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# *Signal Processing, Sensor Fusion, and Target Recognition XX*

**Ivan Kadar**
*Editor*

**25–27 April 2011**
**Orlando, Florida, United States**

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SPIE

**Volume 8050**

Proceedings of SPIE, 0277-786X, v. 8050

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Please use the following format to cite material from this book:
Author(s), "Title of Paper," in *Signal Processing, Sensor Fusion, and Target Recognition XX*, edited by Ivan Kadar, Proceedings of SPIE Vol. 8050 (SPIE, Bellingham, WA, 2011) Article CID Number.

ISSN 0277-786X
ISBN 9780819486240

Published by
**SPIE**
P.O. Box 10, Bellingham, Washington 98227-0010 USA
Telephone +1 360 676 3290 (Pacific Time) · Fax +1 360 647 1445
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# Contents

## SESSION 12 SIGNAL AND IMAGE PROCESSING, AND INFORMATION FUSION APPLICATIONS IV



## POSTER SESSION

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1 Multisensor Fusion, Multitarget Tracking, and Resource Management I
**Ivan Kadar,** Interlink Systems Sciences, Inc. (United States)
**Thiagalingam Kirubarajan,** McMaster University (Canada)
**Kenneth J. Hintz,** George Mason University (United States)

2 Multisensor Fusion, Multitarget Tracking, and Resource Management II
**Thiagalingam Kirubarajan,** McMaster University (Canada)
**Kenneth J. Hintz,** George Mason University (United States)
**Erik P. Blasch,** Defence Research and Development Canada (Canada)

3 Multisensor Fusion, Multitarget Tracking, and Resource Management III
**Kenneth J. Hintz,** George Mason University (United States)
**Ivan Kadar,** Interlink Systems Sciences, Inc. (United States)
**Thiagalingam Kirubarajan,** McMaster University (Canada)

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

5 Multisensor Fusion Methodologies and Applications II
**Michael L. Hinman,** Air Force Research Laboratory (United States)
**Chee-Yee Chong,** BAE Systems (United States)
**Ivan Kadar,** Interlink Systems Sciences, Inc. (United States)

6 Multisensor Fusion Methodologies and Applications III
**Chee-Yee Chong,** BAE Systems (United States)
**Michael L. Hinman,** Air Force Research Laboratory (United States)
**Kenneth Hintz,** George Mason University (United States)
**Ivan Kadar,** Interlink Systems Sciences, Inc. (United States)

7 Multisensor Fusion Methodologies and Applications IV
**Erik P. Blasch,** Defence Research and Development Canada (Canada)
**Chee-Yee Chong,** BAE Systems (United States)
**Michael L. Hinman,** Air Force Research Laboratory (United States)
**Kenneth Hintz,** George Mason University (United States)

8 Multisensor Fusion Methodologies and Applications V
**Kenneth Hintz,** George Mason University (United States)
**Michael L. Hinman,** Air Force Research Laboratory (United States)
**Chee-Yee Chong,** BAE Systems (United States)
**Erik P. Blasch,** Defence Research and Development Canada (Canada)

9 Signal and Image Processing, and Information Fusion Applications I
**Lynne L. Grewe,** California State University, East Bay (United States)
**Alastair D. McAulay,** Lehigh University (United States)
**Mark G. Alford,** Air Force Research Laboratory (United States)

10 Signal and Image Processing, and Information Fusion Applications II
**Lynne L. Grewe,** California State University, East Bay (United States)
**Alastair D. McAulay,** Lehigh University (United States)
**Mark G. Alford,** Air Force Research Laboratory (United States)

11 Signal and Image Processing, and Information Fusion Applications III
**Alastair D. McAulay,** Lehigh University (United States)
**Mark G. Alford,** Air Force Research Laboratory (United States)
**Lynne L. Grewe,** California State University, East Bay (United States)

12 Signal and Image Processing, and Information Fusion Applications IV
**Mark G. Alford,** Air Force Research Laboratory (United States)
**Alastair D. McAulay,** Lehigh University (United States)
**Lynne L. Grewe,** California State University, East Bay (United States)

## Invited Panel Discussion
## Real-World Issues and Challenges in Hard and Soft Fusion

**Organizer**

Ivan Kadar, Interlink Systems Sciences, Inc.

**Co-Organizer**

Chee-Yee Chong, BAE Systems

**Moderators**

Chee-Yee Chong, BAE Systems

Ivan Kadar, Interlink Systems Sciences, Inc.

April 25, 2011

SPIE Conference 8050

"Signal Processing, Sensor Fusion and Target Recognition XX"

Orlando, FL April 25-27, 2011

## Invited Panel Discussion
### *Participants:*

Dr. Richard Antony, SAIC, Inc., U.S.A.

Dr. Erik Blasch, Defence Research and Development, Canada (Canada)

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

Dr. David Hall, The Pennsylvania State Univ., U.S.A.

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

Professor Thiagalingam Kirubarajan, McMaster Univ.(Canada)

Dr. James Llinas, The State Univ. of NY at Buffalo, U.S.A.

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

## Invited Panel Discussion
### *Topics*

**"Issues in Relating Hard and Soft Information For Fusion"**
Dr. Ivan Kadar, Interlink Systems Sciences, Inc.

**"Challenges in Hard and Soft Information Fusion: Worth the Effort?"**
Dr. David Hall, The Pennsylvania State Univ.

**" Automating Soft Data Exploitation: Opportunity and Challenges**
Dr. Richard Antony, SAIC, Inc.

**"Hard-Soft Data Ontology Alignment Challenges"**
Dr. Erik Blasch, Defence Research & Development, Canada (Canada)

## Invited Panel Discussion
### *Topics*

**"Counterinsurgency: Understanding Operational Art & Its Impact on Hard-Soft Fusion Technology"**
Dr. James Llinas, Univ. at Buffalo

**"Challenges of Hard and Soft Data Fusion for a Tracking Problem"**
Dr. Chee-Yee Chong, BAE Systems

**"Hard/Soft Fusion for Prediction and Retrodiction"**
Professor Thia Kirubarajan, McMaster Univ. (Canada)

**"Unified Hard + Soft Information Fusion"**
Dr. Ronald P. S. Mahler, Lockheed Martin Maritime Systems and Sensors

# Issues in Relating Hard and Soft Information for Fusion

Ivan Kadar
Interlink Systems Sciences, Inc.
Lake Success, NY, USA

25 April 2011

Invited Panel Discussion:

"Real-World Issues and Challenges in Hard and Soft Fusion"

SPIE Conference 8050

"Signal Processing, Sensor Fusion and Target Recognition XX"

Orlando, FL 25-27 April 2011

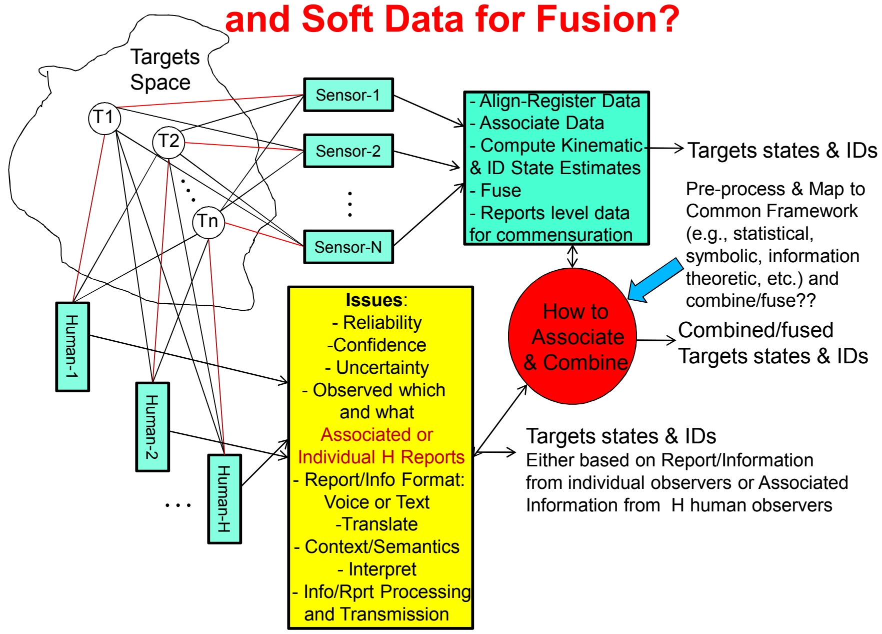
## Motivation

The purpose of this talk is to explore and highlight a naïve view of a not fully understood (by the speaker) basic component needed to implement soft and hard fusion systems.

It should be noted that this presentation was prepared prior to receiving materials from the panel participants.

Hopefully the material presented will serve to motivate discussion by the expert panel participants who will address the subject and detail several important related topics in the presentations to follow.

## How to Align, Register, Associate & Process Hard and Soft Data for Fusion?




## Open Floor for a Short Discussion

The purpose of this talk was to explore a naïve, not fully understood (by the speaker), perspective of the basic component needed to implement hard and soft fusion systems.

Does the stated problem make sense?

What is best way to formulate it and address it?

Panel participant’s presentations to follow.

# Issues in Relating Hard and Soft Information for Fusion

Ivan Kadar
Interlink Systems Sciences, Inc.
Lake Success, NY 11042, USA

## 1.0 INTRODUCTION

The purpose of this position paper, along with the accompanying viewgraphs, is to highlight an essential component of Hard and Soft Fusion, stated in the title, which is associated with the salient problems identified in introductory statement for the "Invited Panel Discussion on Real-World Issues and Challenges in Hard and Soft Fusion":

"The panel will address salient real-world issues and challenges in hard and soft data fusion illuminated by invited experts. Accurate situation assessment [1-4] sometimes cannot be accomplished using just hard or soft data sources alone. Specifically sources of "hard information" are physics-based sources that provide sensor observables such as radar or video data, while "soft information" is usually provided by human-based sources [5, 6]. Fusion of hard and soft data can provide situation pictures that are better than those using hard or soft data alone. For example, patrol reports provide soft data in addition to hard data from physical sensors in urban operational environments. While algorithms for fusing information from physical sensors has a substantial development history as well as maturity [7-14], complex technical issues remain in the representation of human-based information [6] to make it suitable for combining with sensor based information. Conceptual real-world related examples associated with the overall complex problem will be addressed by the panel to highlight issues and challenges. Audience participation is welcomed to provide a forum for exchange of ideas".

**Keywords:** Information Fusion, Hard-Soft Fusion, Human-based information

## 2.0 PROBLEM STATEMENT

The purpose of this position paper and the accompanying viewgraphs is to explore and highlight a naïve view of a not fully understood (by the writer) basic component needed to implement soft and hard fusion systems.

Specifically, the issue is how to "relate" hard and soft information for fusion. It should be noted that the associated presentation was prepared prior to receiving materials from the panel participants. "Hopefully the material presented will serve to motivate discussion by the expert panel participants who will address the subject and detail several important related topics in the presentations to follow" (documented in the individual presenters' viewgraphs and position papers).

The word "relate" is used to describe a set of complex processes needed: align, register, associate and estimate the parameters needed for hard and soft information for fusion in the sense depicted in Figure 1. However, given the nature of human information, while the above processes directly apply to hard information, the stated processes do not explicitly apply to soft data directly making the problem complex.

There have been several papers published discussing many aspects of hard and soft fusion, specifically related to soft data, such as: *ontology* [15, 16] (defined in computer science "as a rigorous and exhaustive organization of some knowledge domain that is usually hierarchical and contains all the relevant entities and their relations" [17]), clearly relevant to the processing and interpretation of textural and voice data from human sources; *text-based data exploitation and uncertainties* [18]; *context; semantics*; *methods of human data representation (e.g., symbolic) and interpretation,* [19], idea of *generation of* a *fundamental data set for hard and soft information fusion* [5], and a book *on human centered information fusion* [6], which represent a small subset of many publications in this area.

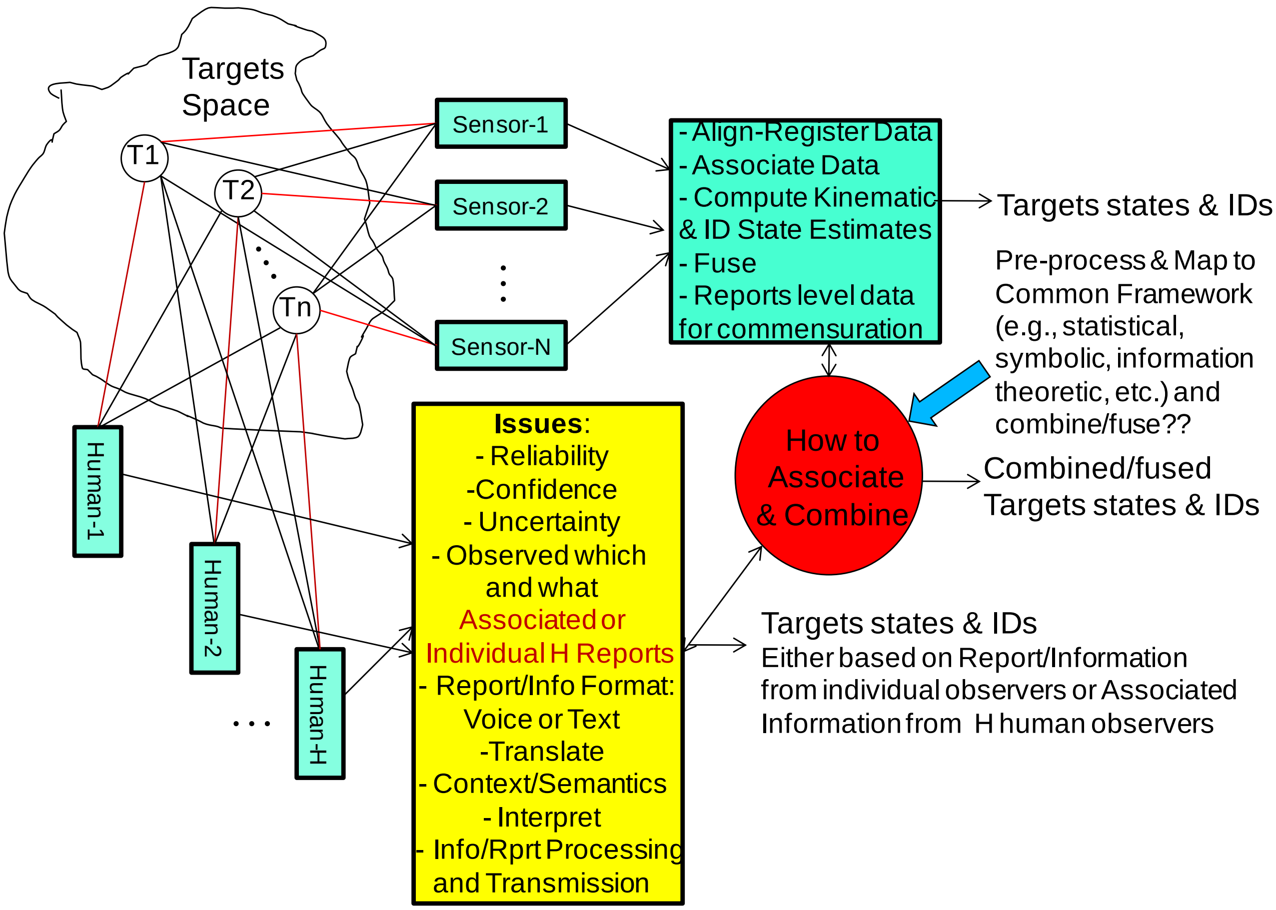



Figure 1: How to Align, Register, Associate and Process Hard and Soft Data for Fusion?

Given the above, the unsolved problem remains is how to align, register, associate and process hard and soft information for fusion. Figure 1 depicts a set of targets potentially observed by both hard and soft sensors.

Both the hard (Sensors: 1, 2,…,N), and soft (Human sensors: 1,2,…,H) sensors could possibly observe all the targets or only a subset of the targets. That is, the hard Sensors can be considered to operate in the well known Multitarget Multi-Sensor Tracking/ID and Fusion mode and/or provide reports level data only for commensuration with unassociated H (human) sensors. The corresponding Human sensors, even if able observe the same targets, may not be able distinguish which target is which, what it is, and where is which, especially in a dynamic environment.

Therefore, H sensors could send incorrect reports, or send false reports. That is the reliability, context, semantics, and interpretation of human textual or voice reports (can be based on visual sightings or on data from human controlled and read adjunct hard sensors in a dynamic environment) can possibly be subject to a high degree of uncertainty and be incomplete. Furthermore, the human reports may be processed and send on an individual report basis rather than "associated H reports" as noted above, and in Figure 1.

## 3.0 SUMMARY

Based on the forgoing, as far as this writer knows, there have not been any general unified theoretic methods established to combine hard and soft information to date. Related works, both the presentations prepared by the expert panelists and the papers listed in the references, did not specifically address the general problem.

Questions arise, such as: how to pre-process and map to a common framework (e.g., statistical, symbolic, information theoretic, etc.) and fuse (combine) hard and soft information on the same basis in a unified manner. These questions await joint solutions.

The purpose of the position paper and the associated presentation was to explore a naïve, not fully understood (by the writer), perspective of the basic component needed to implement hard and soft fusion systems, i.e., relating hard and soft information for fusion.
Issues need to be addressed:

- Does the stated problem make sense?
- What is best way to formulate it and address it?

## REFERENCES


[1] E. P. Blasch, I. Kadar, J.Salerno, M. M. Kokar, S. Das, G. M. Powell, D. D. Corkill, and E. H. Ruspini, "Issues and challenges of knowledge representation and reasoning methods in situation assessment (Level 2 Fusion)", *J. of Adv. in Information Fusion,* 1(2),122-139, (2006).

[2] E. P. Blasch, P. Valin, E. Bossé, M. Nilsson, K. Van Laere, and E. Shahbazian, "Implication of Culture: User Roles in Information Fusion for Enhanced Situational Understanding", *Int. Conf. on Information Fusion*, (2009).

[3] I. Kadar, "Results from Level 2/3 Fusion Implementations: Issues, Challenges, Retrospectives and Perspectives for the Future –An Annotated Perspective", Invited Paper, *Signal Processing, Sensor Fusion and Target Recognition XVII,* edited by Ivan Kadar, Proc. SPIE Vol. 6968, Orlando Fl., April 2008.

[4] E. L. Waltz and J. Llinas, *Multisensor Data Fusion*, Artech House, 1990.

[5] M. A. Pravia, R. K. Prasanth, P. O. Arambel, C. Snider, C.-Y Chong, "Generation of a Fundamental Data Set for Hard/Soft Information Fusion", *Int. Conf. on Information Fusion*, (2008).

[6] D. L. Hall and J. M. Jordan, *Human-centered Information Fusion*, Boston: Artech House, 2010.

[7] Y. Bar-Shalom, P. K. Willet, X. Tian, *Tracking and Data Fusion – A Handbook of Algorithms*, YBS Publishing, Box U -2157, Storrs, CT 06289-2157, USA, March 2011.

[8] M. E. Liggins, D. L. Hall, and J. Llinas, *Handbook of Multisensor Data Fusion: Theory and Practice*. CRC Press, 2nd ed., 2008

[9] R. P. Mahler, *Statistical Multisource-Multitarget Information Fusion*, Artech House, 2007.

[10] D. L. Hall and S. A. H. McMullen, *Mathematical Techniques in Multisensor Data Fusion*, Artech House, 2 ed., 2005

[11] D. L. Hall and S. A. H. McMullen, *Mathematical Techniques in Multisensor Data Fusion*, Artech House 2004.

[12] I. R. Goodman, R. P. Mahler, and H. T. Nguyen, *Mathematics of Data Fusion*, Springer, 1997.

[13] M. Liggins, C. Chong, I. Kadar, M. Alford, V. Vannicola and S. C. A. Thomopoulos, "Distributed Fusion Architectures and Algorithms for Target Tracking", *Proceedings of the IEEE,* Special Issue on Sensor Fusion, Vol. 85, No. 1, January 1997.

[14] R. T. Antony, *Principles of Data Fusion Automation*, Artech House, 1995.

[15] E. P. Blasch, E. Dorion, P. Valin, E. Bossé, and J. Roy, "Ontology Alignment in Geographical Hard-Soft Information Fusion Systems," *Int. Conf. on Info Fusion*, (2010).

[16] E. P. Blasch, E. Dorion, P. Valin, and E. Bossé, "Ontology Alignment using Relative Entropy for Semantic Uncertainty Analysis", *Proc. IEEE Nat. Aerospace Electronics Conf (NAECON)*, 2010.

[17] http://www.thefreedictionary.com/ontology

[18] R. Anthony, and J. Karakowski, "First-Principle Approach to Functionally Decomposing the JDL Model: Emphasis on Soft Target Data", *Int. Conf. on Information Fusion*, (2008).

[19] K. Shambhoos, J. Llinas and E. Little, Graphical Methods for Real-Time Fusion and Estimation with Soft Message Data" *Int. Conf. on Information Fusion*, (2008).

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# Challenges in Hard and Soft Information Fusion: Worth the Effort?

