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Ivan Kadar
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Introduction

Context is present in all aspects of processing and interpreting information—situation, data, text, imagery, target tracking/identification, web-analytics, and intelligence systems outputs; that is, in all aspects/levels of information fusion (IF). Context is a multi-faceted entity and can represent a setting for the assessment/interpretation of an event, scene, presence, situation, condition, constraint, influence, and many other entities clearly scenario/application dependent. There is context within context. Furthermore, context is not a static entity and can change over time (e.g., operating conditions, environment, geography, weather, seasons, roads, traffic, attitudes, behavior, preferences), affecting the performance of a given application if not managed and taken into account. Therefore, it is important to incorporate contextual information at the outset in all IF levels and associated systems designs in order to enhance the performance of the overall IF system and the on-going application.

For a given application, contextual information represents prior domain knowledge about the setting of the scenario/process to commence. The contextual knowledge can be acquired from prior (historical) experience, provided by external sources (e.g., the user), learned from process experience (e.g., context awareness, prediction and search), and it can be updated/corrected if changes are detected (e.g., by machine learning).

For example, one can describe at least five contextual categories in tracking applications: (1) domain knowledge from a user to aid the information fusion process through selection, cueing, and analysis; (2) environment-to-hardware processing for sensor management; (3) known distribution of entities for situation/threat assessment; (4) historical traffic behavior for situation awareness patterns of life (POL); and (5) road information for target tracking and identification. Appropriate characterization and representation of contextual information is needed for future high-level information fusion systems design to take advantage of the large amount of data available for *a priori* knowledge target-tracking algorithm construction, implementation, and application.

The objective of this panel was to bring to the attention of the fusion community the importance of the application of contextual knowledge to enhance IF by highlighting issues, illustrating potential approaches, and addressing challenges. A number of invited experts discussed the challenges of the fusion process as well as the research addressing these challenges. The panelists illustrated parts of the aforementioned areas over different applications and addressed all levels of information fusion. Conceptual and real-world related examples associated with the use of context to enhance IF were used by the panel to highlight impending issues and challenges.

Ivan Kadar
Erik Blasch
Chee-Yee Chong

Invited Panel Discussion

Issues and Challenges in the Application of Context to Enhance Information Fusion

Organizers

Erik Blasch, Air Force Research Lab.

Ivan Kadar, Interlink Systems Sciences, Inc.

Moderators

Ivan Kadar, Interlink Systems Sciences, Inc.

Chee-Yee Chong, Independent Consultant

April 20, 2015

SPIE Conference 9474

“Signal Processing, Sensor Fusion and Target Recognition XXIV”

Baltimore, MD., 20-22 April 2015

Invited Panel Discussion

Panel Participants:

Dr. Erik Blasch, Air Force Research Lab., U.S.A.

Dr. Alex Chan, Army Research Lab., USA

Dr. Chee-Yee Chong, Independent Consultant, U.S.A.

Dr. Laurie Fenstermacher, Air Force Research Lab., U.S.A.

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

Dr. Ronald P. Mahler, Independent Consultant, U.S.A.

Dr. Alan Steinberg, Independent Consultant, U.S.A.

Dr. Paul Tandy, Defense Threat Reduction Agency, U.S.A.

Dr. Shanchieh J. Yang, RPI.edu, U.S.A.

Invited Panel Discussion
Topics

"Perspectives on the Applications of Context to Enhance Information Fusion"
Dr. Ivan Kadar, Interlink Systems Sciences, Inc.

"Determining Relevant Context "
Dr. Alan Steinberg, Independent Consultant

"Probabilistic Model for Context in Fusion "
Dr. Chee-Yee Chong, Independent Consultant

"The Fundemental Statistics of Contextual Information"
Dr. Ronald Mahler, Independent Consultant

" Finding Context In a Complex World
Dr. Erik Blasch, AFRL/RIEA, Rome Research Site

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Invited Panel Discussion
Topics

"CWMD Context and Information Fusion Issues"
Dr. Paul Tandy, Defense Threat Reduction Agency

"The Importance of the "Emic" Perspective in Information Fusion"
Dr. Laurie Fenstermacher, Air Force Research Lab

" Network Attack Modeling with and without Context Fusion"
Dr. Shanchieh J. Yang, Rochester Institute of Technology

" Impacts of Fusion and Context on Tracking and Anomaly Detection in Videos"
Dr. Alex Lipchen Chan, US Army Research Lab.

