view
- Internal sensor noise
- Sensor slew rate
- Sensor platform dynamics
- Search
- False alarms
- Dynamic clutter
- Clutter mitigation
- Conflicting evidence
- Obscuration
- Terrain constraints
- Communications dropouts
- Multisource fusion
- Biases
- Unreliable sources
- Data latency
- Weather
- Communications latency
- Ad hoc comms networks


Top-Down versus Bottom-Up Multitarget Fusion
usual "bottom-up" approach to multitarget tracking
multitarget tracking
heuristically integrate a patchwork of optimal or heuristic algorithms that address specific functions
detection
etc.
localization
motion models
tracking
sensor models
I.D.
data association
"top-down," system-level approach
multiple sensors, multiple targets = single system
specify statistical multitarget measurement & motion models
Bayesian-probabilistic formulation of problem
requires random set theory
multisensor-multitarget recursive Bayes filter
models & functions subsumed in optimally integrated algorithm
need a calculus for computational tractability!


Top-Down Statistics of Multisensor-Multitarget Systems
sensors
"meta-sensor"
single-sensor measurement-vectors
sensor measurement spaces
$\mathbf{z}_1$
$\mathbf{z}_2$
$\mathbf{z}_3,\ldots$
$\ldots,\mathbf{z}_{n-1}$
$\mathbf{z}_n$
unified multisensor measurement space
"meta-measurement"
$Z = \{\mathbf{z}_1,\ldots,\mathbf{z}_m\}$
multisensor-multitarget measurement-set
single-target state space
$\mathbf{x}_1$
$\mathbf{x}_2$
$\mathbf{x}_3,\ldots$
$\ldots,\mathbf{x}_{n-1}$
$\mathbf{x}_n$
single-target state-vectors
"meta-target"
unified multitarget state space
multitarget state-set
$X = \{\mathbf{x}_1,\ldots,\mathbf{x}_n\}$


Systematic-Bayes Multitarget Modeling & Approximation
1.
formal multitarget statistical model of the motions of all targets
2.
formal multisensor-multitarget statistical measurement model of ACTUAL INFORMATION SOUCES
sensors, attributes, features, natural-language statements, inference rules
multitarget calculus
multitarget calculus
– no information lost
– no extraneous information added
3.
"true" multitarget Markov density $f_{k+1|k}(X|X')$
4.
"true" multitarget likelihood function $f_{k+1}(Z|X)$
– no information lost
– no extraneous information added
5.
"true" multitarget Bayes filter $f_{k|k}(X|Z^{(k)})$
(Bayes-optimal multitarget detection & tracking)
multitarget calculus
– no information lost
– no extraneous information added
6.
p.g.fl. multitarget Bayes filter $G_{k|k}[h|Z^{(k)}]$
(less complex formulas)
i.i.d. cluster process approximation
7.
approximate p.g.fl. multitarget Bayes filter $G_{k|k}[h|Z^{(k)}]$
(algebraically tractable formulas)
8.
PHD & CPHD filters $D_{k|k}(\mathbf{x}|Z^{(k)}),\ p_{k|k}(n|Z^{(k)})$
(approximate multitarget detection & tracking)


The Finite-Set Statistics Research Program
Advance 1:
unification of expert systems theory
fuzzy logic
Dempster-Shafer
rules
Bayes
unified Bayes filter
Advance 2:
unification of Level 1 fusion
unified expert systems
detection
tracking
identification
unified Bayes filter
Advance 3:
unification of Level 1 sensor mgmt
unified Level 1 fusion
objective functions
mission goals
principled approximation
unified Bayes filter
Advance 4?
beginnings of a foundation for Levels 2/3?
unified Level 1 sensor mgmt
representation of relationship
group target filtering
principled approximation
?
unified Bayes filter?