April 25, 2011

David Hall
The Pennsylvania State University
University Park, PA 16802
dhall@ist.psu.edu

1

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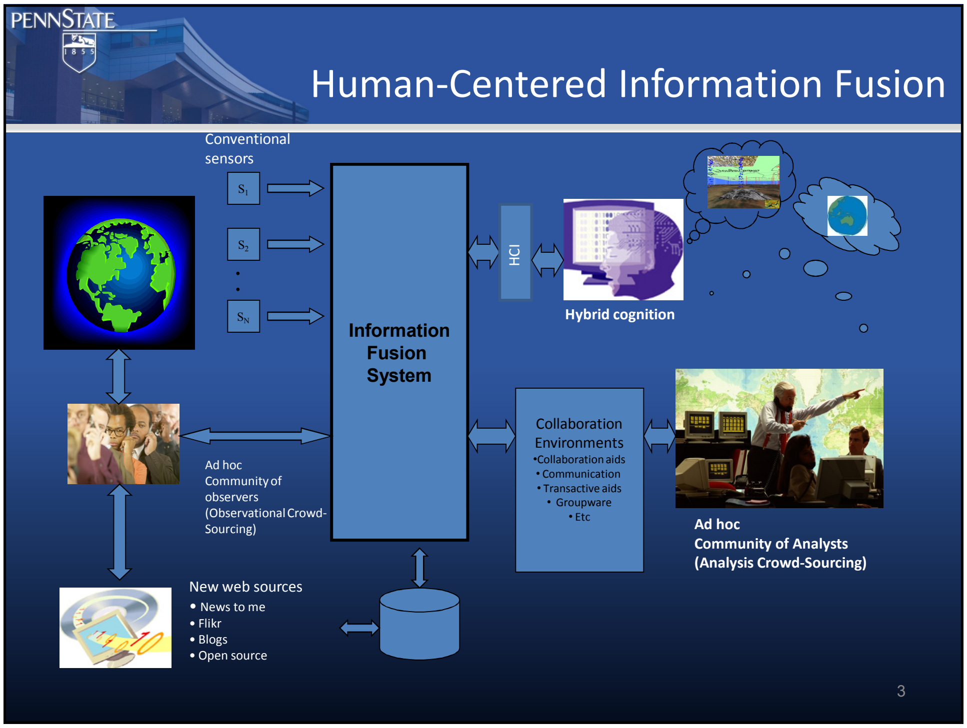
## Discussion Topics

- Introduction – Emergence of Human-Centered Fusion
- Concept of Hard and Soft Fusion
- Challenges in Hard and Soft Fusion
- Perspectives on the Value of Human Observers

2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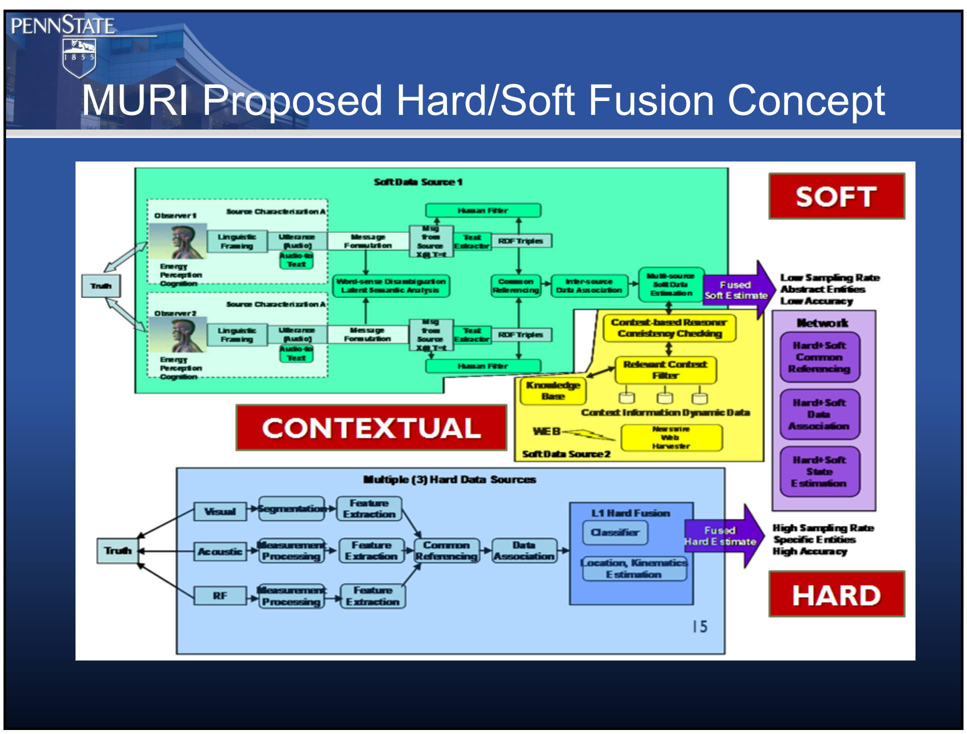
1855
Human-Centered Information Fusion
Conventional sensors
S1
S2
SN
Information Fusion System
HCI
Hybrid cognition
Ad hoc Community of observers (Observational Crowd-Sourcing)
Collaboration Environments
•Collaboration aids
• Communication
• Transactive aids
• Groupware
• Etc
Ad hoc Community of Analysts (Analysis Crowd-Sourcing)
New web sources
• News to me
• Flikr
• Blogs
• Open source
3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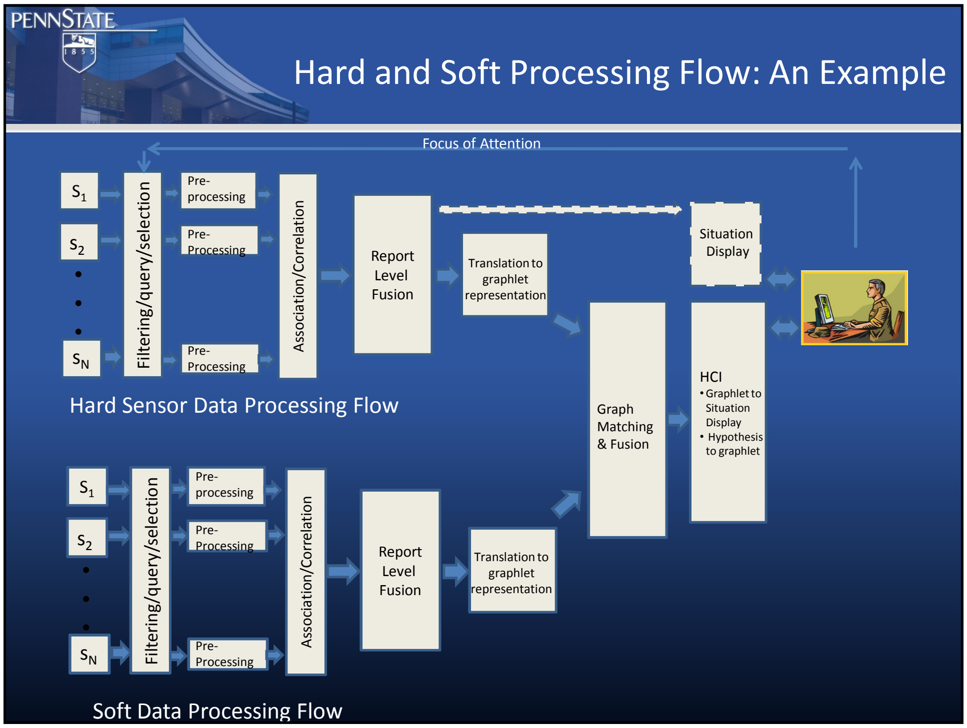
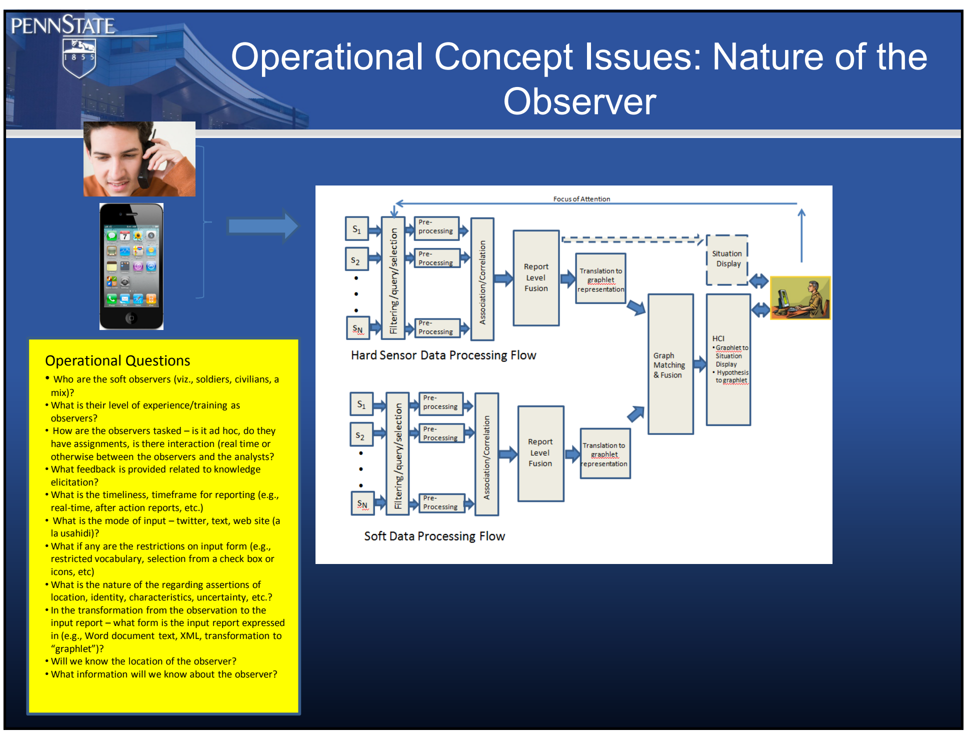
1855
MURI Proposed Hard/Soft Fusion Concept
Soft Data Source 1
Observer 1
Observer 2
Truth
Source Characterization A
Human Filter
Linguistic Framing
Utterance (Audio)
Audio to Text
Message Formulation
Text Extractor
RDF Triples
Word-sense Disambiguation Latent Semantic Analysis
Common Referencing
Inter-source Data Association
Multi-source Soft Data Estimation
Energy Perception Cognition
Fused Soft Estimate
SOFT
Low Sampling Rate
Abstract Entities
Low Accuracy
Context-based Reasoner Consistency Checking
Relevant Context Filter
Knowledge Base
Context Information Dynamic Data
WEB
Newswire Web Harvester
Soft Data Source 2
CONTEXTUAL
Network
Hard+Soft Common Referencing
Hard+Soft Data Association
Hard+Soft State Estimation
Multiple (3) Hard Data Sources
Visual
Acoustic
RF
Segmentation
Measurement Processing
Feature Extraction
Common Referencing
Data Association
L1 Hard Fusion
Classifier
Location, Kinematics Estimation
Fused Hard Estimate
High Sampling Rate
Specific Entities
High Accuracy
HARD
15


PENNSTATE
1855
Hard and Soft Processing Flow: An Example
Focus of Attention
$S_1$
$S_2$
$S_N$
Filtering/query/selection
Pre-processing
Pre-Processing
Pre-Processing
Association/Correlation
Report Level Fusion
Translation to graphlet representation
Situation Display
Graph Matching & Fusion
HCI
• Graphlet to Situation Display
• Hypothesis to graphlet
Hard Sensor Data Processing Flow
$S_1$
$S_2$
$S_N$
Filtering/query/selection
Pre-processing
Pre-Processing
Pre-Processing
Association/Correlation
Report Level Fusion
Translation to graphlet representation
Soft Data Processing Flow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Operational Concept Issues: Nature of the Observer
Operational Questions
• Who are the soft observers (viz., soldiers, civilians, a mix)?
• What is their level of experience/training as observers?
• How are the observers tasked – is it ad hoc, do they have assignments, is there interaction (real time or otherwise between the observers and the analysts?
• What feedback is provided related to knowledge elicitation?
• What is the timeliness, timeframe for reporting (e.g., real-time, after action reports, etc.)
• What is the mode of input – twitter, text, web site (a la usahidi)?
• What if any are the restrictions on input form (e.g., restricted vocabulary, selection from a check box or icons, etc)
• What is the nature of the regarding assertions of location, identity, characteristics, uncertainty, etc.?
• In the transformation from the observation to the input report – what form is the input report expressed in (e.g., Word document text, XML, transformation to "graphlet")?
• Will we know the location of the observer?
• What information will we know about the observer?
Focus of Attention
Filtering/query/selection
Pre-processing
Association/Correlation
Report Level Fusion
Translation to graphlet representation
Situation Display
Graph Matching & Fusion
HCI
Hard Sensor Data Processing Flow
Soft Data Processing Flow

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# Challenges

- Soft sensor characterization
- Soft sensor tasking, motivation and knowledge elicitation
- Soft/hard fusion
- Test and evaluation
- Translation to practice



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# Summary of issues

**Table 1: Summary of Issues in Hard and Soft Data Fusion**

| Issue | Description | Examples of Specific Issues | References |
|---|---|---|---|
| Soft sensor characterization | How to develop the equivalent of a "ROC" curve to quantitatively characterize the performance of a human observer under varying conditions | • Focus of attention<br>• Training and domain expertise<br>• Motivation<br>• Ethnic background<br>• Observer's age and gender<br>• Effects of fatigue, drugs, physical conditioning, etc.<br>• Emotional state | [6], [11], [12] |
| Tasking, motivation and knowledge elicitation | How to task a human observer without prejudicing their observation or unknowingly eliciting false reports | • Tasking of humans (gaming approaches, financial motivation)<br>• Knowledge elicitation – how to elicit information without prejudicing or biasing observers<br>• Addressing unanticipated effects such as creating false observations | [14], [15], [16], [17], [18] |
| Hard and soft fusion | How to combine information from physical sensors and human observations via automated processing | • Architecture – where to fuse<br>• Transformation of soft data into common framework to be compatible with hard data<br>• Uncertainty representation<br>• Data amounts versus value<br>• Tendency to consider humans as "poor" physical sensors | [6], [8], [9] |
| Test and evaluation | How to effectively test and evaluate hard and soft fusion systems and algorithms | • Same as test and evaluation of hard sensor systems<br>• Increased challenges due to human observers<br>• Need for integrated soft and hard "truthed" data set | [2], [20], [21], [22] |
| Translation to practice | How to transition prototype systems into practice | • Addressing new practices of digital natives<br>• Changing doctrine and methodologies to reflect information sources enabled by technology changes | |

# Perspectives

- Human observations will become increasingly important
  - Technology push
  - Digital natives pull
- Technology & user practices will outstrip organization and doctrine
- Despite human limitations, human observations are valuable
- Like it or not – we must address this emerging area

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# Challenges in hard and soft information fusion: Worth the effort?

David L. Hall
College of IST, The Pennsylvania State University, University Park, PA, USA 16802

The simultaneous proliferation of mobile phones and ubiquitous sensing devices such as video surveillance cameras enables a near-continuous monitoring of environmental conditions, extreme events such as tsunamis, hurricanes and earthquakes, and human activities such as crime. A challenge is how to fuse the "soft" (human reported) information with the "hard" (physical sensor) data. Extensive research is on-going related to development of suitable architectures, adaptation of fusion algorithms to treat hard and soft data, and development of test-beds and data sets to allow evaluation of hard and soft fusion techniques. This paper provides a summary of challenges in hard and soft fusion and addresses the question – is this fusion worth the effort.

**Keywords:** hard and soft fusion, human-in-the-loop, humans as sensors

## 1. INTRODUCTION

Traditionally, information fusion systems have focused on fusion of data from physical (hard) sensors regarding an observed physical world ([1], [2]). Examples include environmental surveillance, military situation awareness and threat warning systems and monitoring the condition of complex machines. Moreover, these systems have tended to operate primarily in a data-driven fashion in which sensor data is processed for an information display (e.g., common operational picture) which is observed in a relatively passive way by a user/analyst.

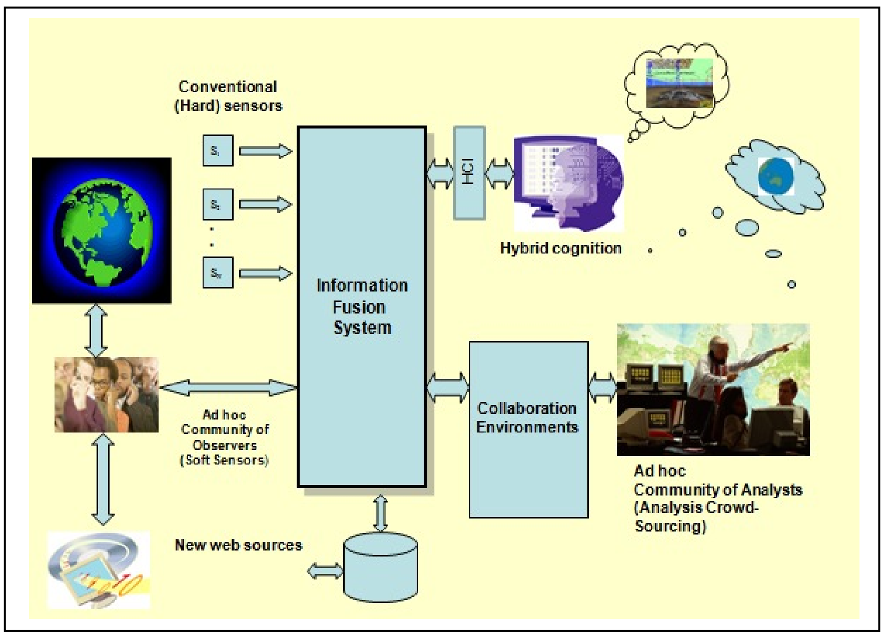



Figure 1: Concept of Human-Centric Information Fusion (adapted from [3])

In recent years, four main factors have changed the concept of traditional data fusion. These include: (1) interest in observing not only a physical environment but also the "human landscape" associated with an environment, event or activity, (2) the proliferation of smart phones [3] and ubiquitous communications that enable human observers to act as participatory observers; (3) the evolution of human computer interaction (including 3-D immersive displays and advanced aural interfaces) to allow a user to participate in the fusion process, conducting pattern recognition and semantic reasoning to assist the automated computations [4]; and (4) improved collaboration environments such as second life [5] and social network tools to allow dynamic collaboration among analysts or decision-makers. Hall and Jordan have described these trends and coined the term human-centric information fusion [6]. The concept of human-centric information fusion is shown in Figure 1. In this paper we focus on the particular issues related to the combined use of human observers and physical sensors, and discuss challenges in hard and soft information fusion.

## 2. OVERVIEW OF HARD AND SOFT FUSION

The concept of hard and soft fusion is illustrated in Figure 2. In that figure, we illustrate a traditional hard sensor data processing flow (in the upper left hand side of the figure) involving the standard functions of pre-processing (e.g., signal and image processing), association and correlation of data from diverse sensors and sensor types, report level fusion involving pattern recognition and statistical estimation to obtain a state vector (time, location, kinematics, attributes and identity) describing an observed target, entity, event or activity. Numerous texts have addressed this processing flow and specific algorithms for the identified functions (e.g., [1], [2]). Some specific examples of fusion processing for hard sensor data related to counter insurgency (COIN) operations are described by [7].

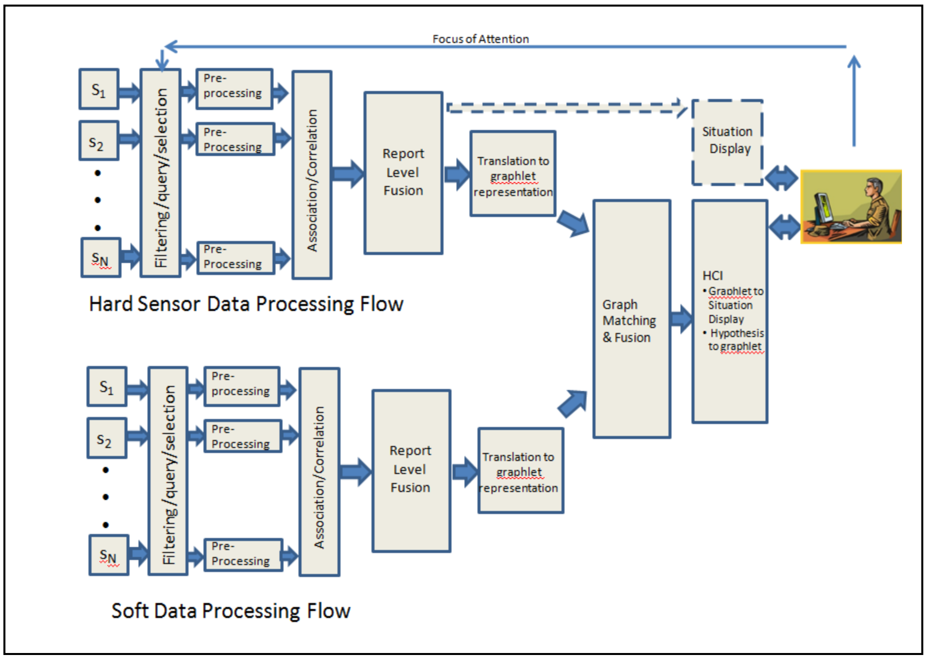



Figure 2: Concept of Hard and Soft Fusion

The lower left hand side of figure 2 shows a conceptual soft processing flow. In this case, observations from human reporters are processed using the same types of functions (viz. preprocessing, association/correlation, report level fusion), as are proscribed for the hard sensor process. Details of techniques for soft sensor processing are still emerging. However, general frameworks for hard and soft fusion are being developed ([8], [9]), and algorithms are being developed utilizing graph matching theory [10]. The fusion of the hard and soft data is illustrated on the right hand side of figure 2.

## 3. CHALLENGES IN HARD AND SOFT FUSION

Table 1 provides a summary of specific issues related to hard and soft fusion. These are categorized into five main areas including: (1) soft sensor characterization – how to characterize the behavior and capability of human observers; (2) soft sensor tasking, motivation and knowledge elicitation – how to task a human observer without prejudicing their observation or unknowingly eliciting false reports; (3) soft/hard fusion – how to combine information from physical sensors and human observations via automated processing; (4) test and evaluation – how to effectively test and evaluate hard and soft fusion systems and algorithms; and (5) translation to practice - how to transition prototype systems into practice.

*Soft Sensor Characterization*

An initial problem in utilizing soft sensor data is the challenge of sensor performance characterization. How can we develop the equivalent of receiver operating characteristic ("ROC") curves that represent how humans perform in transforming their (human) multi-sensory inputs into observations, generally expressed in semantic terms (e.g., I see a suspicious person near the bank)? While humans exhibit sensing limitations based on environmental conditions such as weather, and day/night conditions analogous to the performance changes of physical sensors, they also experience performance differences based on factors such as training, fatigue, expectations, focus of attention, how they are queried or tasked, ethnic background, age, gender and other personal characteristics, physical condition, ingestion of drugs or stimulants such as caffeine and even how they are feeling. The output of the human sensor tends to be expressed in fuzzy semantic terms (e.g., "near", "suspicious") which in turn need to be transformed into standardized terms and scalar measures. Even disregarding the issue of false reports, it is challenging to develop a characterization of the uncertainty of a human observation.

A number of papers provide some insight into this problem. For example, Z. Lu and B. A. Dosher [11] explore the application of traditional signal processing models to human perception and decision-making. Steinberg et al [12] describe the results of a study they conducted for Lockheed Martin on issues in characterizing errors in human generated reports for data fusion. Chapter 3 in Hall and Jordan [6] provides a framework for modeling the human observation and reporting process, and numerous papers exist on specific issues in human observation such as human vision models, etc. The issue of human observations and reports has been studied intensely for understanding the reliability and truthfulness of witnesses in trials. Indeed, the *Journal of Credibility Assessment and Witness Psychology* is dedicated to reporting such studies.

While significant research has been performed, it is still a challenging task to develop appropriate models for characterizing human observers as soft sensors. At this time there does not appear to be a well-grounded "standard" model available for hard/soft fusion system designers to apply to represent model the characteristics of human observers.

*Soft sensor tasking, motivation and knowledge elicitation*

An issue that affects the performance of human observers is how they are tasked for information (e.g., via requests communicated over a cell phone; use of standard data input forms; encouragement of free texting via systems such as Twitter). Unlike physical sensors, humans do not respond on an "on-call basis" to demands for information and are generally an uncontrolled source. Even the use of a trained observer such as soldiers acting as sensors [13], involves a relatively weak interaction between an information fusion system and the observing humans. Generally, such observers may entail *a priori* agreements or instructions and requesting the observers to provide "after action" reports. By contrast, tasking may involve ad hoc reporting such as reporting of emergencies or "gossip" via Twitter [14].

Closely related to observer tasking is observer motivation and the method of knowledge elicitation. Observers may be motivated by a variety of feelings including altruism, fear, greed, competition, a sense of obligation, or malevolence. In the *Wisdom of Crowds* [15], Surowiecki argues that problems presented to a general population of potential respondents can produce results that greatly surpass the capabilities of an individual or small group, including observing phenomena of interest. Palfrey and Gasser [16] describe the characteristics of the new generation of digital natives who have always known cell phones and the internet and have different perspectives on privacy and a sense of obligation in sharing information and observations. Attempts to motivate observers to provide observations of an activity or event include competitions and transformation of the observing process into a game (e.g., "gamification"). McGill [17], for example, has described experiments conducted at The Pennsylvania State University using competitive games to motivate students to act as observers for campus phenomena. At a much larger scale, the Defense Advanced Research Projects Agency (DARPA) sponsored the Red Balloon contest [18]; a challenge contest to explore participatory sensing by offering teams $ 40,000 to find and verify the location of 20 red weather balloons placed around the U. S. on a Saturday in December. Tang et al [19] describe the results of that experiment including issues related to the large percentage of false observations and the analysis methods used to validate observations.