Invited Panel Discussion on "Issues and Challenges of the Applications of Context to Enhance Information Fusion"

Perspectives on the Applications of Context to Enhance Information Fusion.

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

April 20, 2015

SPIE Conference 9474 "Signal Processing, Sensor Fusion and Target Recognition XXIV", 20-22 April 2015, Baltimore, MD

Outline/Motivation

The overall purpose of this talk is two fold:

1 2

- Provide a succinct historical background summary of context definitions, modeling and use,
- Introduce: recent research efforts and challenges in context modeling, definitions and use, and
- Illustrate the extraction, representation and use of contextual information.

Outline/Motivation

The overall purpose of this talk is two fold:

1 **2**

- Introduce unexplored research areas and challenges using **Big Data Predictive Analytics** processing methods:
- Predict context dependent performance information, and
- Detect/identify changes in enormous volume and speed *online* **data streams** information exchange in cyber and fusion systems.

Problem Setting and Challenges

Succinct Background and Review.

Over the past few years, the definition, identification, selection, management, adaptation and use of contextual information has been addressed at several fusion levels and systems applications by, e.g., Alan Steinberg, Chris Bowman, Erik Blasch and Jim Llinas in the USA, and by several others in Italy and Spain, as well elsewhere.

For example, E. Blasch in a recent survey [1] presents an extensive summary of contextual tracking, and in a joint paper with X. Shi et al.[2], performed vehicle detection from wide area motion imagery (WAMI) by extracting contextual information about roads from vehicle trajectories and fed back this information to reduce false alarms. In 2014 S. Phoba [3] investigated context in DDDAS [4] framework.

Problem Setting and Challenges

Challenges and New Perspectives by Predictive Analytics Processing

In Information Fusion (IF) applications high volume and speed data flows in, e.g., collaborating platforms, sensor networks and communications, cyber or program news feeds/communications via e-mail; needs to be explored, which is in the form of **data streams**: ***"Enormous"/"Big Data"*** processed in real-time.

Due to dynamically changing and non-stationary environments, the **pattern and probability distributions of data streams** can change over time yielding the phenomenon of **Concept Drift** (CD): a term introduced in 1986 by Schlimmer et al. [5] in the machine learning/predictive analytics area. At Fusion 2014 was the first time the topic of CD detection was addressed and used for spam filtering using a novel machine learning algorithm by M. Abad et al. [6].

Problem Setting and Challenges

Challenges and New Perspectives by Predictive Analytics Processing

Yet Concept Drift detection has broad applications in Predictive Analytics/Information Fusion area (context ID, use and change).

Challenges in Context Definitions, Modeling and Learning

There have been numerous definitions of context, one often used in mobile computing and sensing, by *Dey, et al.,[7]:

“Any information (either implicit or explicit) that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves.”

“A system is *context-aware* if it uses context to provide relevant information and/or services to the user, where relevancy depends on the users task”.

*Prior to information fusion applications, contextual information was introduced in computer science theory and applications, e.g., focusing in mobile/handheld and ubiquitous computing domains.

Challenges in Context Definitions, Modeling and Learning

For IF applications S. Phoba, et al.[3] in 2014 investigated the notion of context in the DDDAS framework in order to model and learn it, viz.,

- The context is required to be machine-understandable in order to allow machines to autonomously extract it from sensor data and then use it to improve decisions and to adjust the sensing mechanisms.

- Use contextual complementarity of heterogeneous sensors and machine perception to derive actionable intelligence from multiple sources, viz., “cross-sensory fusion”.

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Challenges in Context Definitions, Modeling and Learning

For IF applications S. Phoba, et al.[3] in 2014 investigated the notion of context in the DDDAS framework in order to model and learn it, viz.,