Unified Statistical Integration of Fusion Functions
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Unresolved Targets ✓
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Target tactical priority ✓
Coordinated target motion ✓
Data association N/A
Attribute processing ✓
Feature processing ✓
Language processing ✓
Rule-based processing ✓
Sensor cueing ✓
Sensor scheduling ✓
Sensor search ✓
Probability of detection ✓
Sensor field of view ✓
Internal sensor noise ✓
Sensor slew rate ✓
Sensor platform dynamics ✓
Search ✓
False alarms ✓
Dynamic clutter ✓
Clutter mitigation ✓
Conflicting evidence ✓
Obscuration ✓
Terrain constraints ✓
Communications dropouts ✓
Multisource fusion ✓
Biases ???
Unreliable sources ???
Data latency ???
Weather ???
Communications latency ???
Ad hoc comms networks ???


Thank you!

Real-World Issues and Challenges in the Integration of Fusion Functions

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Fusion for the Real-World

- What are the issues (or the challenges)?

2

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Real-World Fusion and Integration

What are the Challenges ?

1. The real-world

- Unknown environment
- Unknown sensor/data characteristics
- Time-varying resources
- …

2. The integration

- Combine different stages of the processing chain
- Decide how/what to share across the stages
- Account for effects of processing in each stage
- …

3

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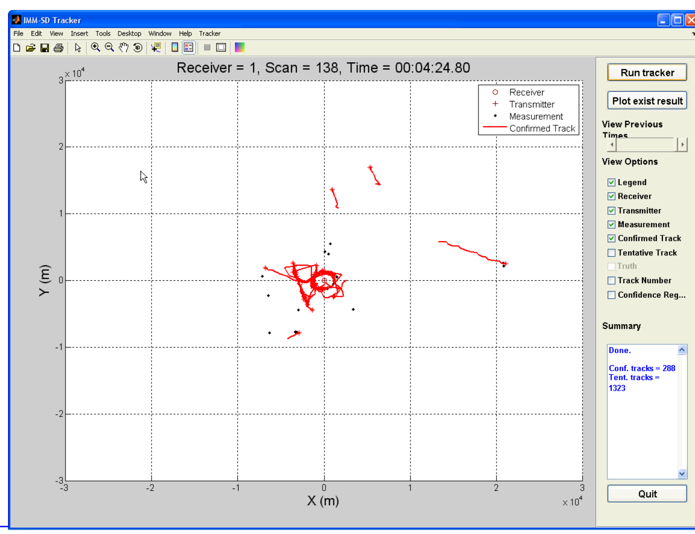
Unknown Environment (Before)



4

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Unknown & Varying Clutter

- Estimate the spatio-temporally varying clutter levels *online*
- Possible to develop sophisticated clutter estimation algorithms
- Seamlessly integrate clutter estimation with tracking
- Difficult to “retrofit” new algorithms to standard trackers like the MHT/MFA/JPDA

5

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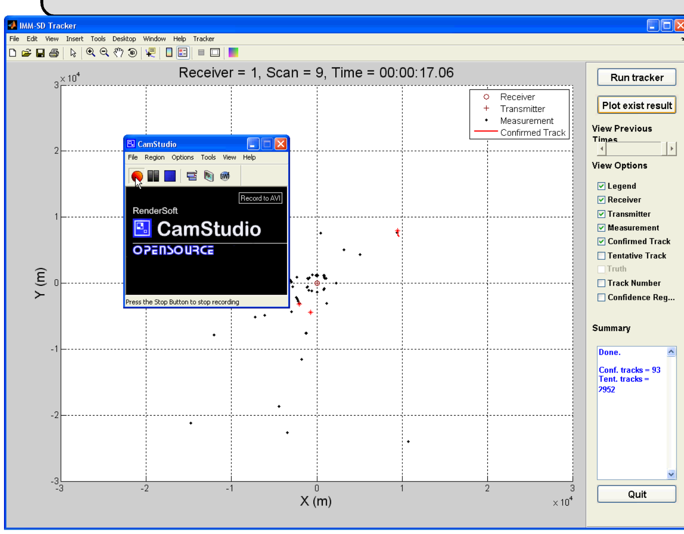
Unknown Environment (After)



6

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Unknown Sensor/Data Characteristics