Finally, the issue of knowledge elicitation is important – What are the specific mechanisms and methods to elicit information from humans; how can one address common biases without "leading" an observer; what is the role of human aided knowledge elicitation (e.g., a 911 emergency operator) versus computer aided elicitation via structured forms or guided questions. Knowledge elicitation is a well studied area for developing the knowledge base for expert systems; however, issues in dynamic, ad hoc elicitation require further study.

*Soft/hard fusion*

Challenges in the processing of hard and soft data involve the fundamental question of how can we effectively combine data from traditional physics based sensors with human reports? As previously noted, challenges in hard and soft fusion involve characterization of the human observer (characterizing the soft sensor data), understanding how to task human observers and how the tasking and knowledge elicitation impacts the reported observations, and challenges in the "down- stream" processing. In particular, challenges exist in the overall processing flow:

- *Soft data transformation* – transformation of soft data into a form and representation scheme that permits fusion with hard data (e.g., translating fuzzy semantic references into scalar and vector data);
- *Fusion architecture* – choosing where in the processing flow to fuse the data (e.g., at the data level, report level, or decision level);
- *Uncertainty representation* – How to represent information uncertainty from both physical sensors and from human observations. Generally this will require a combination of techniques ranging from traditional probability based methods as well as confidence factors and fuzzy membership measures;
- *Addressing temporal inconsistencies* – A challenge in human observations is addressing reports related to time. Physical sensors can simply "time stamp" the time of observation, while human observers may refer to past observations, current observations using fuzzy references "about noon", or temporal relations such as "before" or "after";
- *Data volume versus value* – Almost any physical sensor can provide an overwhelming volume of data compared to a human observation. Clearly, streaming video and persistent sensor surveillance can provide a huge amount of data compared to single human report. It is important to address volume versus value of observations. For example, a single human inference about intent or anomalies may exceed in value a huge amount of physical sensor data;
- *Undervaluing (or overvaluing) human reports* – As above, it is important to seek accurate value of human reports, neither overvaluing a human observer or undervaluing the report and assuming that a human is a poor version of a hard sensor.

General discussion of hard and soft fusion is provided by Hall and Jordan [6], Hall et al [8] and Llinas et al [9].

*Test and evaluation*

In developing new algorithms and techniques for fusion of hard and soft data, a key challenge involves test and evaluation. Traditional hard sensor fusion systems require testing "ground truth" sensor data obtained in a variety of observational conditions. Typically data are obtained from test ranges or live exercises and used to evaluate the performance of data fusion algorithms and systems. A discussion of the test and evaluation of hard sensor fusion systems is provided by Waltz and Llinas [20] and Liggins et al [2]. Issues include; (1) establishment of "ground truth" for the observed data, (2) developing performance characteristics for the sensors, (3) creating a sufficient training set for target identification and pattern recognition algorithms, (4) developing a hierarchy of measures of performance (MOP), measures of effectiveness (MOE), measures of system effectiveness (MOSE), etc., (5) conducting tests involving performance "with" and "without" the fusion processes, and (6) evaluating combined symbolic and numeric processes (e.g., numerical estimation of target location and characteristics as well as symbolic labeling of target identification and behavior), etc.

Additional challenges in test and evaluation of hard and soft fusion systems are described by Graham et al [21] and an experimental laboratory for test and evaluation (T&E) of hard and soft fusion is described by Hall et al [22]. The test and evaluation of hard and soft fusion systems must not only address all of the issues for T&E of hard sensor systems, but also address the added complexities of soft data. In our research, we found a particular challenge was obtaining a set of test data that included both hard and soft data. While a number of data sets exist containing hard data alone or soft data alone, only a very limited number of data sets address both hard and soft data. This is understandable because of the need to construct experimental set ups (or development of simulations) that produce data from physical sensors and coordinated observations by human observers. This human in the loop experimentation is challenging and difficult to replicate. At The Pennsylvania State University, we are developing both synthetic data sets for such T&E purposes

[23]. Our experimental setup allows experiments to address issues such as knowledge elicitation, observer training and other challenges. This data will be made available to the research community to support evaluation of new fusion techniques.

*Translation to practice*

The final challenge area involves translation of hard and soft fusion to practice. On one hand, the experiences and mentality of the digital natives lead to a tendency for routine sharing of information and observations. This is coupled with the rapid increase in enabling technologies. On the other hand, for traditional applications such as military situation awareness and emergency crisis management, organizations and doctrine are not yet established for use of such information. Moreover for military applications, the mix of classified sources of data with open source information becomes problematic. It is anticipated that the enabling technologies and cyber infrastructure will lead the organizational and doctrinal aspects of hard and soft fusion.

**Table 1: Summary of Issues in Hard and Soft Data Fusion**

| **Issue** | Description | Examples of Specific Issues | References |
|---|---|---|---|
| Soft sensor characterization | How to develop the equivalent of a "ROC" curve to quantitatively characterize the performance of a human observer under varying conditions | • Focus of attention<br>• Training and domain expertise<br>• Motivation<br>• Ethnic background<br>• Observer's age and gender<br>• Effects of fatigue, drugs, physical conditioning, etc.<br>• Emotional state | [6], [11], [12] |
| Tasking, motivation and knowledge elicitation | How to task a human observer without prejudicing their observation or unknowingly eliciting false reports | • Tasking of humans (gaming approaches, financial motivation)<br>• Knowledge elicitation – how to elicit information without prejudicing or biasing observers<br>• Addressing unanticipated effects such as creating false observations | [14], [15], [16], [17], [18] |
| Hard and soft fusion | How to combine information from physical sensors and human observations via automated processing | • Architecture – where to fuse<br>• Transformation of soft data into common framework to be compatible with hard data<br>• Uncertainty representation<br>• Data amounts versus value<br>• Tendency to consider humans as "poor" physical sensors | [6], [8], [9] |
| Test and evaluation | How to effectively test and evaluate hard and soft fusion systems and algorithms | • Same as test and evaluation of hard sensor systems<br>• Increased challenges due to human observers<br>• Need for integrated soft and hard "truthed" data set | [2], [20], [21], [22] |
| Translation to practice | How to transition prototype systems into practice | • Addressing new practices of digital natives<br>• Changing doctrine and methodologies to reflect information sources enabled by technology changes | |

# 4. PERSPECTIVES ON THE VALUE OF HUMAN OBSERVERS

There are numerous examples of humans acting as poor observers. Graham et al. [21] cite three examples: (1) Kaplan and Kaplan [24] describe the case in which the Rotterdam Zoo reported (in 1978) the escape of one of its red pandas; hundreds of helpful people called in, having spotted it in places all over the Netherlands – when in fact it had been run over by a train just a few yards from the zoo fence; (2) an experiment conducted by D. Simmons and C. F. Chabris [25] at the University of Illinois involve showing subjects a video clip of two teams of people (in white and black uniforms) passing a basketball back and forth. The subjects were asked to count the number of passes by one team during a 60 second period. During the video, a person in a gorilla suit walks between the players, stops and waves and continues on. A surprisingly high number of subjects fail to notice the gorilla; and (3) the failure of students at Virginia Tech University to observe the precursors to the shooting spree in which a 23 year old student, Seung-Hui Cho killed 27 students, five teachers and himself. Observable precursors included Cho practicing locking a building with chains (to prevent police from entering and stopping his shootings) two days prior to the actual event. These examples and our everyday experiences would suggest that humans are a poor substitute for well placed and calibrated physical sensors.

Despite these examples of poor performance, however, human observers can provide valuable information that simply cannot be obtained from physical sensors. Humans can infer intent, detect anomalies in common situations, provide information about situation context, and determine when and when not to pay attention to physical sensor data. A review of the emerging concept of "participatory sensing" is provided by [26]. Examples of the effective use of human observers can be found in a variety of applications including;

- *Law enforcement* - e.g., monitoring police reports and events and posting these for public use ([27], [28], [29]) or tasking non-police workers such as sanitation workers to identify anomalies [30],
- *Social movements or cultural identity support* – e.g., the Photovoice Movement project in which rural Chinese women documented their daily lives via 35 mm cameras which raised awareness of government officials regarding childcare and midwife needs [31], use of web mash up mechanisms such as Ushahidi [32] to report political oppression;
- *Environmental monitoring* – e.g., use of cell phones and specialized sensors to report air quality [33];
- *Crisis management and reporting* - sharing of information by volunteers to support disaster relief ([34],[35]); and
- *Citizen scientists* – use of civilians as observers for scientific phenomena such as earthquakes [36].

It can be argued that the combination of proliferation of mobile computing/communications devices, the increasing WiFi and cellular communications networks, and the evolution of the digital natives [16] combine to ensure that soft sensing will increasingly become an important information source. The digital natives tend to view sharing of information as both natural and almost an obligation for participation in the current digital world.

# 5. SUMMARY

Rapid changes in communications and mobile computing devices enable a new era of human observations. The combination of ubiquitous sensing and the proliferation of cell phone technology create a self-aware planet in which human and physical sensor observations can be combined for global situation awareness. However, many challenges must be addressed to take advantage of these opportunities. It is anticipated that the data fusion and cognitive psychology communities will focus on these challenges for ultimate routine fusion of hard and soft data.

# 6. ACKNOWLEDGEMENTS

We gratefully acknowledge that this research activity has been supported in part by a Multidisciplinary University Research Initiative (MURI) grant (Number W911NF-09-1-0392) for "Unified Research on Network-based Hard/Soft Information Fusion", issued by the US Army Research Office (ARO) under the program management of Dr. John Lavery.

# REFERENCES


[1] D. Hall and S. A. H. McMullen, *Mathematical Techniques in Multisensor Data Fusion*, Artech House, 2 ed., 2004

[2] M. E. Liggins, D. L. Hall, and J. Llinas, *Handbook of Multisensor Data Fusion: Theory and Practice*. CRC Press, 2nd ed., 2008

[3] J. Brandon, Digital Trends, Feb 16, 2010, http://www.digitaltrends.com/features/the-future-of-smartphones-2010-2015-and-beyond/

[4] D. Hall, C. M. and S. A. H. McMullen, S. A. H., "Perspectives on the Human Side of Data Fusion: Prospects for Improved Effectiveness using Advanced Human-Computer Interfaces," chapter 20 in *Handbook of Multisensor Data Fusion*, 2nd edition, edited by M. Liggins, D. Hall and J. Llinas, CRC Press, 2008

[5] Hall, D. Hall, C., McMullen, S. McMullen. M. and Pursel, B., "Perspectives on visualization and virtual world technologies for multi-sensor data fusion," *Proceedings of the 11th International Conference on Information Fusion*, Cologne, Germany, June 30- July 03, 2008

[6] D.L. Hall and J.M. Jordan, *Human-centered Information Fusion*, Boston: Artech House, 2010

[7] M. S. Baran, D. J. Natale, R. L. Tutwiler, M. McQuillan, C. Griffin, J. Daughtry, J. Rimland and D. Hall, "Hard sensor fusion for COIN inspired situation awareness," *Proceedings of the SPIE Conference*, Orlando, FL, April 26, 2011

[8] Hall, D., McNeese. M., Llinas, J., and Mullen, T., "A framework for hard/soft fusion," *Proceedings of the 11th International Conference on Information Fusion,* Cologne, Germany, June 30 – July 03, 2008

[9] J. Llinas, R. Nagi, D. Hall and J. Lavery, "A multidisciplinary university research initiative in hard and soft information fusion: overview, research strategies and initial results," in *Proceedings of the 13th International Conference on Information Fusion*, Edinburgh, UK, July, 2010

[10] A. Haghighi, A.Y. Ng and C.D. Manning, "Robust textual inference via graph matching. HLT-EMNLP 2005", *Robust Textual Inference via Graph Matching. HLT-EMNLP 2005*, 2005

[11] Z. Lu and B. A. Dosher, "Characterizing observers using external noise and observer models: Assessing internal representations with external noise," *Psychological Review*, vol. 115, No. 1, pp 44-82, 2008

[12] A. Steinberg, J. Llinas, A. Bisantz, C. Stoneking and N. Morizio, "Human Source Characterization", June, 2007 (see http://www.atl.lmco.com/papers/1484.pdf)

[13] S. Magnuson, "Army wants to make 'every soldier a sensor'", *National Defense Magazine*, May, 2007

[14] M. Williams, "Governments use Twitter for emergency alerts, traffic notices and more," *Government Technology*, January 7, 2009

[15] J. Surowiecki, *The Wisdom of Crowds*, Anchor Books, NY, 2004

[16] J. Palfrey and U. Gasser, *Born Digital: Understanding the First Generation of Digital Natives*, Basic Books, 2008

[17] W. McGill, "The gamification of risk management", internet blog at http://www.professormcgill.com/, downloaded on February 22, 2011

[18] https://networkchallenge.darpa.mil/rules.aspx

[19] J. Tang, M. Cebrian, N.Giacobe, Hyun-Woo Kim, T. Kim and D. Wickert, "Reflecting on the DARPA red balloon challenge", accepted for publication in the *Communications of the ACM* (Association for Computing Machinery)

[20] E. Waltz and J. Llinas, *Multisensor Data Fusion,* Artech House, 1990

[21] J. Graham, J. Rimland, M. McNeese, D. Hall and W. McGill, "Human-centric information fusion: Human in the loop experiments to investigate the role of humans in situation awareness," *Proceedings of the 14th International Conference on Information Fusion*, Chicago, IL, July, 2011

[22] D. Hall, B. Hellar, and M. D. McNeese, "The Extreme Events Laboratory: A cyber infrastructure for performing experiments to quantify the effectiveness of human-centered information fusion," *Proceedings of the 2009 International Conference on Information Fusion (Fusion 2009),* Seattle, Washington, July, 2009

[23] J. Graham, D. Hall and J. Rimland, "A synthetic dataset for evaluating soft and hard fusion algorithms," accepted for publication in the *Proceedings of the SPIE Defense, Security and Sensing Symposium*, 25-29 April, 2011, Orlando, Fl

[24] M. Kaplan and E. Kaplan, *Bozo Sapiens: Why to err is Human*, Bloomsbury Press, New York, 2009

[25] D. J. Simons and C. F. Chabris, "Gorillas in our midst: sustained in-attentional blindness for dynamic events," *Perception*, 1999, vol. 28, pp 1059-1074

[26] Participatory Sensing: A Review of the Literature and State of the Art Practices, technical report prepared by the staff of the Penn State Center for Network Centric Cognition and Information Fusion, November 20, 2009

[27] Crime reports (http://crimereports.com)

[28] Crime mapping (http://www.crimemapping.com)

[29] Spot crime reporting (http://www.spotcrime.com)

[30] J. D. Glater, "Helping keep a city clean, and maybe safer," New York Times, January 18, 2009

[31] J. Burke and D. Estrin, "Participatory sensing", WSW'06 at SenSys'06, Boulder, CO, ACM, 2006

[32] http://www.ushahidi.com/

[33] E. Paulos, R. J. Honicky, et al, "Citizen science: enabling participatory urbanism", in *Handbook of Research on Urban Informatics: The Practice and Promise of the Real-Time City*, edited by M. Foth, Hershey, PA, 2009

[34] C. Jones and S. Mitnick, "Open source disaster recovery", First Monday, 2006, see http://131.193.153.231/www/issues/issue11_5/jones/index.html

[35] B. Schneiderman and J. Preece, "911.gov: community response grids", *Science*, 315 (5814): 944, 2007

[36] A. L. Hughes, L., Palen, "Twitter Adoption and Use in Mass Convergence and Emergency Events", *Proc. of the 6th International ISCRAM Conference*, Gothenburg, Sweden, 2009

## Automating Soft Data Exploitation: Opportunity & Challenges

Richard T. Antony
**SAIC**

Invited Panel Discussion
25 April 2011

SPIE Conf 8050 Signal Processing, Sensor Fusion, and Target Recognition XX

## Position & Perspectives

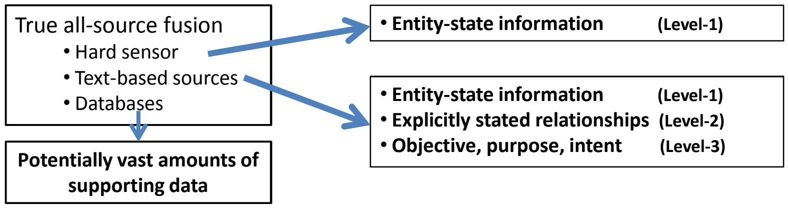
### On automated fusion of hard & soft data sources

**Opportunity:** Fusion of hard & soft data sources offers more holist (& more robust) approach to Situation Awareness (SA) development

**Some of the challenges to text-based data exploitation**

- **Ingestion:** *Information extraction* from unstructured text
- **Source normalization:** Across *soft* & *hard* information
- **Source registration:** Dealing with *semantic descriptions* of space & time
- **Effective utilization of domain context :** Context discovery & exploitation

## Opportunity
### More Holistic Approach to Situation Awareness




| | Hard sensor | Soft source | DB |
|---|---|---|---|
| **Hard sensor** | ELINT correlated to GMTI vehicle tracker | Real time soldier report of blue pickup with missing front fender linked to vehicle tracker | ATM transaction linked to vehicle tracker |
| **Soft source** | Iris scan linked to suspicious person report | Informant report linked to surveillance report | Suspicious person report linked to existing criminal reports |
| **DB** | Vehicle tracker constrained to road network | Text information linked to social, cultural, economic, etc. overlays | Traditional data mining |

**Traditional fusion focus**

## Challenge 1:
### Extracting & exploiting *relevant* information from unstructured text

| Challenge | Issues | Examples |
|---|---|---|
| Hard for even a human to know what is *relevant* | Needle in the haystack<br>Hidden relations | *Blue pickup with missing fender*<br>*Khalid Sattar* |
| Fact extraction from free text is beyond the state of the art | Tagging, parsing, pronoun resolution, non-grammatical, …<br>Semi-automated parsing | *Complex syntax & semantics* |
| Appropriate data element selection | *Subject-verb-object-location-time…* | *Indirect objects, how, why* |
| Entity & word resolution | Aliases, code names, code words | *KS, apples & flour* |

## Sample Challenges

**Challenging *syntax/grammar***
"He said a man in a tattered coat who later ran away acted highly suspicious"

***Semantics* tend to be context sensitive**

*Predator*

- Deviant behavior (bad person)
- Carnivorous animal
- Tactical UAV

***Codes words* employed to obscure meaning**
"Toothpaste" used in place of "bomb"

***Ambiguous meaning, use of slang***
The "goods" have arrived

***Ambiguous pronoun reference***

***Source reliability, information fidelity, deliberate deception, …***

## Challenge 2:
### Normalizing Hard-Soft Information

Accommodate traditional sources **&** text-based input through "fact" normalization*

**Fact** = ***Subject – verb – object – location - time*** independent of data source

| Source | Subject | Verb | Object | Location | Time |
|---|---|---|---|---|---|
| HUMINT (Level-1) | Khalid Sattar | was seen | NA | al-Anbia Mosque | afternoon 2 June 2010 |
| HUMINT (Level-2) | Khalid Sattar | spoke with | Suffian Mashhadan | al-Anbia Mosque | mid afternoon 2 June 2010 |
| HUMINT (Level-3) | Khalid Sattar | intends to bury | IED | near al-Anbia Mosque | next week |

*Including verb and noun taxonomies

## Challenge 2:
### Normalizing Hard-Soft Information

Accommodate traditional sources **&** text-based input through “fact” normalization*

| Source | Subject | Verb | Object | Location | Time |
|---|---|---|---|---|---|
| HUMINT (Level-1) | Khalid Sattar | was seen | NA | al-Anbia Mosque | afternoon 2 June 2010 |
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| HUMINT (Level-3) | Khalid Sattar | intends to bury | IED | near al-Anbia Mosque | next week |
| Radar | UNK 2301 | detected (default) | NA | (lat/lon) | 14:10:16 2 June 2010 |
| Imagery report | Air defense node | detected (default) | NA | (lat/lon); ellipse | 14:10:16 2 June 2010 |

*Including verb and noun taxonomies

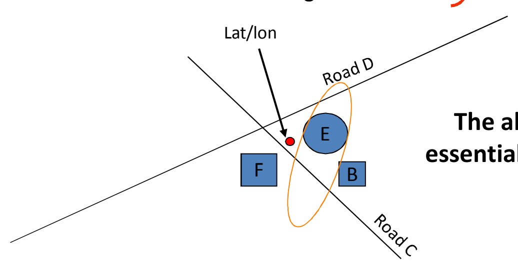
## Challenge 3:
### Space-time registration

- (36.7654, 24.12345) degrees (implied accuracy)
- Error ellipse

*Deterministic* & *probabilistic* location descriptions

- *Near* Building B
- *Between* Building B & Mosque E
- *IVO* intersection of Roads C & D
- *Along* Road D near Mosque E
- *Near* Road C & Mosque E
- *Just northeast* of Building F

*Semantic* location descriptions



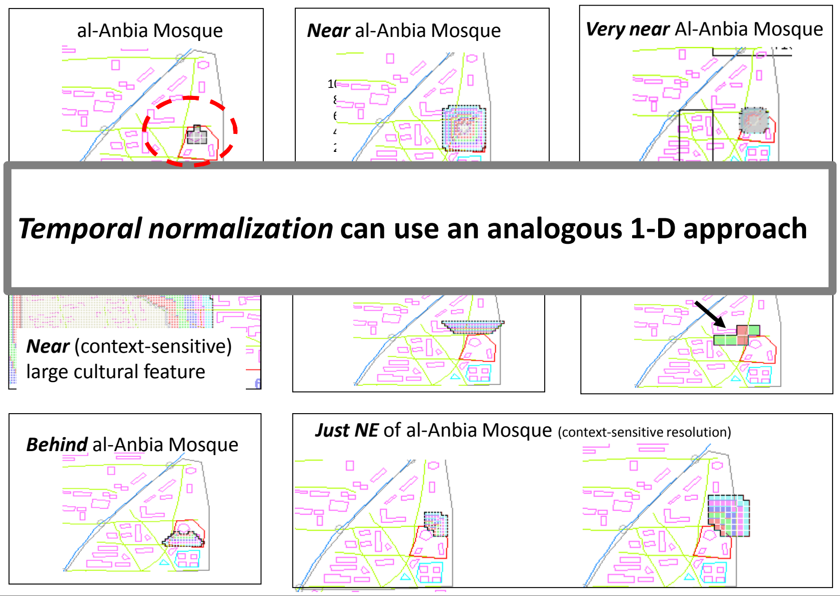

**The above 8 locations describe essentially the same region in space**

Spatial normalization across all Intel sources is a key component of effective all-source fusion