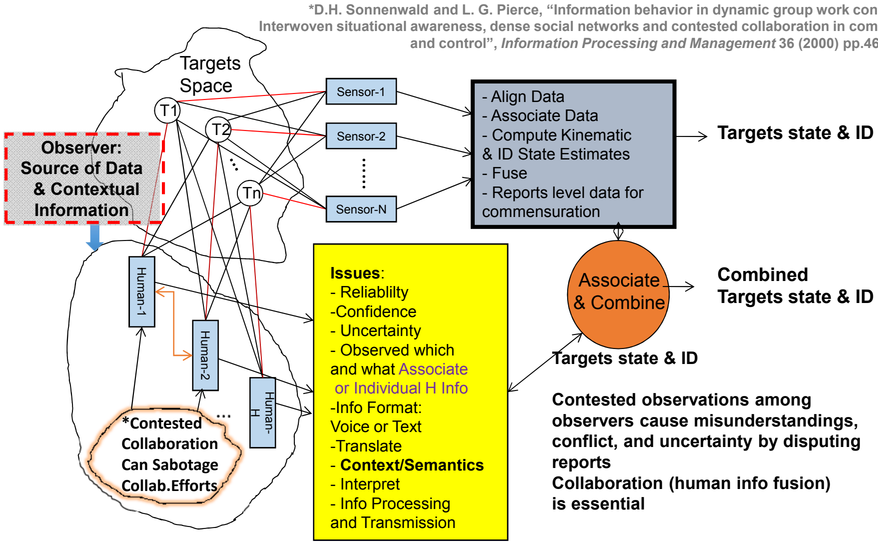
- Identified two different types of contexts based on their influence on the sensor data, and developing mathematical definitions and modeling of context via set and graph theory.

"**Intrinsic Context**: Factors that directly influence the sensor measurements for a particular event are called the intrinsic context" (e.g., environment changes that affect sensor response).

"**Extrinsic Context**: Factors that do not affect the sensor measurements for any particular event, but influence the interpretation of sensor data are called the extrinsic context.", (e.g., operator doesn't trust sensor).

Example: Data Collection for Physics and Human Derived Data & Context Fusion "Challenges"

*D.H. Sonnenwald and L. G. Pierce, "Information behavior in dynamic group work contexts: Interwoven situational awareness, dense social networks and contested collaboration in command and control", *Information Processing and Management* 36 (2000) pp.461-479



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Concept Drift Evolution

Machine learning uses supervised learning, which can be defined as follows:

The aim is to *predict* a target variable $y \in \Re^1$, given a set of *input features* $X \in \Re^p$ [Gama]. For example X is a set of sensor readings from a system at 2pm on April first 2014, and "y is good", i.e., exactly meets all specifications at that time.

In the *training samples,* that are used for model building, both X and y are known. In the new examples, on which a *predictive model* is applied, X is known, but y is not known at the time of the prediction.

J. Gama et al., "A Survey of Concept Drift Adaptation", *ACM Computer Surveys*, Vol.1, Jan 2013.

Concept Drift Evolution

Machine learning uses supervised learning, which can be defined as follows:

Per Bayesian Decision Theory [Duda], a classification can be be described by prior probabilities of the classes p(y) and the class conditional probability density functions of p(X/y) for all classes y=1, …,c, where c is the number of classes. The classification decision is made according to the posterior probabilities of the classes, which for class y can be represented as:

$$p(y/X) = \frac{p(y)p(X/y)}{p(X)} \quad (1)$$

where $p(X) = \sum_{y=1}^{c} p(y)p(X/y)$. Here equal costs of misclassifications are assumed.

R. Duda et al., *Pattern Classification*, J. Wiley and Sons, 2000.
J. Gama et al., "A Survey of Concept Drift Adaptation", *ACM Computer Surveys*, Vol.1, Jan 2013.

Concept Drift Evolution

Given a non-stationary environment, the underlying distribution of the data stream can change unexpectedly (in real world situation could be predicted in association with the occurrence of an expected event)

Formally Concept Drift between time point t_o and time point t_1 can be defined as [Gama]:

$$\exists X : p_{t_o}(X, y) \neq p_{t_1}(X, y) \quad (2)$$

where, p_{t_o} denotes the joint distribution at time t_o between the set of input variables X and the target variable y. Changes in data are represented by changes in Eq.(2) [Gama]. That is:

- the prior probabilities of the classes p(y) may change
- the class conditional probabilities p(X/y) may change, and
- as a result the posterior probabilities of classes p(y/X) may change affecting prediction.

J. Gama et al., "A Survey of Concept Drift Adaptation", *ACM Computer Surveys*, Vol.1, Jan 2013.

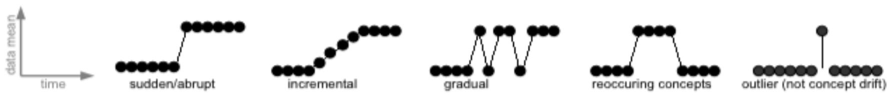
Concept Drift Evolution

The overall effect induces **learning problems** associated with the changed distributions because the learned reference is no longer a match. Therefore, novel algorithms are needed to **learn** and **adapt** to the changes in the process, and to **detect** the occurrence of a CD. Approaches are dependent on drift type [Gama, Zliobaite].