- Need to know sensor/tracker accuracies, biases, etc., accurately for effective fusion
- Many real-world tracking systems don't provide accuracies!
- We don't have the accuracies for legacy sensors
- Often real data don't make sense (even to the providers)
- Real-world sensor data/tracker output may be counter-intuitive and fusion counterproductive

7

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Unknown Sensor/Data Characteristics (2)

- Some data issues may be inherent to sensor systems
- Estimate sensor accuracies, biases, etc., online (can degrade overall performance) before tracking and fusion
- Understand the sensor, modify processing and quantify output so as to improve tracking/fusion results

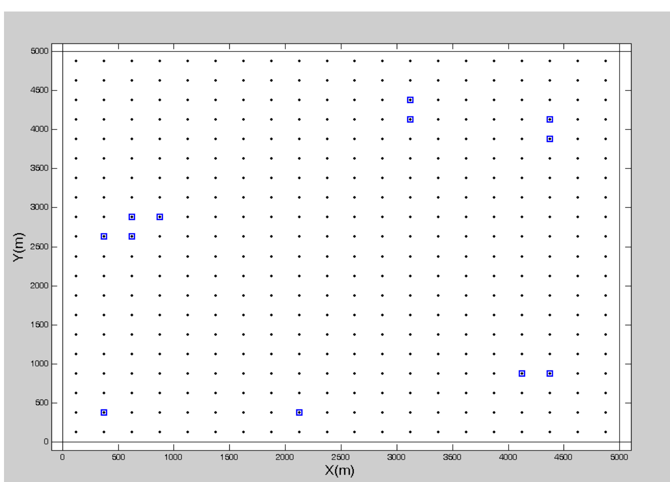
8

Resource Management

- Sensor, bandwidth and computational resources are limited (and time-varying)
- *Integrate* tracking/fusion with sensor management (e.g., waveform design, sensor placement/selection)
- Need short-term (myopic) and long-term (open-loop) resource allocation
- There may be conflicting criteria (=> multi-objective sensor management)

9

Resource Management (2)



10

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Communication Issues

- Need to decide what/when to transmit across platforms
- Account for the effect of communication strategy on accuracies, correlations, etc.
- Need to work with heterogeneous sensor data *and* tracker output (e.g., estimates/covariances vs. multiple hypothesis output vs. particles)
- How to fuse outputs from MHT trackers and particle (-like) filters

11

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Feeding Higher Level Fusion

- Ultimately, need to use lower-level tracking/fusion results to infer higher level unknown (e.g., class, intent)
- How to classify targets using track estimates (and feature information) and use classification to improve tracking in an *unknown* environment
- How to predict destination (and intent) with tracking and fusion

12

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Integration

- How to integrate all these functions (even at low levels from signal processing to track-to-track fusion) or across fusion levels
- How to exchange data among disparate (and possibly incompatible) algorithms at different stages
- How to optimize performance at different stages of processing

13

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Performance Evaluation

- Let us not forget performance meaningful evaluation!
- How to quantify performance of a fusion system with different stages of performance
- Is there a single (or a mixture of) performance metric(s) that can characterize the system?
- What are the trade-offs among different options for architecture, processing, communication, etc.?

14

Integration of Fusion Functions for Multisensor-Multitarget Tracking

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Abstract

Multisensor fusion for multitarget tracking is becoming a mature field of research, at least at the lower levels of fusion. In spite of many advances in sensor and processing technologies, a number of research and development problems remain, especially in handling real-world problems and in integrating different stages of the fusion chain. In this paper, we summarize some key current issues in multisensor fusion that are of interest and some possible solutions to them.

1. Introduction

While a number of tracking and fusion algorithms appear to work well on simulated data, when they are applied on real data, their performances are as not as good as the theory would indicate. This is often due to the mismatch between the assumptions made in the tracker and the state of the real world. For example, trackers assume uniform and stationary clutter, but in the real-world the clutter is rarely uniform and it is spatio-temporally time-varying. In this case, the trackers do no perform uniformly well over the whole surveillance region with time- (or space-) varying clutter. In addition to unknown target number and target characteristics, unknown environment and unknown sensor/data characteristics are the two primary reasons for the mismatch between the expected and the actual performances. With these limitations, it is essential to understand the environment, estimate parameters of interest (e.g., clutter density, bias, sensor parameters) automatically and integrate them into the tracker in order to optimize the final performance.