## Normalizing Semantic Spatial Descriptions

*Vision-Inspired Spatial Engine (VISE)*

Spatial distribution functions for sample shapefile-based features

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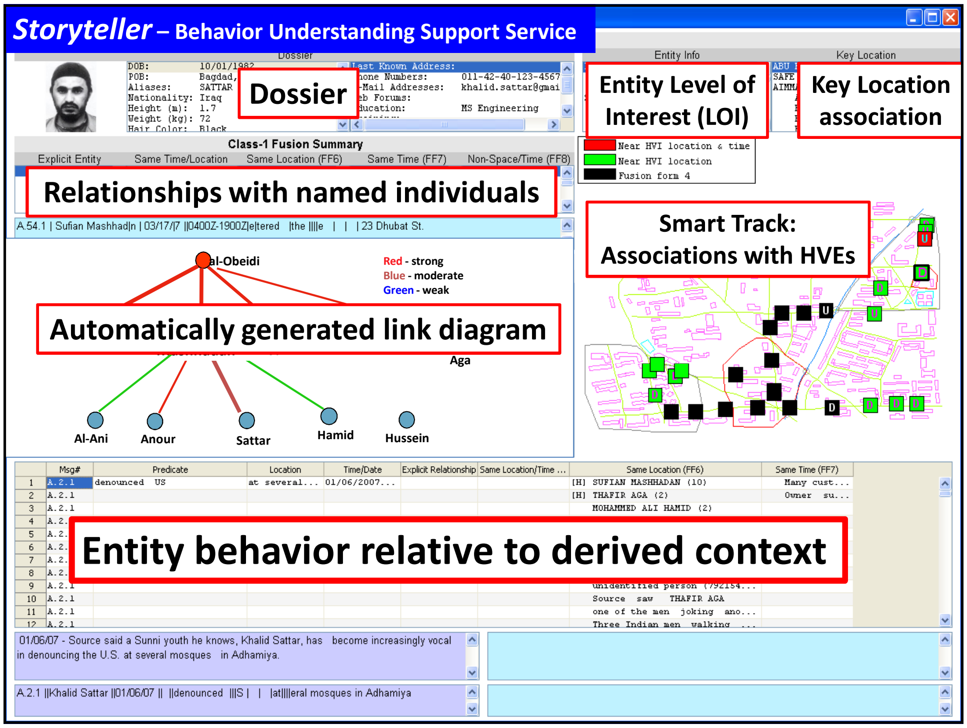
## Challenge 4:
### Effective Exploitation of Problem/Domain Context

Humans naturally exploit context when analyzing data & solving problems
→ Automated fusion demands *automated context exploitation*

**Static context**
- Natural features – terrain, vegetation, water ways, soil type, …
- Cultural features – buildings, roads, power lines, bridges, …

**Quasi-static context**
- Natural features – weather, sunspots, diurnal cycle
- Cultural features – economic, religious, ethnic, economic, atmospherics, language
- Recent activity

**Dynamic context**
- "Current" individuals and activities




## Context Exploitation Example

*SAIC *Storyteller*

Story Summarization Report* for **Khalid Sattar** (scenario data set)

- Khalid appears to hate the US
- Khalid has possible (**fusion-discovered context**) relationships with high value individuals (HVI)
- He cut ties with this family
- He is in charge of "something very big"
- He had been associated with a user define key location (**fusion-discovered context**) where officials (***later***) found documents about liquid explosives (**fusion-discovered context**)
- He has applied for a job as an ambulance driver at Yarmuk Hospital even though he showed no prior interest in health care or emergency services

  **Fusion-discovered context**
  - The ambulance service at Yarmuk hospital has been deteriorating,
  - Doctors there suspect insurgents have infiltrated the services, and
  - Ambulance drivers there don't seem to know what they were doing
- He spent several hours with known HVI (Suffian Mashhadan) at a suspected safe house (**fusion-discovered context**)
- Map with red circles around hospital and a building that looked like a school found in (known al Qaeda member) Ziyad al-Obeidi's home near Yarmuk hospital (**fusion-discovered context**)

## Position Summary

**Objective:** Develop a more holist approach to Situation Awareness that fully integrates the broadest range of data sources

- Physics-based sensors
- Text-based data sources
- Databases

**Challenges discussed (text-based sources)**

- **Ingestion:** Improved automated *information extraction* from unstructured text
- **Normalization:** *Compatible* data structures (hard & soft sources)
- **Registration:** Fuzzy semantic distribution functions for space & time
- **Domain context exploitation:** Context *discovery* supports more robust fusion
  - Static
  - Quasi-static
  - Dynamic

# Automated Soft Data Exploitation: Opportunity & Challenges

Richard T. Antony
SAIC
Arlington, VA U.S.A.
rantony@ieee.org

Data fusion automation has made considerable strides in fields from military to medical applications. Traditional fusion systems have focused largely on the combination of output from physics-based sensors. However, in many fields, exploiting both text-based as well as database resident information has the potential to further enhance product robustness. Whereas hard sensors tend to provide only entity state information (attributes, location, time), text-based information can express (1) entity state, (2) entity relationships, and (3) objectives or intent. Databases can potentially be mined for a wide range of supporting information that can be used to infer/refine entity attributes as well as suggest potential relationships between and among entities.

Table 1 provides examples of the nine possible binary combinations of the three primary data classes: (1) hard sensor output, (2) soft (or text-based) sources, and (3) databases. Given that virtually all information sources possess both strengths and weaknesses, a holistic approach to fusion must seek to combine the broadest range of relevant data sources. Given the ever-expanding range of those sources and the exponentially increasing volume of available information, effective exploitation demands increased levels of fusion automation.

Table 1. Examples of the nine possible binary combinations across the three principal data sources.

| | **Hard sensor** | **Soft source** | **DB** |
|---|---|---|---|
| Hard sensor | License plate detection system correlated to vehicle tracker | Real time soldier report of blue pickup with missing front fender linked to vehicle tracker | ATM transaction linked to vehicle tracker |
| Soft source | Iris scan linked to suspicious person report | Informant report linked to surveillance report | Suspicious person report linked to existing criminal reports |
| DB | Vehicle tracker linked to road network | Text information linked to social, cultural, economic, etc. overlays | Traditional data mining |

While the advantages of fusing data from a wide range of data sources tend to be self-evident, automating such a process involves many challenges. In this short position paper, we address four specific challenges:

Extracting & exploiting *relevant* information from unstructured text
Normalizing hard-soft information
Space-time registration
Effective exploitation of problem context

Automated fact extraction from free text involves more than word tagging and parsing. Individual words tend to be context sensitive; sentence syntax may not follow well-structured rules of grammar; combinations of words can have multiple meanings; pronoun, location, and time resolution are far from trivial. Dealing with source reliability, deliberate deception, and alias resolution all present challenges. Assuming the objective of the system is to find a specific class of "needles hidden in a haystack," the information value of any given fact is hard to judge in isolation (e.g., due, in part, to unknown or purposely hidden relationships and motives of both individual entities as well as groups of entities). Table 2 summarizes a number of these considerations.

Table 2. Variety of challenges to a holistic approach to fusion automation

| Challenge | Issues | Examples |
|---|---|---|
| Hard for a human to know what is relevant | Needle in the haystack<br>Hidden relations | *Blue pickup with missing fender*<br>*Khalid Sattar* |
| Fact extraction from free text is beyond the state of the art | Tagging, parsing, pronoun resolution, … | *Complex syntax & semantics* |
| Appropriate data element selection | Subject-verb-object-location-time… | *Indirect objects, how, why* |
| Entity resolution | Aliases & code names | *KS, apples & flour* |
| Managing semantic descriptions of space & time | "Register" with conventional space/time representations | *Behind the mosque, IVO an intersection, mid afternoon* |
| Appropriate DB structure | Capture "meaning" of facts & pedigree for all products | *Hybrid entity-relationship + RDBMS + …* |

In order to fuse information from a wide range of sources, some form of normalization is required (fusion level-0). Because soft data tends to have a richer set of attributes than hard sensors, normalization of soft data must drive the normalization process. A minimal set of fact attributes for text-based extraction would include the following:

*Subject (entity) – state of being or activity – direct object (entity) – location – time*

Because text can contain indirect objects, relevant phrases, and other types of information, a robust approach to normalization must address these issues, as well. In many cases, facts can be re-expressed (a sentence or sentence fragment rewritten) to fit into the above five-attribute form. As seen in Table 3, this five-attribute formulation readily accommodates traditional hard sensor data.

Table 3. Source normalization

| Source | Subject | Verb | Object | Location | Time |
|---|---|---|---|---|---|
| HUMINT (Level-1) | Khalid Sattar | was seen | NA | al-Anbia Mosque | afternoon<br>2 June 2010 |

| | | | | | |
|---|---|---|---|---|---|
| HUMINT (Level-2) | Khalid Sattar | spoke with | Suffian Mashhadan | al-Anbia Mosque | mid afternoon 2 June 2010 |
| HUMINT (Level-3) | Khalid Sattar | intends to bury | IED | near al-Anbia Mosque | next week |
| Radar | UNK 2301 | detected (default) | NA | (lat/lon) | 14:10:16 2 June 2010 |
| Imagery report | Air defense node | detected (default) | NA | (lat/lon); ellipse | 14:10:16 2 June 2010 |

Note that Table 3 references both traditional spatial and temporal representations (deterministic with possible statistical error distribution functions) as well as semantic descriptions (*near, mid afternoon*). In order to seamlessly handle source data that may have mixed representations, a systematic methodology is required. During the US Army STEF program the author developed a hierarchical fuzzy representation approach that automatically converts spatial and temporal attributes to a consistent internal (fuzzy distribution function) representation permitting fully automated space-time intersection among all ingested data.

Finally, automated fusion approaches need to exploit relevant context in order to generate appropriately robust products. Humans naturally “integrate” context into their reasoning process but in an automated system, context must be deliberately introduced and effectively utilized. Context can loosely be divided into three broad categories:

Long-term (static) - natural & geographic features, historical, conventions

Medium-term (quasi-static) – cultural, economic, religious, ethnic, recent events

Short-term (dynamic) – current possibly related activities and entities

An application (referred to as *Storyteller*) was developed to provide analysts with potentially relevant fusion-discovered context in order to support behavior understanding of both individual entities and groups of entities.

# Hard-Soft Data
# Ontology Alignment Challenges

**Erik Blasch**
erik.blasch@gmail.com



## Outline

- **Hard (physics-based) and Soft (human-based reports)**
- **Hard-Soft Information Fusion Challenges**
  - Data registration (Common Coordinates)
  - Data association (Ontology Alignment)
  - Data fusion (Uncertainty Analysis)
- **Ontology Alignment based on Uncertainty**
  - **Metrics:** Measures of Quality and Uncertainty (Vocabulary)
  - **Human Processing:** Semantic Distance and Coding (Meaning)
- **Geographical Hard-Soft Fusion**
  - **Example :** Maritime Domain Awareness (AIS)
  - **Image (Hard) Processing**: determine areas of vehicle traffic
  - **Semantic (Soft) Fusion:** translation of multiple databases

# Hard/Soft –Ontology

**Ontology Alignment Evaluation Initiative**

**http://oaei.ontologymatching.org**

**with the goals of:**

HARD SOFT

- assessing strength and weakness of alignment/matching systems;
- comparing performance of techniques;
- increasing communication among algorithm developers;
- improving evaluation techniques;
- most of all, helping improving the work on ontology alignment/matching.

**To meet these goals, controlled experimental evaluation of the techniques and performances are conducted.**



# Ontology

**Gruber succinctly defines an**

***ontology* *is a* *specification of a conceptualization*.**

**Ontologies have been designed for knowledge management, use, and sharing.**

**Since an ontology is a theory of a consistent (but not complete) formal vocabulary, agents operate on the information which can be uncertain.**

**Classes, relations, functions, or other objects in normal human discourse and readable text describing what the names mean enable communication; however, if agents do not share the exact vocabulary, there can be mismatches or inexact meanings in the understanding of knowledge.**

# Semantics

In computer science, where it is considered as an application of mathematical logic, formal semantics of programming languages reflects the meaning of programs or functions.

In this regard, semantics permits programs to be separated into their syntactical part (grammatical structure) and their semantic part (meaning). For instance, the following statements use different syntaxes, but issue the same instructions:

x += y *(C, Java, Ruby, etc.)*

x := x + y *( Pascal)*

LET X = X + Y *(early BASIC)*

x = x + y *(most BASIC dialects, FORTRAN)*

(incf x y) *(COMMON LISP)*

Generally these operations would all perform an arithmetical addition of 'y' to 'x' and store the result in a variable called 'x'.

Semantics for computer applications falls into three categories:

**HARD**

Operational Semantics: The meaning of a construct is specified by the computation it induces when it is executed on a machine. In particular, it is of interest *how* the effect of a computation is produced.

Denotational Semantics : Meanings are modeled by mathematical objects that represent the effect of executing the constructs. Thus *only* the effect is of interest, not how it is obtained.

Axiomatic Semantics : Specific properties of the effect of executing the constructs as expressed as *assertions*. Thus there may be aspects of the executions that are ignored.

**SOFT**

The Semantic Web refers to the extension of the WWW through the embedding of additional semantic metadata; s.a. Web Ontology Language (OWL).

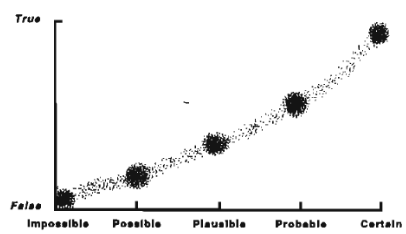
Erik Blasch – SPIE11 From http://en.wikipedia.org/wiki/Generative_lexicon 5

# Evidence

## Evidence Terms

| *Term* | *Evidence Relative to Hypothesis* |
|---|---|
| impossible | definitely known against |
| possible | not definitely disproved |
| plausible | some evidence exists |
| probable | some evidence for |
| certain | definitely known supporting |

**SOFT**




**HARD**

From *EXPERT SYSTEMS - Principles and Programming*, Giarratano, PWS-Kent 1989

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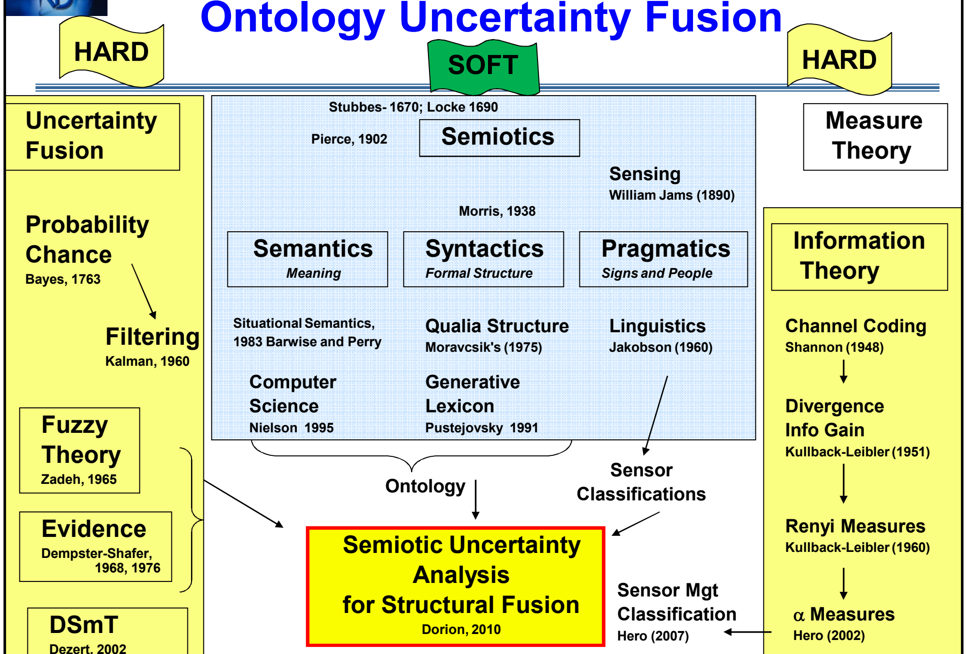
  - **Semantic (Soft) Fusion:** translation of multiple databases

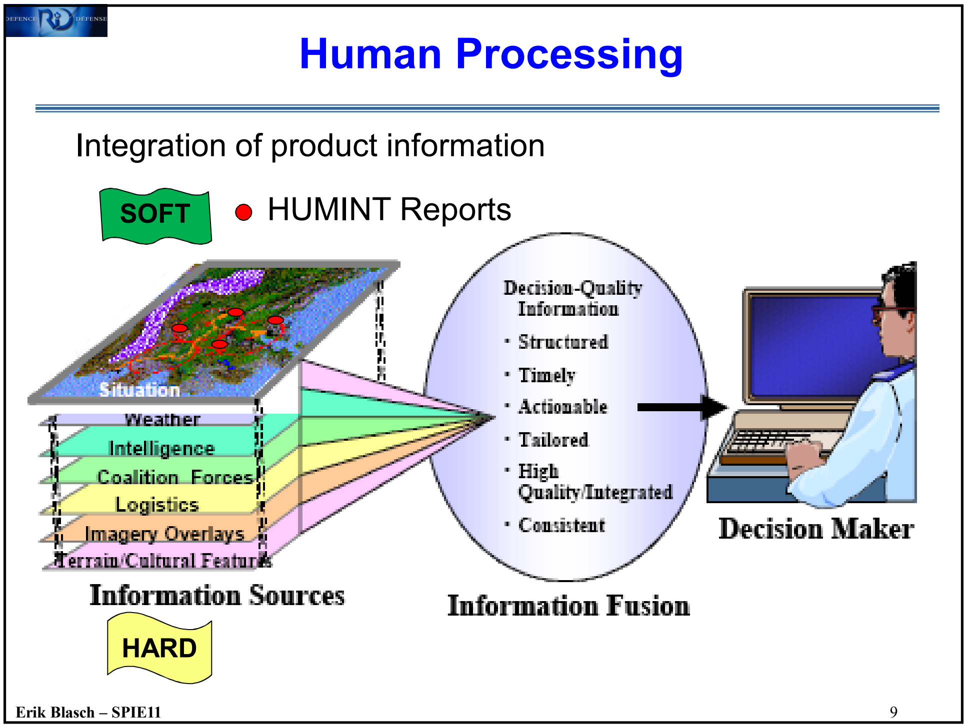


# Ontology Uncertainty Fusion




From http://en.wikipedia.org/wiki/Semiotics

From http://en.wikipedia.org/wiki/Information_Theory


Human Processing
Integration of product information
SOFT
HUMINT Reports
Situation
Weather
Intelligence
Coalition Forces
Logistics
Imagery Overlays
Terrain/Cultural Features
Information Sources
HARD
Decision-Quality Information
· Structured
· Timely
· Actionable
· Tailored
· High Quality/Integrated
· Consistent
Information Fusion
Decision Maker
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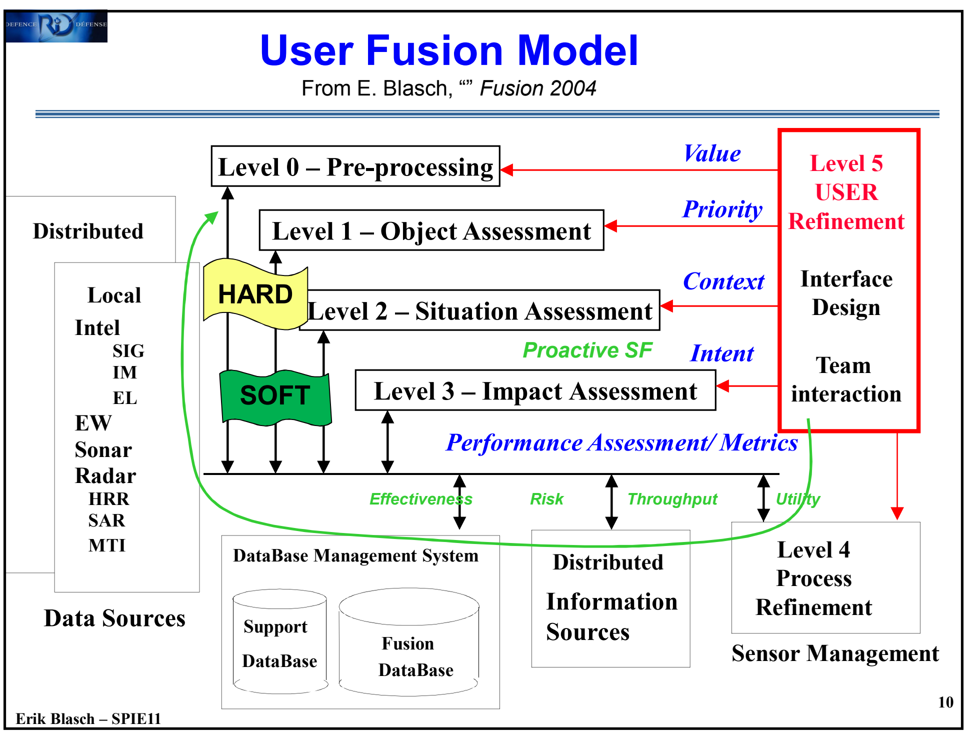
9


User Fusion Model
From E. Blasch, “” Fusion 2004
Level 0 – Pre-processing
Level 1 – Object Assessment
Level 2 – Situation Assessment
Level 3 – Impact Assessment
Value
Priority
Context
Intent
Proactive SF
Level 5 USER Refinement
Interface Design
Team interaction
HARD
SOFT
Distributed
Local
Intel
SIG
IM
EL
EW
Sonar
Radar
HRR
SAR
MTI
Data Sources
Performance Assessment/ Metrics
Effectiveness
Risk
Throughput
Utility
DataBase Management System
Support DataBase
Fusion DataBase
Distributed Information Sources
Level 4 Process Refinement
Sensor Management
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10

# Outline

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# Geographical Ontology Alignment

**Duckham and Worboys list many categories of GIS data uncertainty**

***Semantic alignment*: whether or not the labeling correspond to meaningful categories of alignment.**

***Inaccuracy of information*: the segmentation of the geographical boundaries**

***Imprecision*: the representation of the segmented areas**

***Vagueness*: uncertainty in the boundaries**

***Uncertainty*: the stochastic randomness in the collection boundaries.**

**HARD**

***Geo-pragmatics* enhances ontologies by establishing context for users to reason over the data.**

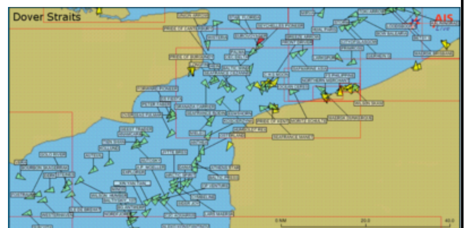
**SOFT**

**Using "situated concepts" to help guide ontology development, both method-driven and knowledge (epistemic-driven) determine the dimensions of origin, use, and effects of information for humans and machines.**

M. Duckham and M. Warboys, "Automated Geographical Information Fusion and Ontology Alignment", Ch 6 in *Spatial Data on the Web* (eds.) A. Belussi, B. Catania, E. Clementini, and E. Ferrari, Springer, 2007.

# Automatic Identification System (AIS)

The Automatic Identification System (AIS) is a short range coastal tracking system used on ships and by Vessel Traffic Services (VTS) for identifying and locating vessels by electronically exchanging data with other nearby ships and VTS stations. Information such as unique identification, position, course, and speed can be displayed on a screen or an ECDIS. AIS is intended to assist the vessel's watchstanding officers and allow maritime authorities to track and monitor vessel movements




HARD

SOFT

FROM : http://en.wikipedia.org/wiki/Automatic_Identification_System

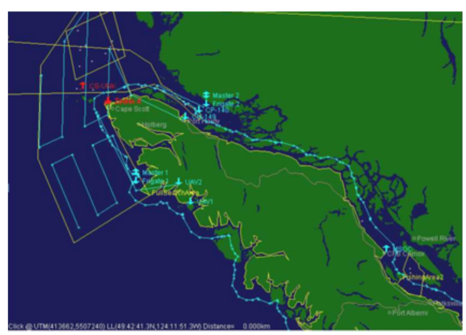


# CanCoastWatch Example

Want to align

Geographical (Hard) data with

HARD



Semantic (Soft) Data

SOFT

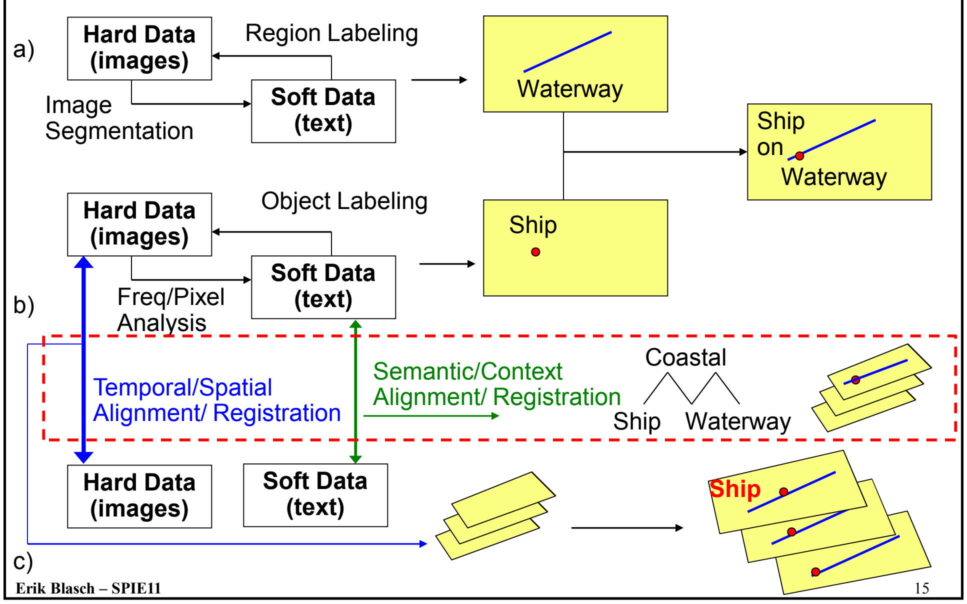
Data Set A: Commercial, Recreational

→ Fused Data Set: Comm. (Ship, Comm. Tourist), Tourist (Comm. Tourist, Rec.) ←

Data Set B: Shipping, Tourist

# Ontological Fusion

E. Blasch, É. Dorion, P. Valin, E. Bossé, and J. Roy, "Ontology Alignment in Geographical Hard-Soft Information Fusion Systems," *Fusion2010*, 2010.



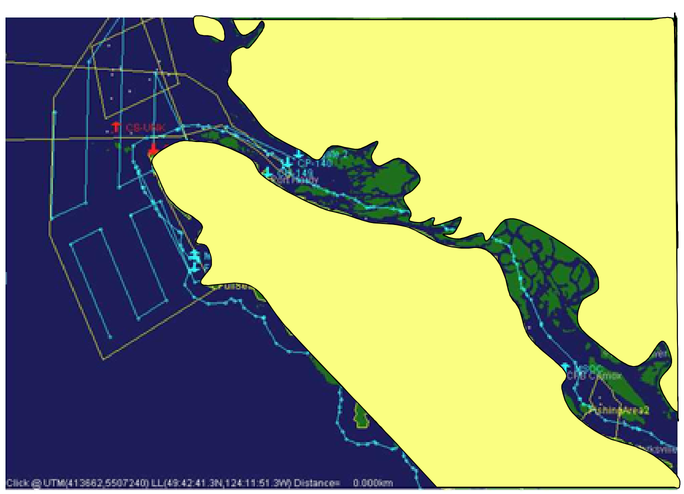



# CanCoastWatch Example

E. Blasch, É. Dorion, P. Valin, E. Bossé, and J. Roy, "Ontology Alignment in Geographical Hard-Soft Information Fusion Systems," *Fusion2010*, 2010.

**Geographical Information**

**Overlay of Land and Sea/Coastal Areas**



## CanCoastWatch Example

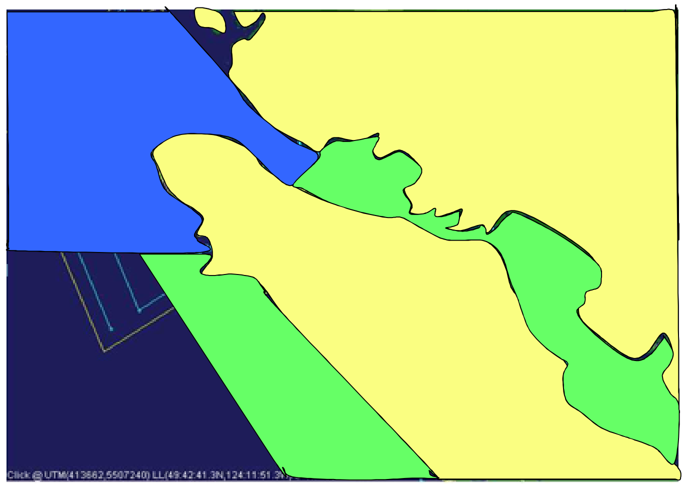
Extensional Information

SOFT

Data Set A – Waterway Traffic

Commercial

Recreational



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17

## CanCoastWatch Example

Extensional Information

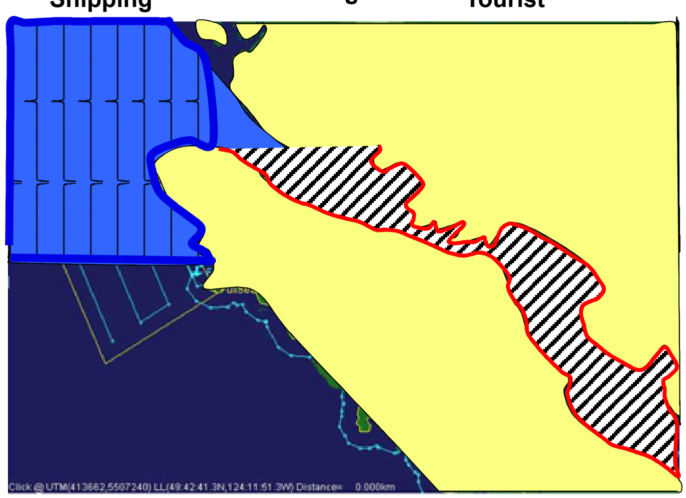
SOFT

Data Set B

Shipping

Fishing

Tourist



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18

# CanCoastWatch Example

Extensional Information

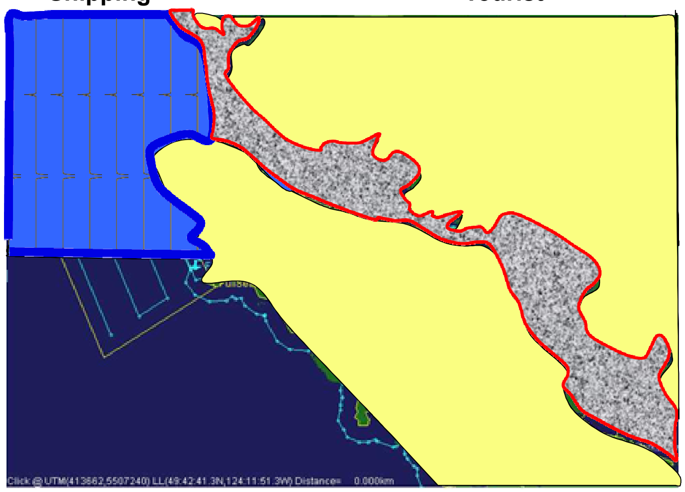
SOFT

Data Set B

Shipping

Fishing

Tourist



HARD



# CanCoastWatch Example

Extensional Information

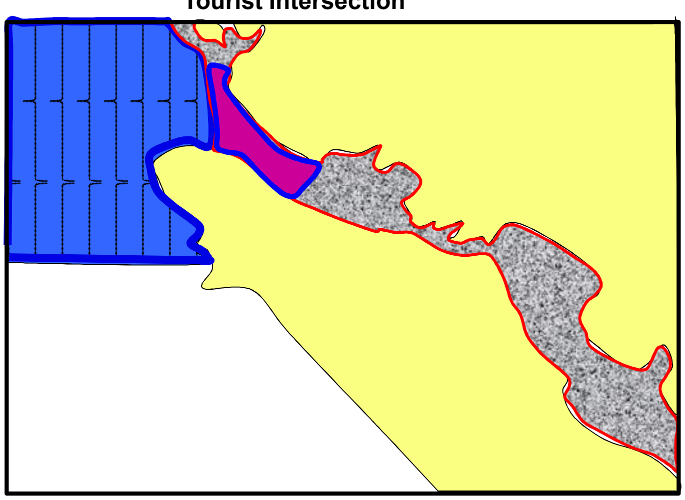
SOFT

Fused Results

Shipping

Commercial Tourist Intersection

Tourist



HARD

# Geographical Ontology Alignment(1)

E. Blasch, É. Dorion, P. Valin, E. Bossé, and J. Roy, "Ontology Alignment in Geographical Hard-Soft Information Fusion Systems," *Fusion2010*, 2010.

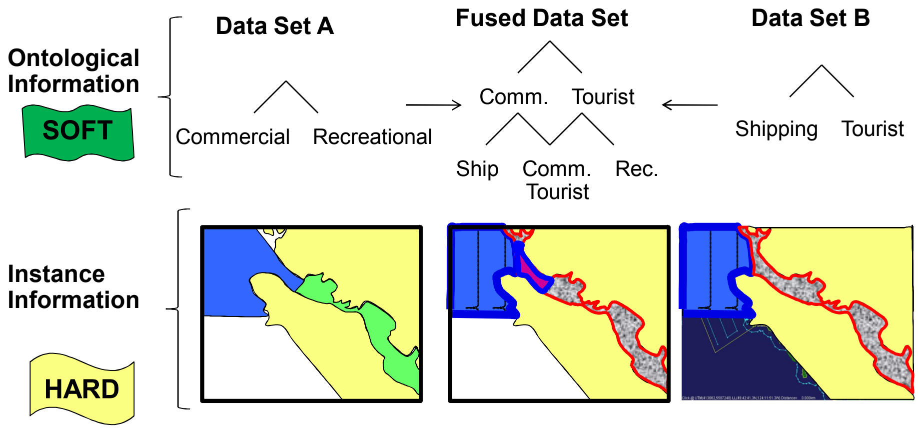



**Fig. 6.1. Simplified example of inductive reasoning for automated geographical information fusion**



# Outline

- **Hard (physics-based) and Soft (human-based reports)**
- **Hard-Soft Information Fusion Challenges**
  - Data registration (Common Coordinates) → Geographic
  - Data association (Ontology Alignment) → Meaning
  - Data fusion (Uncertainty Analysis) → Distance Error
- **Ontology Alignment based on Uncertainty**
  - **Metrics:** Measures of Quality and Uncertainty (Vocabulary)
  - **Human Processing:** Semantic Distance and Coding (Meaning)
- **Geographical Hard-Soft Fusion**
  - **Example :** Maritime Domain Awareness (AIS)
  - **Image (Hard) Processing**: determine areas of vehicle traffic
  - **Semantic (Soft) Fusion:** translation of multiple databases

# Hard-Soft Data Ontology Alignment Challenges

Erik P. Blasch[a,b]

[a]Defence R&D Canada-Valcartier, 2459 Pie-XI Blvd. North, Quebec, QC, Canada;

[b]Air Force Research Laboratory, Rome, NY, 13441, USA

**Abstract**: With the advent of the world-wide web, social media, and mobile communications, there are numerous sources for human-based soft reports (e.g. textual and voice communications) that can augment traditional hard physics-based sensing (e.g. video and weather maps. Combining the information can be cross-cueing, alerting, and simultaneous displays. Merely presenting the data would overload the human processing limits, so there is a need for more fundamental assessment of how to combine and link the hard and soft information. One commonality of the challenges is developing a ***shared ontology*** that enables a combination of the various sources of structured and unstructured data. Using such an ontology might enable a solution to the operational hard-soft data challenges of *data/information source* (1) registration in a common coordinate system, (2) correlation of information in data bases, (3) association through ontology alignment, (4) characterization with standard metrics, and (5) collection, presentation, and manipulation to support user's needs for uncertainty reduction and situational awareness extension.

**Keywords:** Information Fusion, Hard-Soft Fusion, Ontologies, IMINT, HUMINT, User Refinement

Recent efforts are underway to look at the developments that have enabled seamless communication anywhere to augment traditional sensor-based collections. Summarizing the types of data, the technologies, algorithms, and various programs would not catch up to the applications that are being developed in real time. However, there has yet to be vetted formalism that is able to generally relate the developments in soft processing to that of hard processing. One example is situation assessment [1] of combining a social network analysis (SNA) with that of annotated imagery, shown in Figure 1 [2]. From the simple example, there is a common reference frame (persons address), static information (authors name) that can be associated in a database, and the display fusion of information for operator use (world map). Another example is relating the textual properties to the terrain [3]. These examples provide a useful illustration of discussion of future challenges for a dynamic situation that is altered by the vocabulary of an organization.

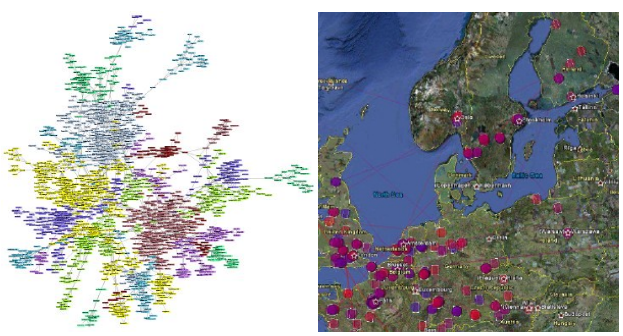


Figure 1. SNA linked to Annotated Imagery [1].

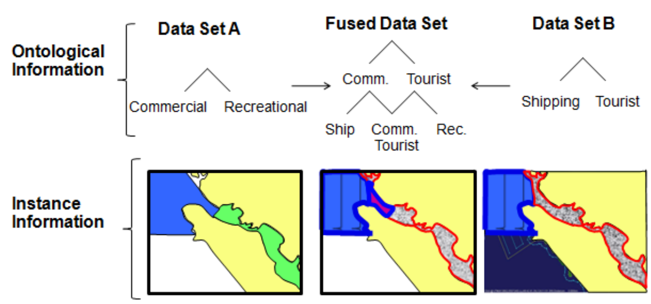



Figure 2. Textual Labeling of Geographic Imagery [2].

To fully exploit the fusion hard and soft data requires further analysis when the information is incomplete, uncertain, and dynamic. Relating events in time and space would require data extraction, reordering, and tagging that presents a new set of challenges shown in Table 1. Furthermore a ***shared ontology*** (representation of a knowledge conceptualization) is needed between physics-based sensing and human-derived data products to process the meaning and provide contextual reasoning. The shared ontology challenge covers the alignment/registration [4], information exchange for correlation and association [5], as well as utilization of contextual culture for user refinement [6].

| **Hard-Soft Fusion Challenge** | **Issues of Sensing, Processing, Exploitation, and Assessment** |
|---|---|
| Registration | Relating textual reports to imagery in common and meaningful coordinates |
| Correlation | Linking, processing, and reducing uncertainty through information fusion |

| | |
|---|---|
| Association | Extraction of sensor/database information and linking activities in space and time |
| Metrics | Determining measures of performance and effectives for resource control |
| User Refinement | Answering user queries and utilizing human reasoning over abstract reports |

- ***Registration*** of H/S information is difficult as most data is collected and stored in an unstructured format. Soft data (e.g. images, documents) does not have a codified hard sensing-based protocol. There are needs to provide joint data management so that future processes of data correlation and association are attainable. [2]
- ***Correlation*** of data relates to the processing of the data through H/S extraction and representation. A shared vocabulary of quality is needed to relate conflicting, partial, and incomplete information. [7]
- ***Association*** of information (i.e. data mining and linking) is altered by the characterization of the data. If the H/S systems do not share the same vocabulary then inexact meanings and imprecise knowledge understanding cannot be determined. [8]
- ***Metrics*** are needed to determine the strength of association, evaluation of uncertainty reduction, and methods to interact with the user. Standards are need for homogeneous and heterogeneous hard and soft collection systems before the data quality can be determined. With hard quality of service and soft information quality standards, methods of fusion could be corrected assessed and evaluated. [9, 10, 11]
- ***User refinement*** (or human-centered engineering) requires the both the presentation of information and the ability of the user to interact and provide inputs [12, 13]. Since a user can reason over both hard and soft information, there is a challenge to effectively and appropriately utilize a variety of users with different mental models, perceptions, bias, expertise, skill sets, and organization affiliation through a common ontology [14].

Practically, the need for hard/soft fusion is connected with the application, mission, and ***organization***. The H/S application is determined from the above relations. The mission is usually within a geo-political environment that includes business operations, cultural factors, security/proprietary restrictions, and ideology. Sharing of information could be enhanced by need for collaboration or reduced due to competition, biased based on language and communication mechanisms, or altered based on weather and community infrastructure availability. Table 2 presents relationships between hard and soft fusion that are affected by the organization. Figure 3 is a representation of the intelligence (INT) information that can be gathered as a function of hard/soft collection resources, but does not capture the organization constructs that could relate the information in each collection INT column. One example is MOVINT (intelligence about a dynamic object) that can be sensed with physical sensors for object time and space, but does not capture the changing organizational affiliations associated with soft information.

| Soft | Hard | Organization |
|---|---|---|
| Ancestry | Location | Geo-political |
| Language | Geography | Cultural Context |
| Documents | Citizenship | Affiliations |
| Agreements | Transactions | Business Associations |
| Agents | Social Events | Friends Network |
| Transportation | Road Networks | Infrastructure |
| Activities | Meteorology | Planned events |
| Networks | Datalinks | Chain of command |
| Behavior | Legal Protocols | Ideology |

Table 2: Organization effects on H/S Data

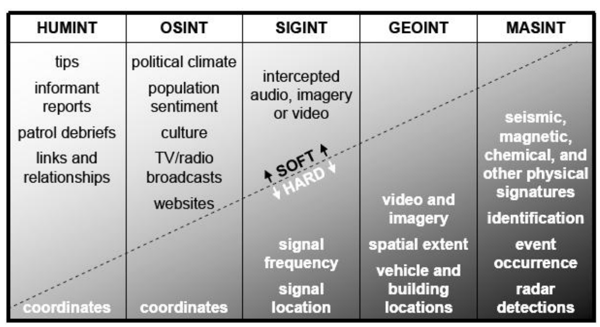



Figure 3: Hard/Soft Relations of Intelligence Information [7]


**References**

[1] Blasch, E. P., Kadar, I., Salerno, J., Kokar, M. M., Das, S., Powell, G. M., Corkill, D. D., and Ruspini, E. H., "Issues and challenges of knowledge representation and reasoning methods in situation assessment (Level 2 Fusion)", *J. of Adv. in Information Fusion,* 1(2), 122-139, (2006).

[2] Johansson, F., Mårtenson, C., and Svenson, P. "A Social network analysis of the Information Community", *Int. Conf. on Info. Fusion*, (2011)

[3] Blasch, E., Dorion, E., Valin, P., Bossé, E., and Roy, J., "Ontology Alignment in Geographical Hard-Soft Information Fusion Systems," *Int. Conf. on Info Fusion*, (2010).

[4] Blasch, E., Dorion, E., Valin, P., and Bossé, E., "Ontology Alignment using Relative Entropy for Semantic Uncertainty Analysis", *Proc. IEEE Nat. Aerospace Electronics Conf (NAECON)*, 2010.

[5] Lee, H. J. [*Ontology-based Data Fusion within a Net-centric Information Exchange Framework*], PhD Dissertation, Univ. Arizona, (2009).

[6] Blasch, E., Valin, P., Bosse, E., Nilsson, M., Van Laere, K., and Shahbazian, E., "Implication of Culture: User Roles in Information Fusion for Enhanced Situational Understanding", *Int. Conf. on Information Fusion*, (2009).
[7] M. A. Pravia, R. K. Prasanth, P. O. Arambel, C. Snider, C.-Y Chong, "Generation of a Fundamental Data Set for Hard/Soft Information Fusion", *Int. Conf. on Information Fusion*, (2008).
[8] Anthony, R. and Karakowski, J., "First-Principle Approach to Functionally Decomposing the JDL Model: Emphasis on Soft Target Data", *Int. Conf. on Information Fusion*, (2008).
[9] Llinas, J., "Assessing the Performance of Multisensor Fusion Processes," Ch 20 in *Handbook of Multisensor Data Fusion*, (Eds.) D. Hall and J. Llinas, CRC Press, (2001).
[10] Blasch, E., Pribilski, M., Daughtery, B., Roscoe, B., and Gunsett, J., "Fusion Metrics for Dynamic Situation Analysis," *Proc SPIE* 5429, (2004).
[11] Blasch, E., Breton, R., and Valin, P. "Information Fusion Measures of Effectiveness for Decision Support," *Proc. SPIE 8050,* (2011)
[12] Hall, D. L. and McMullen, S. A., [*Mathematical Techniques in Multisensor Data Fusion*], Artech House, (2004).
[13] Blasch, E. P., and Plano, S. B., "DFIG Level 5 (User Refinement) issues supporting Situational Assessment Reasoning," *Intl. Conf on Info. Fusion*, (2005).
[14] Blasch, E. & Plano, S., "Ontological Issues in Higher levels of Fusion: User Refinement in the Fusion Process", *Intl. Conf on Info. Fusion*, (2003).