In order to optimize overall performance, each stage of the processing chain has to be carried out *in conjunction with* other stages, not as separate steps from tracking. That is, signal processing, detection, tracking, identification and classification have to be carried out interactively with feedback among them from one stage to the other in one unified framework. This will substantially improve the results in every stage of output in the decision support system chain. This need to share information across various stages of the processing chain in a multisensor-multitarget surveillance system generates a number of other questions. What do we share across the stages? When? How? What is the effect of processing in each stage?

2. Stages of Processing for Environment-Aware Tracking

Clutter model is one of the critical aspects in a tracking algorithm with measurement-origin uncertainties. Incorrect modeling of clutter background can lead to higher estimation errors, more false tracks and lower track purity. While standard tracking algorithms like the Joint Probabilistic Data Association Filter (JPDAF), Multiple Hypothesis Tracker (MHT), Probability Hypothesis Density (PHD) Filter and Multiframe Assignment (MFA) assume an a priori clutter model, extensions have been proposed to estimate clutter online. The objective here is to estimate the spatio-temporally varying clutter levels online and seamlessly integrate clutter estimation with tracking. In spite of the existing clutter estimation techniques based on simple counting techniques or the much more complex PHD algorithm, the real challenge is to "retrofit" new algorithms to standard trackers like the MHT, MFA and JPDA, which have been used in many fielded systems.

Another issue is the need to know sensor/tracker accuracies, biases, etc., accurately for effective fusion. Surprisingly, many real-world tracking systems do not provide accuracies! Often, we do not have the accuracies for legacy sensors and real data does not make sense (even to the providers). Real-world sensor data/tracker output may be counter-intuitive and fusion counterproductive because of this lack of knowledge. Then, it is necessary to estimate sensor accuracies, biases, etc., online without degrading overall performance. Signal processing is another area that needs to be integrated with tracking. It is essential to understand the sensor, modify processing and quantify output so as to improve tracking/fusion results. The key is optimal sensor utilization through improved signal processing integrated with tracking.

In addition to time-varying surveillance environment, sensor, bandwidth and computational resources are also limited (and time-varying). Then, the surveillance system needs to integrate tracking/fusion with sensor management (e.g., waveform design, sensor placement/selection). Sensor management needs to have short-term (myopic) and long-term (open-loop) resource allocation strategies in conjunction with adaptive environment estimation techniques. This may result in conflicting criteria, which will necessitate multi-objective sensor management.

Tracking results are only an intermediate output in a decision support system. In view of possible high clutter and false targets that are not of interest to the surveillance system, it is necessary to classify the threats that are detected and tracked. The purpose of this classification is to eliminate erroneous confirmation of spurious tracks and identify valid threats. In order to reach decisions and take actions, identification and classification of threats have to be carried out in conjunction with tracking, not as separate steps from tracking. That is, detection, tracking, identification and classification have to be carried out interactively with feedback among them from one stage to the other in one unified framework. This will substantially improve the results in every stage of output in the decision support system chain.

While some work has been done on integrated tracking approach, which can enhance tracking results and make target identification feasible, a common assumption is that the statistical description of classes is predefined or known a prior. This is not true in general. Thus, automatic multiple target classification algorithms, which can automatically classify targets without prior information, are needed. Such algorithms need to learn the class (or other attribute) description from the target behavior history from noisy target state estimates, which in turn depends on target class. That is, attribute description may have to be learnt from target behavior history rather than being predefined. Algorithms capable of doing such automatic tracking, identification and classification have to be developed.

Only when all stages of the surveillance system, namely, registration, detection, tracking, fusion, identification, classification and resource management are optimized, can the overall performance be made accurate and reliable with multiple targets (or threats) evolving dynamically in large-scale scenarios with multiple sources of noisy heterogeneous data.