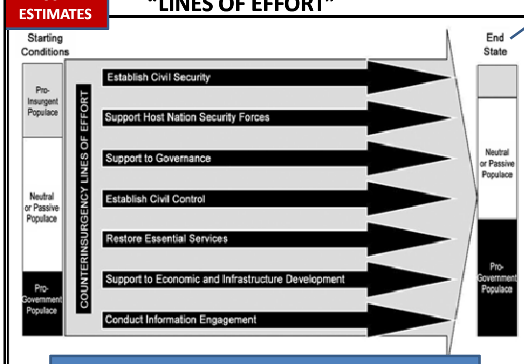
# Counterinsurgency: Understanding Operational Art and Its Impact on Hard-Soft Fusion Technology


Dr. James Llinas
Research Professor (Emeritus), Executive Director
Center for Multisource Information Fusion
State University of New York at Buffalo
Buffalo, NY 14260
llinas@buffalo.edu


## CONCEPT OF EMPLOYMENT—OPERATIONAL ART

FUSED ESTIMATES

"LINES OF EFFORT"



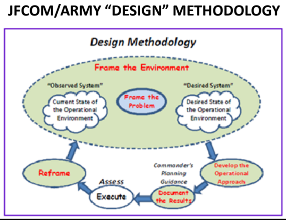

BEHAVIORS

INDIRECT (Influential)

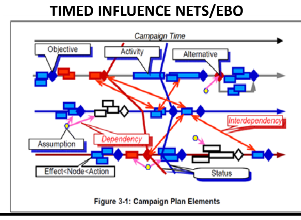
DIRECT ("Kinetic")

Course of Action Development

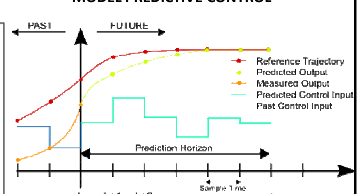
JFCOM/ARMY "DESIGN" METHODOLOGY



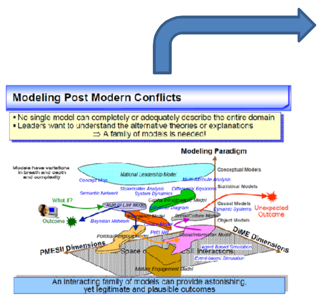

INTERDEPENDENT STOCHASTIC TIMED INFLUENCE NETS/EBO




MODEL PREDICTIVE CONTROL

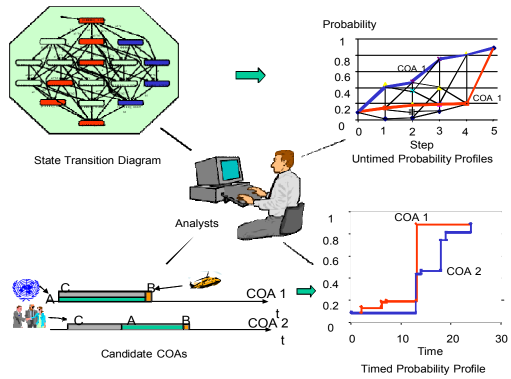


## COURSE OF ACTION DEVELOPMENT AND OPTIMIZATION




**(KOTT, 2007)**

Weak A Priori Deductive Knowledge
(Second order Uncertainty)




**(LEVIS, 2000)**

Sequential Decision-Making
Under Strict Uncertainty
(~Black Swan conditions)

## SOFT DATA AND SOFT DECISIONS
## SOFT FUSION PROCESS DESIGN CHALLENGES

**FUSION PROCESS DESIGN INFORMATION/KNOWLEDGE**:

- OBSERVATIONAL DATA
- A PRIORI DEDUCTIVE KNOWLEDGE
- CONTEXTUAL INFORMATION/KNOWLEDGE
- LEARNED KNOWLEDGE

**Observational data**: Soft data that come from:

--Uncalibrated and uncalibrate-able humans of all description under a wide variety of observational conditions, observing (and judging) all kinds of things

--And are expressed in ambiguous unconstrained natural language, with the NLP problem far from solved

**A priori deductive knowledge**: Very weak a priori deductive knowledge

**Contextual Information and Knowledge**: Generally weak and ephemeral

Socio-cultural knowledge

**SOFT DATA AND SOFT DECISIONS**
**SOFT FUSION PROCESS DESIGN CHALLENGES**

- **Common Referencing/Alignment:**
  - Temporal: very complex due to mixed tenses of language and metadata
    - Past-present-future tenses all complexly mixed
    - Imputes OOSM problem beyond what the fusion community has addressed
  - Uncertainty: mixed representational forms that are natural to Hard (probabilistic) and Soft (possibilistic)
- **Data Association:**
  - Requires robust semantic scoring techniques
  - Potentially high dimensionality Assignment problems
  - Most human observations unqualified
  - Requires robust Ontology for efficiency
- **State Estimation:**
  - Lack of reliable a priori dynamic knowledge models imputes a Discovery-Learning-based approach

## Counterinsurgency: Understanding Operational Art

## and Its Impact on Hard-Soft Fusion Technology

Dr. James Llinas
Research Professor (Emeritus), Executive Director
Center for Multisource Information Fusion
State University of New York at Buffalo
Buffalo, NY 14260
llinas@buffalo.edu

### 1. Trying to Understand the Counterinsurgency Operational and Decision-Making Domains

### 1.1 The Operational Domain

Managing and executing Counterinsurgency (COIN) operations is complicated business. Before entering into a discussion on this topic, it is useful to discuss the definition(s) and nature of insurgency and COIN. Insurgency is defined in US Joint Publication 1-02 as "an organized *movement* aimed at the overthrow of a constituted government through use of subversion and armed conflict". This definition as a movement sets it apart from both guerilla warfare and terrorism, as they are both *methods* available to pursue the goals of the political movement; insurgencies do however typically employ violent means toward their ends but those means could, by explicit choice, exclude terrorism. The action space for COIN can be broken into "direct" and "indirect" classes of actions, where direct actions are those focused on insurgent force structure in the traditional military sense, and indirect actions those focused on undermining support to the insurgents while simultaneously attacking them militarily. *Notice that there is an immediate impact of dimensionality for Information Fusion (IF) support that now involves both the repertoire of "kinetic" actions and soft actions.* Another way to look at these distinctions is from the viewpoint of theories of war and action, and in particular the notion of "lines of operation", a principle of war put forward by the famous war theorist Antoine-Henri Jomini, who was a French and later Russian general [Shy, 1986]. Jomini asserted that there were natural lines of operation—in his day these were largely topographically based; alternately, other lines of operation were those concerned exclusively with strategic choice about where to fight, to what purpose, and with what proportional force, etc.

These principles seem present in the modern Army Field Manual literature, for example in [Tactics in Counterinsurgency, 2009] where there is a discussion about "Lines of Effort (LOE)", defined as a line that links multiple tasks and missions using the logic of purpose—cause and effect—to focus efforts toward establishing operational and strategic conditions. A plan based on LOEs unifies the efforts of all actors participating in a counterinsurgency toward a common purpose. Each LOE represents a conceptual category along which the COIN force commander intends to attack the insurgent strategy and tactics. Figure 1 below shows example COIN LOEs.

### 1.2 Effects-Based Operations

It can also be argued that the End States of any LOO or LOE are "Effects" created by the sequence of actions (the "Course of Action", discussed later) "along" the LOE. Our research on Effects Based Operations (EBO), not a new term but interestingly actively revisited for the COIN problem (e.g. [Davis, 2001]), shows that many references suggest that EBO is a viable concept for COIN, in part because effects are soft-type results, and subsume behavioral end-states, reflecting a human focus. EBO is not

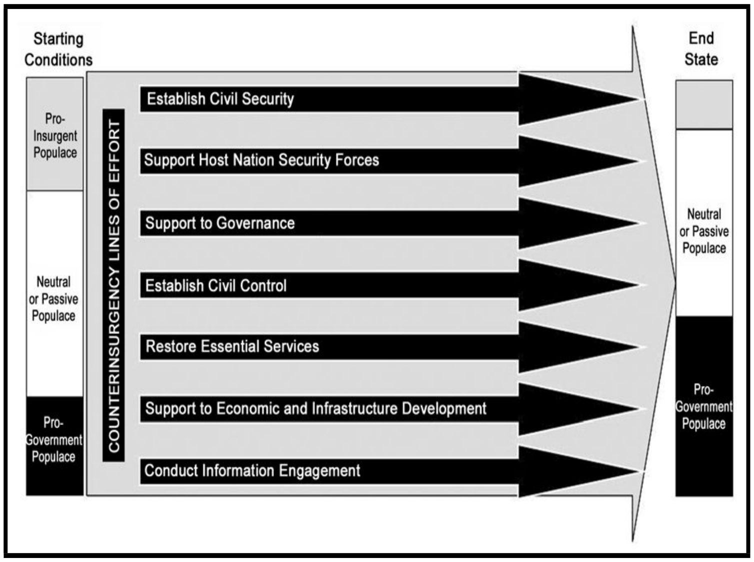



***Figure 1  Lines of Effort for COIN Operations (Stability Operations); from [Operations, 2011]***

an element of Doctrine but rather one way of conducting operations and thus falls into the category of Operational Art. EBO was studied over a long period of time until the mid-2000's, and is somewhat controversial since some consider it a reductionist approach which is largely incorrect, since most technical treatments of EBO treat it as stochastically/probabilistically-based (e.g., [Yan-guang, 2010]). Influence Nets of various type have been the most used paradigm in studying EBO, and most are framed in a probabilistic context. The most recent U.S. Army guidance on this aspect provides guidance for a systemic "Design" approach as in Figure 2 [JFCOM, 2010] but we see this as not really different than the EBO concept; the "reframing" step defines it as sequential, and so this process seems to embody many of the action-effect steps of an EBO type course of action.

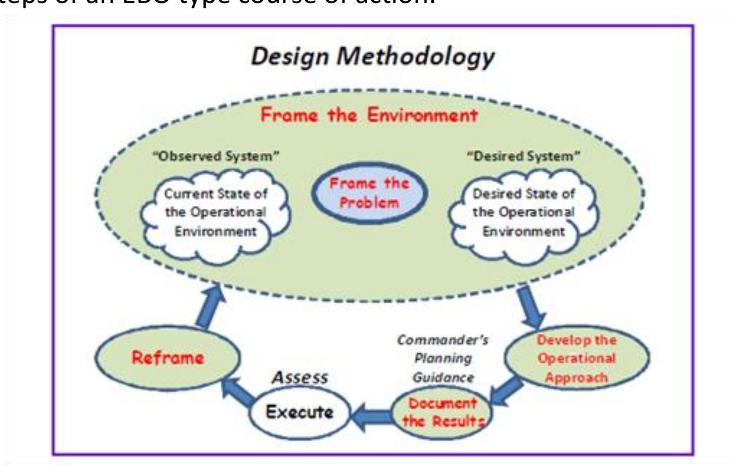



***Figure 2  The "Design" Methodology (from [JFCOM, 2010])***

If we examine the characterization of a typical Course of Action, a COA is sensibly always defined as a sequential operation (a series of partial plans is another way to characterize it). Darr et al [Darr, 2009] provide an ontological definition of a COA in which a COA has activities within phases, with those activities oriented toward specific outcomes, and where the activities should have some MOPs by which they can be measured, and the outcomes some MOE's which allow their measurement in turn.  Figure 3 shows the idea:

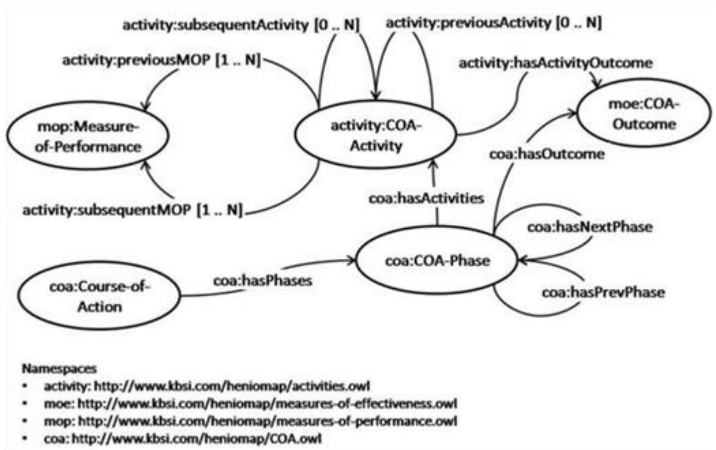



***Figure 3  Ontological Characterization of a COA (from [Darr, 2009])***

Building upon this "neutral" characterization of activities and outcomes, a Counterinsurgency LOE may involve an operation as follows:

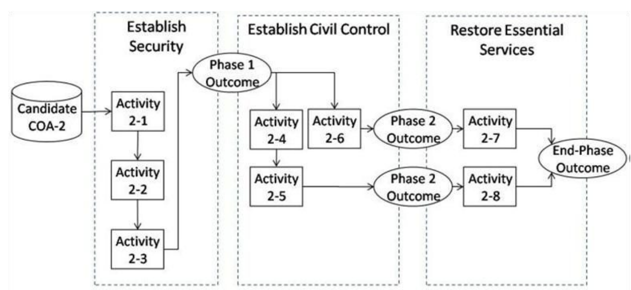



***Figure 4 Notional Course of Action***

Still further extensions of this idea are in [Wagenhals, 2007] that addresses the important aspect of socio-cultural influences on a COA prototype, shown here as a Timed Influence Net:

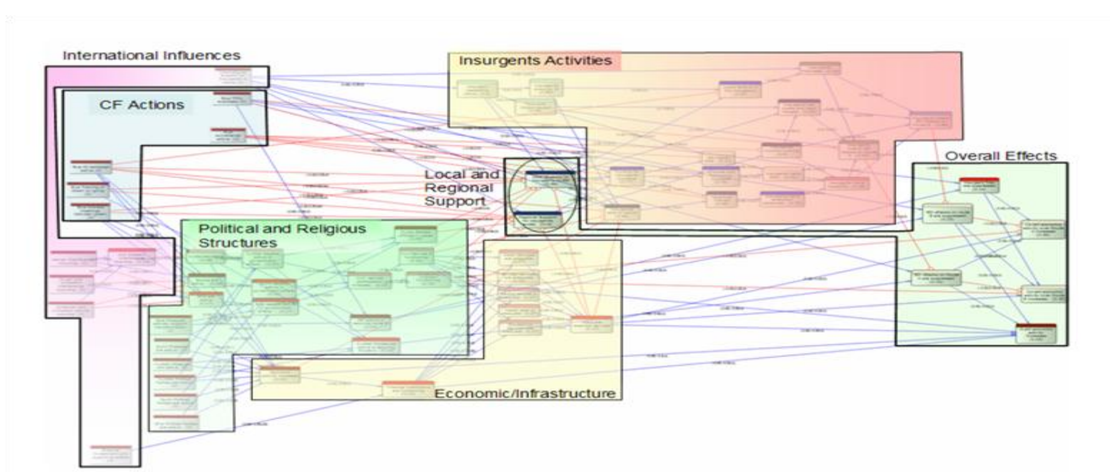



***Figure 5 Timed Influence Net with Socio-cultural Influences Accounted (from [Wagenhals, 2007])***

Note that this is a single COA or LOE; in a COIN campaign of multiple LOE's as per Figure 1, there is the need to account for inter-COA/LOE interactions and interdependencies; Allen et al [Allen, 2006] study this in a DARPA effort program initially called Integrated Battle Command and then named as Conflict Modeling, Planning and Outcomes Experimentation Program (COMPOEX); they depict these interactions as in Figure 6:

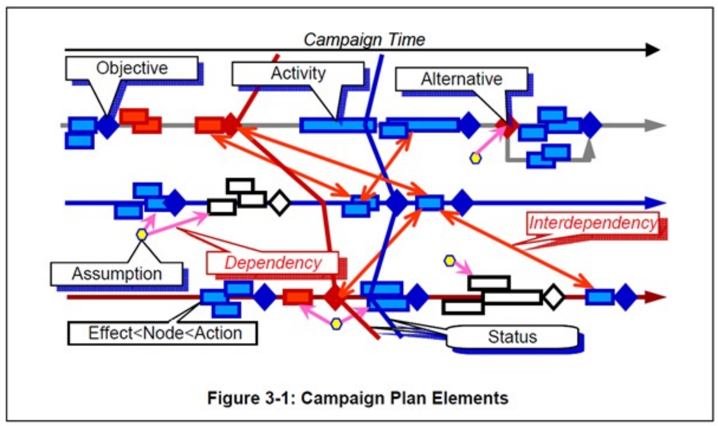



***Figure 6** Notion of a Campaign Plan Employing Multiple LOEs (from [Allen, 2006])*

**1.3 Developing a Course of Action**

Assuming that the consequences or outcomes of any action can be modeled to some degree (else why would anyone take a specific action?), and allowing that such dependencies have some type of unpredictability—say expressed probabilistically—and also realizing that the temporal inter-action/outcome sequences have a temporal uncertainty as well, a decision-maker might be faced with the type of problem environment shown in Figure 7:

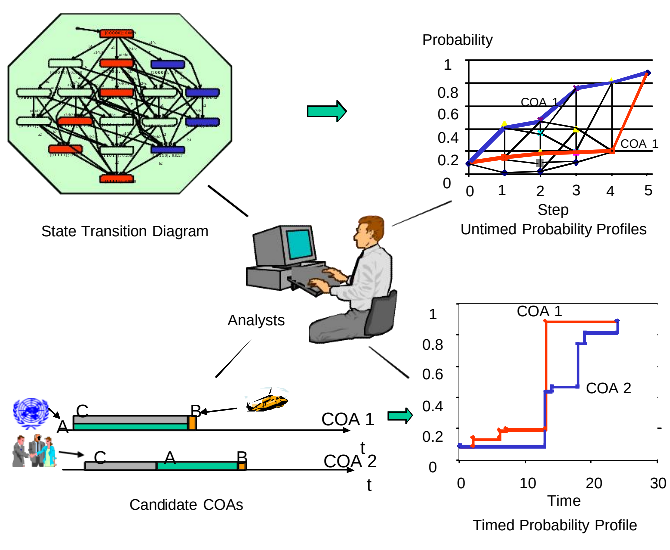



***Figure 7 The User's Dilemma in Choosing COA's and Making Decisions (from [Levis, 2000])***

Here, the user would have the "Plausible Futures" projections from the fusion/decision-support system and COA-modeling system that would provide timed, probabilistically-framed projections of the likelihood of the various outcomes. Each would have some level of value and thereby provide a quantitative basis for option selection. The process is not unlike Model-Predictive Control (MPC) from control theory that involves an n-step projection process over a future horizon, but where, using these projections, only the best current option is chosen and the process repeated as the actual outcome unfolds and estimates of that unknown true outcome are made. The notional MPC process is shown in Figure 8:

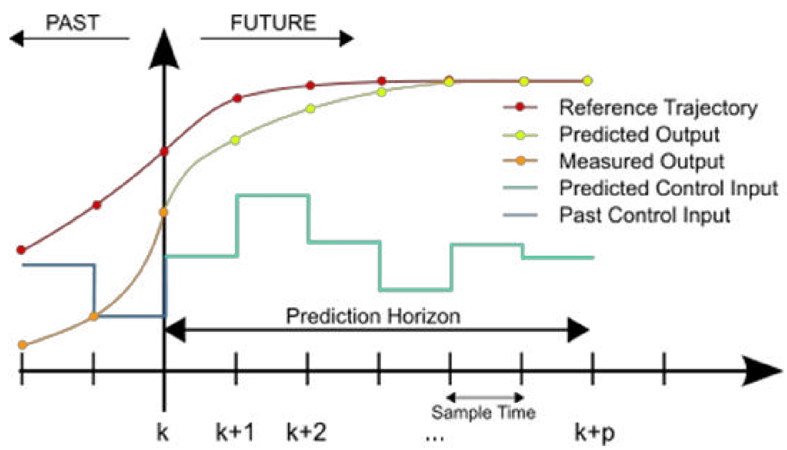



***Figure 8 Concept of Model Predictive Control***

**2. Impacts on Hard and Soft Fusion**

The ramifications of this decision-making environment on a Hard and Soft Fusion process are considerable. If we think about the informational components that support the design of any IF process we have:

- Observational data (and known sensor characteristics, as well as metadata)
- A priori deductive knowledge (classical example is object dynamic model for Kalman Filter design)
- Contextual information and knowledge
- Knowledge learned in runtime (discovery, data mining, inductive processes)

For the modern COIN problem we have:

- Observational data: Soft data that come from:
    - Uncalibrated and uncalibrate-able humans of all description under a wide variety of observational conditions, observing (and judging) all kinds of things
    - And are expressed in ambiguous unconstrained natural language, with the NLP problem far from solved
- A priori deductive knowledge: Very weak a priori deductive knowledge—a good example is the range of required deductive models as described by Kott [Kott, 2007] in the DARPA COMPOEX program, shown in Figure 9:

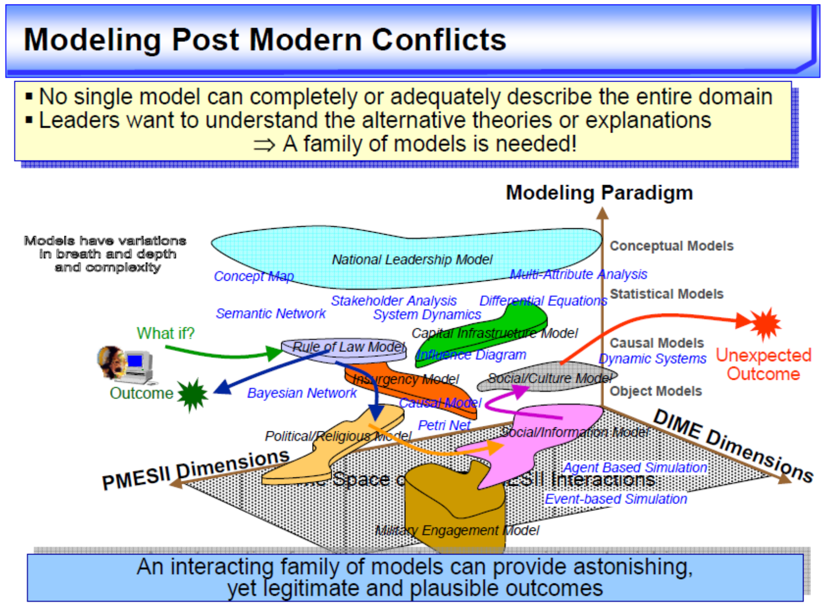



***Figure 9 COIN Modeling Dilemma (from [Kott, 2007])***

- Contextual Information and Knowledge: Generally weak and ephemeral Socio-cultural knowledge

These factors result in a process design environment that has much higher than traditional uncertainties and mixed representations of uncertainty (probabilistic for hard sensor data and very likely possibilistic for linguistic data); the weak knowledge environment can also result in the use of second-order uncertainty such as interval or parametric representations of knowledge uncertainty.

In turn, these factors result in very difficult Data Association problems related to developing effective methods for semantic similarity scoring and potentially high dimensionality in Assignment problem formulations.

Complexities can also result from the temporal alignment problem, since any linguistic message of a few phrases or larger can have past, present, and future tense references of non-trivial extent ("last week/month….I saw…..") that impute out-of-order processing requirements onto the fusion process.

Thus, the core functionalities of any Information Fusion process can be seriously impacted by this new operating environment.  Note too that the decision-making problem may need to be cast into the domain of decision-making under "strict uncertainty", involving "best of the worst" type paradigms such as Wald's Maximin, etc.

**3. References**

Allen, J.G., et al, Integrated Battle Command Program: Decision Support Tools for Planning and Conducting Unified Action Campaigns in Complex Contingencies, 2006 Command and Control Research and Technology Symposium, June 20 - 22, 2006

Darr, T.P., Benjamin, P., and Mayer, R., Course of Action Planning Ontology, Ontology for the Intelligence Community Conf., 2009 (OIC 2009), *c4i.gmu.edu/oic09/papers/OIC2009_8_Darr.pdf*

Davis, P.K., Effects Based Operations: A Grand Challenge for the Analytical Community, RAND Report, Santa Monica, CA, 2001

JFCOM, United States Joint Forces Command, The Joint Warfighting Center, Joint Doctrine Series Pamphlet 10, Design in Military Operations A Primer for Joint Warfighters, September 2010

Kott, A. and Corpac, P.S., COMPOEX Technology To Assist Leaders in Planning And Executing Campaigns In Complex Operational Environments in Proc of the 12th International Command and Control Research and Technology Symposium, June 2007

Levis, A.H., An Architecture for Effects Based Course of Action Development, Paper presented at the NATO RTO SCI Symposium on "System Concepts for Integrated Air Defense of Multinational Mobile Crisis Reaction Forces", held in Valencia, Spain, 22-24 May 2000, and published in NATO RTO MP-063

Operations, FM 3-0, February 23, 2011

Shy, John. "Jomini", In Paret, Peter. Makers of Modern Strategy: From Machiavelli to the Nuclear Age. Princeton: Princeton University Press, 1986

Tactics in Counterinsurgency, FM 3-24.2, Dept of the Army, March 2009

Wagenhals, L.W. and Levis,A.H., Course of Action Analysis in a Cultural Landscape Using Influence Nets Proceedings of the 2007 IEEE Symposium on Computational Intelligence in Security and Defense Applications (CISDA 2007)

Yan-guang, Z. and Yong-lin, L., Stochastic Timed Influence Nets; An Extension of Timed Influence Nets with Uncertain Delay, 2010 International Conference on Computer Application and System Modeling ICCASM 2010

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# Challenges of Hard and Soft Data Fusion for a Tracking Problem

Chee-Yee Chong
BAE Systems

SPIE Panel on "Real World Issues and Challenges in Hard and Soft Fusion"
April 25, 2011

 

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## Introduction

- Many challenges of fusing hard and soft data have been identified, e.g., Fusion XX conferences, NSSDF, SPIE
  - Challenges of using soft data
    - 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
  - Challenges of fusing with hard data
    - Common representation
    - Alignment and association of non-numeric with numeric data
    - Reasoning with different uncertainty representations
- This talk will discuss challenges for a simple tracking problem

 

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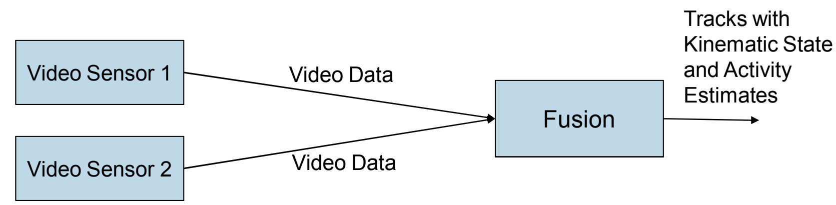
## Tracking with Hard Data from Physical Sensors




- Fusion combines video data to form tracks and estimate kinematic states and activities by
  - Forming video tracklets from each sensor
  - Associating video tracklets from both sensors over time to form tracks
  - Estimating kinematic state for each track
  - Estimating activity for each track

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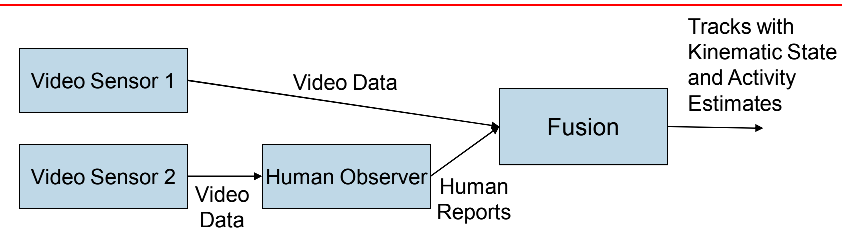
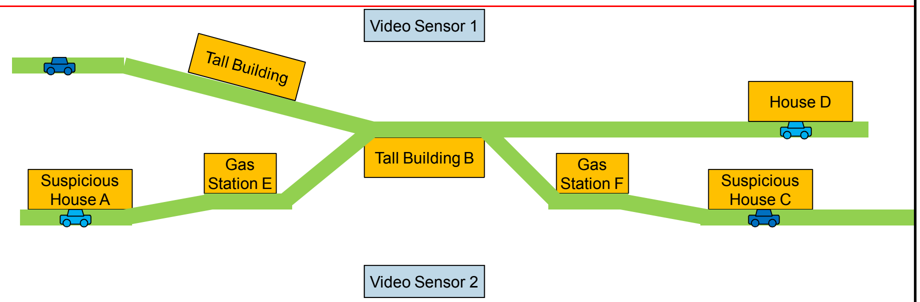
## Tracking with Hard Data and Soft Data




- Bandwidth limits communication from Video Sensor 2 to Fusion
- Human observer processes data from Video Sensor 2 to generate reports by
  - Forming tracks manually
  - Adding attributes to tracks
  - Inferring activities from tracks and context
  - Summarizing results in text, with possible reference to map

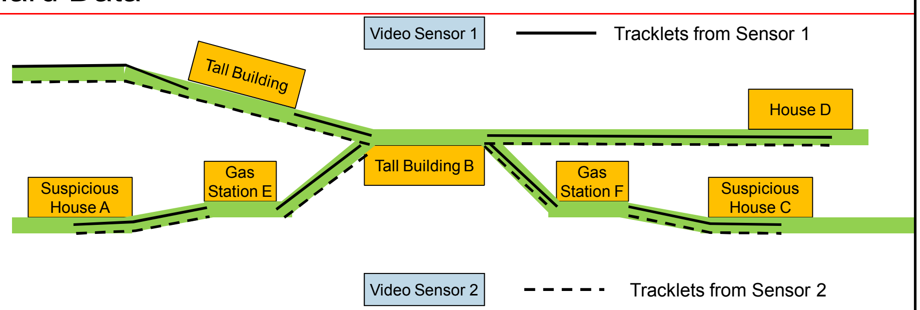
## Scenario




- Light blue vehicle:
  - 1200: leaves A
  - 1215 to 1230: stops at gas station E
  - 1245 to 1300: stops behind B
  - 1325: arrives at D
- Dark blue vehicle:
  - 1210: leaves starting point
  - 1240 to 1255: stops behind B
  - 1305 to 1315: stops at gas station F
  - 1330: arrives at C




## Hard Data




- Sensor/processors generate video tracks with kinematic state and attribute estimates
- Video tracks will break when vehicles stop (e.g., at gas stations) or go behind obscurations
- Fusion stitches tracklets together

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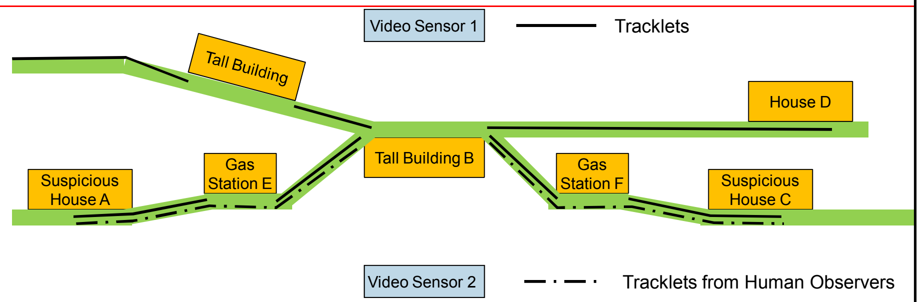
## Hard and Soft Data




- Human observer watches video and generates reports for vehicles of interest
  - Report 1: Light blue vehicle leaves A at about noon, stops for gas, and disappears behind building B at about 1245
  - Report 2: Blue vehicle leaves building B at just before 1300, refuels, and reaches C at 1320
  - ,

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## Characteristics of Human Reports

Attribute Location Time Activity
Report 1: Light blue vehicle leaves A at about noon, stops for gas, and disappears behind building B at 1245

Report 2: Blue vehicle leaves building B at just before 1300, refuels, and reaches C at 1320

- Summarize information by text: attribute, location, time, activity
- Exploit human understanding and context
  - Focus of attention on (perceived) high value targets
  - Visual continuous tracking
  - Activity inference from tracks and context
- Reflect human limitations and bias
  - Not all targets reported
  - Not all attributes reported
  - Imprecise location and time

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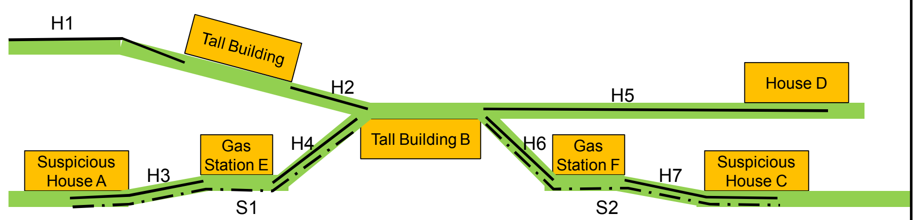
## Association of Hard and Soft Tracklets




- Hard tracklets
  - H1: t_start, x_start, t_end, x_end, attribute
  - H2: t_start, x_start, t_end, x_end, attribute
  - H3: t_start, x_start, t_end, x_end, attribute
  - H4: t_start, x_start, t_end, x_end, attribute
  - H5: t_start, x_start, t_end, x_end, attribute
  - H6: t_start, x_start, t_end, x_end, attribute
  - H7: t_start, x_start, t_end, x_end, attribute
- Soft tracklets
  - S1: Light blue vehicle leaves A at about noon, stops for gas, and disappears behind building B at 1245
  - S2: Blue vehicle leaves building B at just before 1300, refuels, and reaches C at 1320

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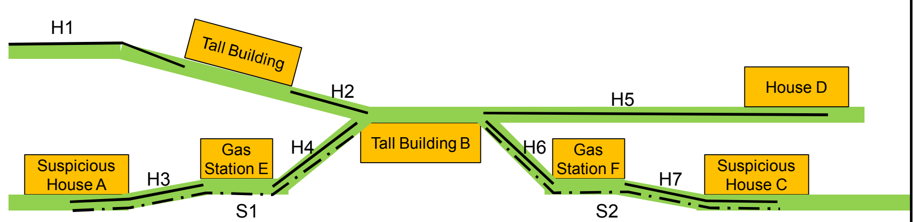
## Track and Association Hypotheses




- Track hypotheses
  - Hard data only: H1H2H5, H3H4H5, H1H2H6H7, H3H4H6H7, H2H5, H3H4
  - Soft data only: S1, S2, S1S2
  - Hard and soft data: H1H2H6H7S2, H3H4S1H5, H3H4S1H6H7S2
- Association hypotheses
  - {H1H2H6H7S2, H3H4S1H5}
  - {H3H4S1H6H7S2, H1H2H5}
  - {H1, H2H5, H3S1H4, H6S2H7}

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## Hypothesis Scoring Challenges

- Associating likelihood of tracklets involves alignment and comparison of non-numeric, non-probabilistic quantities
  - Kinematic
  - Attribute
  - Activity

| Tracklet | Hard | Soft |
|---|---|---|
| Time | 1205 | about noon |
| Kinematic state | estimate, covariance | near A |
| Attribute | prob (color) | light blue |
| Activity | prob(activity) | refuel |

| Tracklet | Soft | Soft |
|---|---|---|
| Time | At 1245 | Just before 1300 |
| Kinematic state | behind B | At B |
| Attribute | light blue | blue |
| Activity | stop at gas station | refuel |




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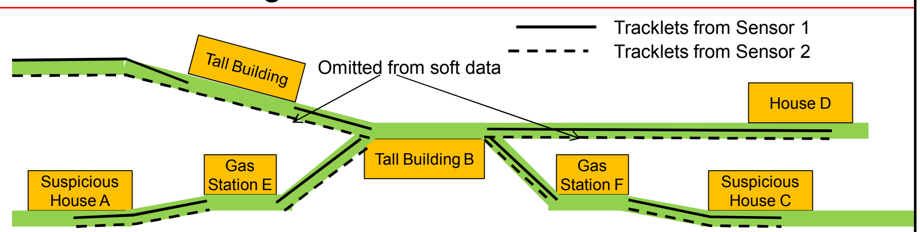
## Additional Challenges in Association




- Human observers do not report everything they see
  - Only targets that they care about
  - Leaving out tracks that could be associated with hard data
- Human observers do not report what they don't see
  - Only what they can see
  - Negative information cannot be used for association

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## Conclusions

- Human observer acts as intelligent tracker
  - Exploitation of human understanding and context to estimate activities
  - Focus of attention on (perceived) high value targets
- Track association with soft data has to address challenges due to
  - Processing of non-numeric data
  - Incomplete reporting of human observers
- Hard and soft data fusion for tracking can benefit from
  - Training of human observers to produce information that fusion needs
  - Characterization of human observer performance

# Challenges of Hard and Soft Data Fusion for a Tracking Problem

Position Paper for SPIE Panel on "Real World Issues and Challenges in Hard and Soft Fusion"

Chee-Yee Chong*
BAE Systems, 5050 El Camino Real, Suite 113, Los Altos, CA 94022

**ABSTRACT**

Hard and soft data fusion can potentially produce better results than fusion with hard or soft data alone because the sources provide different but complementary information. However, many challenges have to be addressed before the potential of hard and soft data fusion can be realized. In particular, soft data exploitation has to deal with the human operator as a sensor. Target tracking with multiple sensors is a common and important fusion problem. Many challenges of hard and soft data fusion are revealed by considering a tracking problem where one of the sensors is replaced by a human source.

**Keywords:** hard and soft data fusion, target tracking, physical sensors, human sensors

## 1. INTRODUCTION

Hard and soft data fusion has become an active area of research recently [1 – 5] because of its potential to produce good results in mission areas such as counter-insurgency and urban operations, where human reports are often the most important sources of information. In these mission areas, fusion is used to gather information about individuals, such as their activities and behaviors, as well as their social networks. While physical sensors can provide some data on movements and even activities, their utility is limited due to obscuration in urban environments. On the other hand, human sources can collect information close to the entities of interest and produce information not available from physical sensors, e.g., relationships.

Since soft data are generated by humans, the challenges of hard and soft data fusion are also the challenges of dealing with human sources and how to fuse these data with hard data from physical sensors. These challenges include:

- 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
- Human sources may intentionally lie

The manifestation of these challenges in fusion problems depends on the specific nature of problem, e.g., the physical and human sources, the entities of interest, and the contextual environment. Target tracking with multiple sensors is a common and important fusion problem. Many challenges of hard and soft data fusion are revealed by considering a tracking problem where one of the sensors is replaced by a human source.

## 2. HARD AND SOFT DATA FUSION FOR TARGET TRACKING

Most traditional tracking systems process data from physical sensors such as video cameras. When multiple sensors are involved, the tracking system associates the data across sensors and over time to generate tracks. Then it estimates the kinematic state and activity for each track. This type of system can be converted into one that fuses hard and soft data if a human observer processes the data from one sensor before communicating it to the fusion component. By performing some front-end processing, the human compresses the data and reduces the bandwidth required. More importantly, the human observer is good at exploiting context to infer activities.

*chee.chong@baesystems.com, cychong@ieee.org; phone 1 650-210-8822; fax 1 650-210-8824

The human observer produces soft data that is different in both form and content from the hard data from physical sensors (Figures 1). Most of the information is in natural language with its inherent imprecision and ambiguity, without a standard representation of uncertainty. A main challenge of exploiting this soft data is extracting the information and aligning it with the hard data to support tracking functions such as gating, association, state estimation, etc.

Attribute Location Time Activity

Report 1: Light blue vehicle leaves A at about noon, stops for gas, and disappears behind building B at 1245

Report 2: Blue vehicle leaves building B at just before 1300, refuels, and reaches C at 1320

Figure 1: Soft data from human observer

Furthermore, human observers do not report everything they see, only those targets that they care about, and leave out tracks that could be associated with hard data. Human observers also do not report what they do not see, and only what they can see. Thus, negative evidence not reported cannot be used for association with the hard data.

## 3. SUMMARY

Human observer acts as intelligent tracker that provides soft data into the fusion system. A human observer can exploit human understanding and context to estimate activities, and focuses attention on (perceived) high value targets. However, track association with soft data has to address challenges due to processing of non-numeric data, and incomplete reporting of human observers. Hard and soft data fusion for tracking can benefit from training the human observers to produce information that fusion needs, e.g., using a controlled format. Furthermore, characterization of human observer performance is essential before any fusion can be performed.

## REFERENCES


[1] D. L. Hall, J. Llinas, M. McNeese, and T. Mullen, “A framework for dynamic hard/soft fusion,” Proceedings of 11th International Conference on Information Fusion (2008).

[2] M. A. Pravia, R. K. Prasanth, P. O. Arambel, C. Sidner, and C. Y. Chong, “Generation of a fundamental data set for hard/soft information fusion,” Proceedings of 11th International Conference on Information Fusion (2008).

[3] R. T. Antony, and J. A. Karakowski, “Fusion of HUMINT and conventional multiple source data,” 2007 MSS National Symposium on Sensor and Data Fusion (2007).

[4] J. Llinas, R. Nagi, D. Hall, and J. Lavery, “A multi-disciplinary university research initiative in hard and soft information fusion: overview, research strategies and initial results,” Proceedings of 13th International Conference on Information Fusion (2010).

[5] E. Blasch, E. Dorion, P. Valin, E. Bosse, and J. Roy, “Ontology alignment in geographical hard-soft information fusion systems,” Proceedings of 13th International Conference on Information Fusion (2010).

McMaster University

# Soft and Hard Fusion to Improve Prediction and Retrodiction

**T. Kirubarajan (Kiruba)**

**Estimation, Tracking and Fusion Research Laboratory**
**Electrical and Computer Engineering Department**
**McMaster University, Hamilton, Ontario**

**SPIE 2011**

McMaster University

## Beyond Tracking and Fusion

- **Motion pattern extraction:**
  - Automatic classification of targets based on kinematic and non-kinematic data (motion patterns)
  - Extraction of road maps or "movement maps"
  - Motion change detection (e.g., application to IED)
  - Extract collaborative/group patterns
- **Prediction:**
  - Destination/intent prediction (e.g., urban environments, probability of attack)
  - Consideration of external factors (e.g., weather, shipping lanes, roads, intelligence)
- **Forensic analysis (retrodiction):**
  - Extract past path
  - Find origin
  - Associate past path with events (e.g., oil spill, IED) and targets

# Soft and Hard Fusion to Improve Prediction and Retrodiction

T. Kirubarajan
Estimation, Tracking and Fusion Research Laboratory (ETFLab)
Electrical & Computer Engineering Department, McMaster University, Canada
kiruba@mcmaster.ca

## Abstract

Multitarget tracking and multisensor fusion have received much attention in the literature during the last four decades. Significant advances have been made in these fields during this period. With the existing computational resources, it is possible to track thousands of targets and fuse information from a multitude of heterogeneous sensors in real-time. However, the threats faced today are radically different from those during yesteryears and they continue to evolve, increasingly becoming difficult to track. In order to improve overall results, soft and hard fusion is essential in that highly quantifiable hard data and fuzzy soft data need to be fused. Soft and hard fusion can improve the results not only at the current time, but it can be used to improve prediction and retrodiction results as well. In this position paper, we explore the use of soft and hard fusion to improve tracking, prediction and forensic results.

## 1. Soft/Hard Fusion for Tracking

While the use of hard kinematic measurements alone may suffice in sparse scenarios with few measurement origin ambiguities, it will result in poor tracking performance in dense scenarios with closely spaced targets and heavy clutter. In this case, additional non-kinematic (or attribute or feature) information will significantly improve the overall tracking results by reducing the data association ambiguities. With the availability of large knowledge databases like intelligence data, road maps and video, it is possible to enhance the results even further. In addition to the massive size of these databases, their disparate nature also poses problems in consistently integrating them into the tracker while ensuring real-time feasibility. It is necessary to develop optimal search and matching technique for using information from large databases in conjunction with kinematic data. These algorithms must incorporate database information in a systematic manner, not be distracted by (or robust against) spurious data contained in the database, and be able to improve tracking performance in a quantifiable manner. In addition, occasional (i.e., with long revisit intervals), and possibly, out-of-sequence, data input from people, satellites and intelligence sources must be incorporated without the need to reprocess the previous datasets. Another candidate for incorporating uncertain, occasional database information is Monte Carlo methods. Because of their high computational complexity, the practical value of Monte Carlo methods in such large-scale problems is limited in spite of their robustness against uncertainties. It is then necessary to develop efficient sampling (Monte Carlo) strategies to probe large-databases for useful information for integration with tracker.

In most tracker extensions that handle non-kinematic information [Bar-Shalom05], composite tracks that consist of kinematic and non-kinematic information are maintained. That is, tracks subsume kinematic and non-kinematic input data and the corresponding resultant estimates. The Flexible Association ID-Aided Tracking (FA/IDAT) [Sinha10] provides an alternative framework in which tracks and IDs are maintained in two lists and then a dynamic association between track and ID lists is performed in order to resolve any ambiguities. That is, kinematic and non-kinematic information are maintained separately in contrast to traditional trackers like the MHT or MFA. This provides a flexible framework in resolving past ambiguities and, in preliminary experiments, FA/IDAT yielded better results combining kinematic and non-kinematic information at the association level. In [Chong09], the MHT algorithm was augmented with a track segment graph to represent association ambiguities. The idea is to improve long-term tracking by generating long term track hypotheses and compactly representing them with track segment graphs. An extended duration MHT (EDMHT) addition module that can also incorporate feature measurements was used to augment the standard MHT tracker, which processes only kinematic data. The development of these algorithms is incomplete (e.g., details such as the extension to handle false alarms and the specific way to integrate feature/ID information are missing in [Chong09] and the number of targets is assumed to be known in [Sinha10]**).** In addition they are not capable of handling group targets or coordinated motion.

**2. Beyond Tracking…**

In addition to obtaining track estimates, it is desirable, wherever possible, to identify and classify the targets and predict their intent. The state estimation and classification go hand-in-hand in asset protection where classification results can play a significant role in the countermeasures against identified targets. The biggest challenge in soft hard fusion will be the scale of available data in making inferences on a large number of significant threats and connecting them for overall threat detection and evaluation. The handling of possibly non-informative data is important because of the nature of the problem, where multiple disparate sources produce data on unknown events that do not occur on a regular basis. The challenge is in quantifying the information contributed by each piece of data, for which one may not have an accurate statistical model. Another difficulty with terrorism related events is their time-varying multi-modal nature.

In [Garcia06] the application of a machine-learning approach to classify ATC trajectory segments from recorded opportunity traffic was addressed. In [He10] a joint class identification and target classification algorithm that can simultaneously build class types on the basis of target kinematic and feature measurements and classify targets according to the identified classes even when there is switching among classes is proposed. In [Pang11] models and algorithms for detection and tracking of group and individual targets were described. Two group dynamical models within a continuous time setting using stochastic differential equations (SDE) that aim to mimic behavioural properties of groups were developed.

The problem of detecting an anomaly (or abnormal event) is such that the distribution of observations is different before and after an unknown onset time, and the objective is to detect the change by statistically matching the observed pattern with that predicted by a model. In [Singh09] feature-aided tracking combined with HMMs for analyzing asymmetric threats was proposed. Also it provided a summary of various related work, ranging from visualization to algorithmic threat projection, and described a human-centered framework that associates situation assessment processes and models with requirements needed to enhance situation awareness. In [Sathyan06] a framework was presented for tracking multiple mobile targets in an urban environment based on data from multiple sources of information, and for evaluating the threat these targets pose to assets of interest. In [Blasch04] a method was developed to incorporate intent into a tracking and target identification system to improve performance.

**References**

**[Bar-Shalom05]** Y. Bar-Shalom, T. Kirubarajan and C. Gokberk, “Tracking with classification-aided multiframe data association”, IEEE Trans. AES, Vol. 41, No. 3, pp. 868-878, July 2005.

**[Chong09]** C.-Y. Chong, G. Castanon, N. Cooprider, S. Mori, R. Ravichandran and R. Macior, “Efficient multiple hypothesis tracking by track segment graph”, Proc. Int. Conf. Information Fusion, July 2009.

**[Garcia06]** J. Garcia, O. Concha, J. Molina, G. Miguel, “Trajectory classification based on machine-learning techniques over tracking data”, Proc. Int. Conf. Information Fusion, July 2006.

**[He10]** X. He, R. Tharmarasa, M. Pelletier and T. Kirubarajan, “Two-level automatic multiple target joint tracking and classification”, Proc. SPIE Conf. Signal and Data Processing of Small Targets, vol. 7698, April 2010.

**[Pang11]** S. K. Pang; J. Li and S. J. Godsill, “Detection and tracking of coordinated groups”, IEEE Trans. AES, Vol. 47, No. 1, pp. 472-502, January 2011.

**[Sathyan06]** T. Sathyan, K. Bharadwaj, A. Sinha and T. Kirubarajan, “Intelligence-aided multitarget tracking for urban operations: A case study in counter terrorism”, Proc. of SPIE, Vol. 6201, April 2006.

**[Singh09]** S. Singh, H. Tu, W. Donat, K. Pattipati and P. Willett, “Anomaly detection via feature-aided tracking and hidden Markov models”, IEEE Trans. on Systems, Man and Cybernetics – Part A: Systems and Humans, Vol. 39, No. 1, pp. 144-159, January 2009.

**[Sinha10]** A. Sinha and D. Peters, “New developments in flexible ID association-based tracking algorithm”, Proc. Int. Conf. Information Fusion, July 2010.

**[Blasch04]** E. Blasch, “Modeling intent for a target tracking and identification scenario”, Proc. SPIE Conf. Signal and Data Processing of Small Targets, Vol. 5428, August 2004.

## Unified Hard + Soft Information Fusion

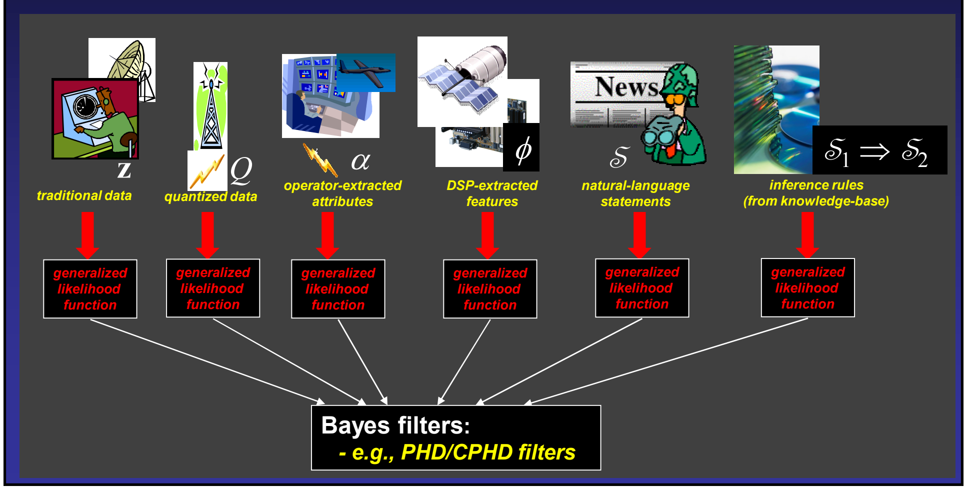
**Panel on Real-World Issues and Challenges in Hard and Soft Fusion**

**Ronald Mahler**
*Lockheed Martin MS2, Eagan MN*
*651-456-4819 / ronald.p.mahler@lmco.com*

*SPIE Defense, Security + Sensing Symposium*
*April 25 2011, Orlando*

## Optimal Processing of Hard + Soft Measurements, 1

- **My claim:**
  - *I have developed a systematic, unified, and Bayesian solution to the hard + soft fusion problem*



## Optimal Processing of Hard + Soft Measurements, 2

- **The core approach:**
  - *unified theory of measurements*
    - *represents both hard and soft information in a common probabilistic framework: the generalized measurement*
  - *unified single- and multi-target Bayes filtering theory*
    - *based on the concept of a generalized likelihood function*

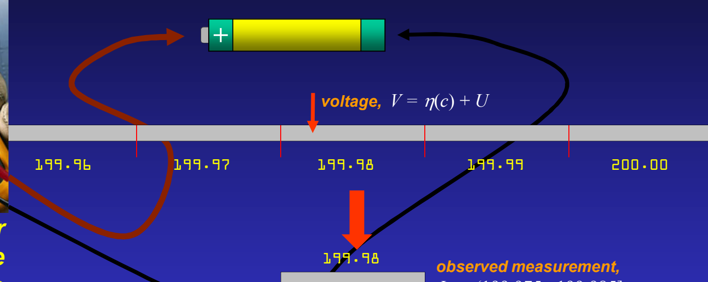
- **Consequence:** ***Hard and soft measurements can be processed in exactly the same way:***

*radiar detection* → *single-target or multitarget Bayes filter*
*natural-language report* → *single-target or multitarget Bayes filter*
*single-target or multitarget Bayes filter* → *fused state-estimates and error-covariances*

## Conceptual Starting Point: Quantized Measurements

*digital voltmeter displays a voltage rounded off to two decimal points (quantization)*

- *voltage source of type* $c$




*the measurement is an INTERVAL (a SUBSET) of measurement space, not a POINT in measurement space*

*in expert-system theory, this is known as an IMPRECISE MEASUREMENT*

## Measurements in General

Chapter 3

- **First step: formulate the "measurement" concept so that it encompasses both hard and soft information:**
  - *a measurement is an opinion ventured by an information source (a sensor, a human expert) regarding what has or has not been observed.*
- **Consequence:**
  - *if a measurement is an opinion or interpretation, then it is implicitly a collection of hypotheses about what has or has not been observed.*
- **Types of measurements:**

| *precise* | *imprecise* | *Vague ("fuzzy")* | *Uncertain ("Dempster-Shafer")* |
|---|---|---|---|
| $\mathbf{z} \in Z_0$ <br> *measurement (e.g., vector)* — *measurement space (e.g., Euclidean)* | $\mathbf{z} \in S_1 \subseteq Z_0$ <br> *constraint on* $\mathbf{z}$ *(e.g., quantized measurement)* | *nested constraints* <br> $\mathbf{z} \in S_1 \subseteq \ldots S_n \subseteq Z_0$ <br> $w_1 + \ldots + w_n = 1$ <br> *weights (degrees of belief in constraints)* | $\mathbf{z} \in S_1, \ldots, \mathbf{z} \in S_n \subseteq Z_0$ <br> $w_1 + \ldots + w_n = 1$ |
| *source believes that it has identified the measurement with complete certainty* | *source knows measurement only to within some constraint* | *source is uncertain about the correct degree of constraint* | *source believes that constraints are not nested* |

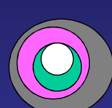
## Measurements = Random Subsets of Measurement Space

Chapter 4

*precise* $\quad \eta(\mathbf{x}) = \mathbf{z} - \mathbf{V}$

*imprecise* $\quad \eta(\mathbf{x}) \in S_0$

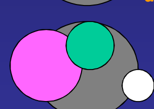
*vague* *(fuzzy)*



$\eta(\mathbf{x}) \in S_0 \subset \ldots \subset S_m$

*draws from random set* $\Theta$ $\quad \Pr(\Theta = S_i) = p_i$

*uncertain* *(Dempster-Shafer)*



$\eta(\mathbf{x}) \in S_0, \ldots, S_m$

*draws from* $\Theta$ $\quad \Pr(\Theta = S_i) = p_i$

*in general* $\quad \Theta \quad \eta(\mathbf{x}) \in \Theta$

*arbitrary random subset of measurement space*

## Generalized Likelihood Functions

Section 5.3

- *likelihood function for conventional measurements:*

$$f_{k+1}(\mathbf{z}|\mathbf{x}) \;=\; f_{\mathbf{V}}(\mathbf{z}-\eta(\mathbf{x})) \;=\; \text{“}\Pr(\;\eta(\mathbf{x})\in\{\mathbf{z}-\mathbf{V}\}\;)\text{”}$$

- *generalized likelihood function for general measurements:*

$$f_{k+1}(\Theta|\mathbf{x}) \;=\; \Pr(\eta(\mathbf{x}) \in \Theta)$$

- *joint generalized likelihood function for general measurements:*

$$f_{k+1}(\Theta,\Theta'|\mathbf{x}) \;=\; \Pr(\eta(\mathbf{x})\in\Theta,\;\; \eta(\mathbf{x})\in\Theta')$$

## Generalized Likelihoods: Summary

*fuzzy measurements* $g(\mathbf{z})$

$$f_{k+1}(g|\mathbf{x}) \;=\; g(\eta(\mathbf{x}))$$

*Dempster-Shafer measurements* $\mu(S_j) = p_j$

$$f_{k+1}(\mu|\mathbf{x}) \;=\; \sum\nolimits_{j=1}^{m} p_j \cdot \mathbf{1}_{S_j}(\eta(\mathbf{x}))$$

*fuzzy D-S measurements* $\mu(g_j) = p_j$

$$f_{k+1}(\mu|\mathbf{x}) \;=\; \sum\nolimits_{j=1}^{m} p_j \cdot g_j(\eta(\mathbf{x}))$$

*fuzzy rules* $g \Rightarrow g'$

$$f_{k+1}(g \Rightarrow g'|\mathbf{x}) \;=\; (g \wedge_{A,A'} g')(\eta(\mathbf{x})) + \tfrac{1}{2}\,(1 - g(\eta(\mathbf{x})))$$

## Single-Target Unified Measurement Fusion

- *given: general measurements* $\Theta, \Theta'$

- *Bayesian fusion of independent general measurements:*

$$f_{k+1|k+1}(\mathbf{x}|\Theta,\Theta') = \frac{f_{k+1}(\Theta|\mathbf{x}) \cdot f_{k+1}(\Theta'|\mathbf{x}) \cdot f_{k+1|k}(\mathbf{x})}{\int f_{k+1}(\Theta|\mathbf{y}) \cdot f_{k+1}(\Theta'|\mathbf{y}) \cdot f_{k+1|k}(\mathbf{y}) d\mathbf{y}}$$

- *Bayesian fusion of non-independent general measurements:*

$$f_{k+1|k+1}(\mathbf{x}|\Theta,\Theta') = \frac{f_{k+1}(\Theta,\Theta'|\mathbf{x}) \cdot f_{k+1|k}(\mathbf{x})}{\int f_{k+1}(\Theta,\Theta'|\mathbf{y}) \cdot f_{k+1|k}(\mathbf{y}) d\mathbf{y}}$$

## Unified Multisource-Multitarget Fusion & Filtering


Section 14.4.2

- *given new nontraditional measurement-set,* $Z_{k+1} = \{\Theta_1, \ldots, \Theta_m\}$

*generalized likelihood function:* $L_\Theta(\mathbf{x}) = f_{k+1}(\Theta|\mathbf{x})$

$$L_{Z_{k+1}}(\mathbf{x}|Z^{(k)}) = 1 - p_D(\mathbf{x}) + \sum_{\Theta \in Z_{k+1}} \frac{p_D(\mathbf{x})\, L_\Theta(\mathbf{x})}{\lambda_{k+1} c_{k+1}(\mathbf{z}) + D_{k+1|k}[p_D L_{\mathbf{z}}]}$$

$$D_{k+1|k+1}(\mathbf{x}|Z^{(k+1)}) \cong L_{Z_{k+1}}(\mathbf{x}|Z^{(k)}) \cdot D_{k+1|k}(\mathbf{x}|Z^{(k)})$$

***same reasoning applies to CPHD filter***

# Unified Hard + Soft Information Fusion

Position Paper: Panel on Real-World Issues and Challenges in Hard and Soft Fusion
Ronald Mahler
Lockheed Martin MS2, Eagan, MN

In the context of this panel discussion, *hard fusion* refers to the process of fusing and exploiting "hard information"—i.e., data generated by physical sensors such as radars, sonars, cameras, etc. *Hard and soft fusion*, by way of contrast, refers to information fusion and exploitation when data can be "soft" as well as hard. Soft information typically (but not always) involves human mediation, and "soft measurements" include such things as (1) *attributes* extracted from an image by human operators; (2) *natural-language statements* reported by human observors; (3) *inference rules* drawn from knowledge-bases compiled by human experts; and (4) *target-signature databases* constructed by human domain experts. In addition to these, I include (5) *features* extracted from a sensor signature by digital signal processing (DSP) algorithms. This is because features are often ambiguous in somewhat the same way that human-generated attributes are ambiguous, even though they are typically not human-mediated.

According to the panel problem statement, the fundamental problem to be addressed is as follows: "While algorithms for fusing information from physical sensors has a substantial development history as well as maturity, complex technical issues remain in the representation of human-based information to make it suitable for combining with sensor based information." In the book *Statistical Multisource-Multitarget Information Fusion*,[1] I have proposed what I believe is the first and only *systematic, unified, and probabilistic (indeed, Bayesian) solution to the hard + soft fusion problem*. The core approach has two parts:

- a *unified theory of measurements*, which represents both hard information and soft information in a common probabilistic framework called a "generalized measurement"; and

- a *unified single-target and multitarget Bayes filtering theory for generalized measurements*, which is based on the concept of a "generalized likelihood function."

Taken together, these two approaches *permit soft measurements (e.g., a natural language report) to be processed in exactly the same way as hard measurements (e.g., a radar detection).* The purpose of this position paper is to briefly summarize and advocate this unified hard/soft fusion approach: measurements in general, statistical representations of general measurements, generalized measurement models, generalized likelihood functions, and single- and multi-target Bayes filtering of both hard and soft measurements.

**Measurements in General.**[1,Chapter 3] The first step is to formulate the concept of a "measurement" so that it encompasses both hard and soft information sources: *A measurement is an opinion ventured by an information source (a sensor, a human expert) regarding what has or has not been observed.*[1,p.97] But if a measurement is an opinion or interpretation, then, at least implicitly, it is actually *a collection of hypotheses about what has or has not been observed.*

The theory of measurements that I have proposed is based on standard expert systems concepts. It employs a taxonomy of increasingly more general kinds of measurements: *precise* (a.k.a. "crisp"), *vague* (a.k.a. "fuzzy"), *uncertain* (a.k.a. "Dempster-Shafer"), *contingent* (as with rules), and *general*. Suppose that the measurement space $\mathfrak{Z}_0$ of the sensor/source is a Euclidean space. Then a *precise measurement* is just a conventional measurement-vector $\mathbf{z} \in \mathfrak{Z}_0$. In this case, the source believes that it has identified the measurement with complete certainty. Not all measurements are precise, however. *Quantized measurements* are the most familiar non-precise measurements. A quantized measurement is a "cell"—that is, a subset $S_1 \subseteq \mathfrak{Z}_0$ of $\mathfrak{Z}_0$—that contains the actual measurement $\mathbf{z}$. It specifies that $\mathbf{z}$ is known only to within containment in $S_1$. In the expert-systems literature, such measurements are commonly known as *imprecise*. Suppose now that the source believes that $\mathbf{z}$ is constrained to being within $S_1$, but cannot be completely certain that $S_1$ is the actual or best constraint. In this case, the measurement reported by the source might be best represented by a nested sequence $S_1 \subset S_2 \subset ... \subset S_n$ of subsets of $\mathfrak{Z}_0$, together with degrees of belief $w_1, ..., w_n$ in these different interpretations, with $w_1 + ... + w_n = 1$. Each $S_i$ is a different hypothesis about what the correct bound on $\mathbf{z}$ should be. Such a measurement is commonly described as *vague* or "fuzzy". Finally, suppose that the observer cannot be certain that the interpretations $S_1, ..., S_n$ should be nested. Then the measurement $S_1, ..., S_n$ is *uncertain* ("Dempster-Shafer").

**Statistical Representation of Measurements in General.**[1,Chapter 4] Note that an uncertain measurement can be represented as a *random subset* $\Theta$ of $\mathfrak{Z}_0$ which has the instantiations $\Theta = S_1, ..., S_n$ and whose probability of selecting $S_i$ is $\Pr(\Theta = S_i) = w_i$. This leads us to the *general definition of a (fixed) measurement*: it is *an arbitrary random (closed) subset* $\Theta$ *of* $\mathfrak{Z}_0$. Though I cannot explain why here, it turns out that even more general kinds of measurements, such as inference rules, can be represented as random subsets of $\mathfrak{Z}_0$. Furthermore, this definition also encompasses *randomness in the usual sense*. For example, even though a measurement is known to be precise, the sensor/source may observe different versions of it at different times. In this case the measurement is actually a random vector. Similarly, even though the observer may "see" a particular imprecise measurement $S_1$ at a particular time, it may observe different versions of it at different times. In this case, the measurement is actually a random subset of $\mathfrak{Z}_0$. More generally, even though any particular observation is known to be interpretable as a set of hypotheses $S_1, ..., S_n$, the sensor/source may observe different versions of these hypotheses at different times. So the sequence $S_1, ..., S_n$ of hypotheses may itself be random—and can in turn be represented as a particular random subset $\Theta$ of $\mathfrak{Z}_0$.

**Generalized Measurement Models.**[1,Chapters5,6] It is not possible to exploit any kind of measurement unless one has some idea about how measurements are related to targets. The relationship between precise measurements and targets is conventionally specified by a *measurement model* of the form

$$\mathbf{Z} = \eta(\mathbf{x}) + \mathbf{V}, \tag{1}$$

where $\mathbf{x}$ is the target state-vector, where $\mathbf{z} = \eta(\mathbf{x})$ is a deterministic description of which measurements are generated by which targets, and where $\mathbf{V}$ is a zero-mean noise vector. It turns out that, for a generalized measurement $\Theta$, the corresponding measurement model has the form

$$\eta(\mathbf{x}) \in \Theta. \tag{2}$$

(This model is consistent with the traditional model. Suppose that

$$\Theta_{\mathbf{z}} = E_{\mathbf{z}} - \mathbf{V} = \{\mathbf{w} - \mathbf{V} | \, \mathbf{w} \in E_{\mathbf{z}}\} \tag{3}$$

where $E_{\mathbf{z}}$ is a very small (hyper)sphere centered at $\mathbf{z}$. Then the model $\eta(\mathbf{x}) \in \Theta_{\mathbf{z}}$ approximates the model $\eta(\mathbf{x}) = \mathbf{z} - \mathbf{V}$.)

However, note that there is a hidden assumption here, namely that the function $\eta(\mathbf{x})$ is presumed to be precisely known. That is, we know with certainty that, if the effects of (conventional) randomness are ignored, then a target with state-vector $\mathbf{x}$ will always produce measurement-vector $\eta(\mathbf{x})$. But in many cases—if $\mathbf{z}$ is an attribute that describes target identity, for instance—the precise value of $\eta(\mathbf{x})$ may not be known. (For example, suppose that $\eta(c)$ is the observed number of wheels on a vehicle of class $c$. Then there may be a target type $c_0$ for which the exact number of wheels is not known with certainty. Indeed, it may even be completely unknown.) In this case, the generalized measurement model $\eta(\mathbf{x}) \in \Theta$ must be further generalized, to the form

$$\Theta \cap \Sigma_{\mathbf{x}} \neq \emptyset \tag{4}$$

where $\Sigma_{\mathbf{x}}$ is a random set representation of the uncertainty involved in the specification of $\eta(\mathbf{x})$. That is, target $\mathbf{x}$ "matches" the generalized target-model $\Sigma_{\mathbf{x}}$ if it does not completely contradict the observed measurement $\Theta$.

**Generalized Likelihood Functions.**[1,Chapters5,6] In a Bayesian approach, measurements are not processed directly—they are mediated by likelihood functions. Thus the model $\mathbf{Z} = \eta(\mathbf{x}) + \mathbf{V}$ must first be transformed into the corresponding likelihood function

$$f(\mathbf{z}|\mathbf{x}) = f_{\mathbf{V}}(\mathbf{z} - \eta(\mathbf{x})), \tag{5}$$

where $f(\mathbf{z}|\mathbf{x})$ is the probability that measurement $\mathbf{z}$ will be collected if a target with state $\mathbf{x}$ is present. Intuitively speaking, $f(\mathbf{z}|\mathbf{x})$ is the probability that $\eta(\mathbf{x}) \in \{\mathbf{z} - \mathbf{V}\}$. In like manner, if a Bayesian approach is to be applied, then the generalized measurement models $\eta(\mathbf{x}) \in \Theta$ and $\Theta \cap \Sigma_{\mathbf{x}} \neq \emptyset$ must be converted to likelihood function form. These are the "generalized likelihood functions"

$$f(\Theta|\mathbf{x}) = \Pr(\eta(\mathbf{x}) \in \Theta) \tag{6}$$

$$f(\Theta|\mathbf{x}) = \Pr(\Theta \cap \Sigma_{\mathbf{x}} \neq \emptyset) \tag{7}$$

(For example, if $\Theta_{\mathbf{z}}$ is as defined earlier, then it can be shown that $f(\Theta_{\mathbf{z}}|\mathbf{x}) \propto f(\mathbf{z}|\mathbf{x})$ as the hypervolume of $E_{\mathbf{z}}$ becomes arbitrarily small, provided that $f(\Theta_{\mathbf{z}}|\mathbf{x})$ is defined as in Eq. (6).)

**Bayes Filtering of Hard and Soft Measurements.**[1] For single targets, Bayesian fusion and filtering of (independent) precise measurements $\mathbf{z}_1, ..., \mathbf{z}_m$ is accomplished using Bayes' rule:

$$f(\mathbf{x}|\mathbf{z}_1, ..., \mathbf{z}_m) = \frac{f(\mathbf{z}_1|\mathbf{x}) \cdots f(\mathbf{z}_m|\mathbf{x}) \cdot f_0(\mathbf{x})}{\int f(\mathbf{z}_1|\mathbf{y}) \cdots f(\mathbf{z}_m|\mathbf{y}) \cdot f_0(\mathbf{x}) \, d\mathbf{y}} \tag{8}$$

where $f_0(\mathbf{x})$ is the prior distribution. Bayes fusion and filtering of (independent) generalized measurements $\Theta_1, ..., \Theta_m$ is similarly accomplished using Bayes' rule:

$$f(\mathbf{x}|\Theta_1, ..., \Theta_m) = \frac{f(\Theta_1|\mathbf{x}) \cdots f(\Theta_m|\mathbf{x}) \cdot f_0(\mathbf{x})}{\int f(\Theta_1|\mathbf{y}) \cdots f(\Theta_m|\mathbf{y}) \cdot f_0(\mathbf{x}) \, d\mathbf{y}} \tag{9}$$

Now consider multiple targets. Since (independent) precise measurements are mediated by likelihood functions, they can be processed using the PHD, CPHD, or multi-Bernoulli filters. Generalized measurements can be processed by the same filters, since they are mediated by generalized likelihood functions (which can simply be substituted in place of conventional likelihood functions in the formulas for these filters.)

# 1 REFERENCES


[1] R. Mahler, [Statistical Multisource-Multitarget Information Fusion], Artech House, Norwood, MA, 2007.