J. Gama etal., "A Survey of Concept Drift Adaptation", *ACM Computer Surveys*, Vol.1, Jan 2013.
I. Zliobaite, "Learning under concept drift: an overview", 2010, CoRR abs/1010.4784

Concept Drift Evolution

Predictive Processing/Analytics models, given enormous data streams can only be trained and process data in an online mode. In this case most models are usually trained/learn incrementally or by retraining using recent batches of data.



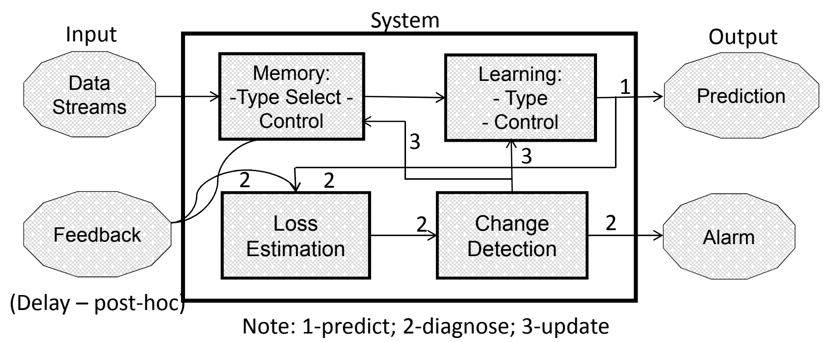
The plots above show a "toy" 1D data [Gama] with expected pattern changes in the mean value over time. A drift can happen suddenly {e.g.,(1) sensor failure p(X/y) changes, (2) analyst viewing e-mail news-feeds or Twitter feeds changes context and changes to new concept, p(y), y=1, ….c, changes}. There are many types of drifts. Only changes in p(y/X) that effect the prediction decision require adaptation.

J. Gama etal., "A Survey of Concept Drift Adaptation", *ACM Computer Surveys*, Vol.1, Jan 2013.
I. Zliobaite, "Learning under concept drift: an overview", 2010, CoRR abs/1010.4784

Concept Drift Evolution

Drifts needs to be **detected** as they provide significant information by: e.g., change detect and use (scene, roads; viz., contexts), spam, malware, anomaly, novelty, sentiments/emotion/context intent in Twitter feeds, unanticipated events, changes.

*Generic Schema for an Online Adaptive Learning Algorithm[1]

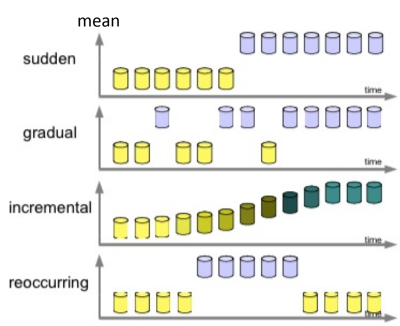


*Adapted & Modified from: J. Gama etal, “Survey on Concept Drift Adaptation”, *ACM Computing Surveys*, Vol.1, No. 1, January 2013.

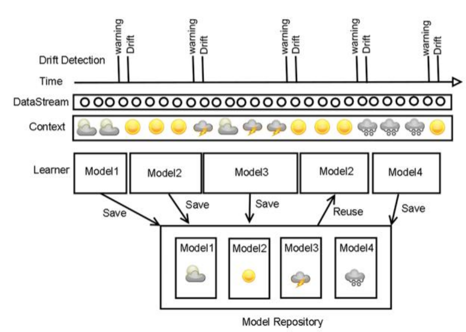
[1]The generic Schema has also been applied to: e.g., (all context functional) management and strategic planning, DARPA Grand Challenge; Smart Grid; Sentiment Classification; and generalized to “Complex Adaptive Networks and Systems”, e.g., with applications to studies in *Complex Adaptive Systems for Defense in Australia.*

Note: Also analogous to the Perceptual Reasoning Model (PRM) paradigm.

Data Pattern Changes and Data Stream Learning System (recurring concepts)



I. Zliobaite, “Learning under concept drift: an overview”, 2010, CoRR abs/1010.4784



J. B. Gomes,et al., “Tracking recurrent concepts using context”, *Intelligent Data Analysis, IOS* Press (2012), pp.1-23.

Note: Assumes that contexts are associated with recurring concepts. Stored learned models for re-use. Warns for drift detection.

Summary of Applications of Concept Drift

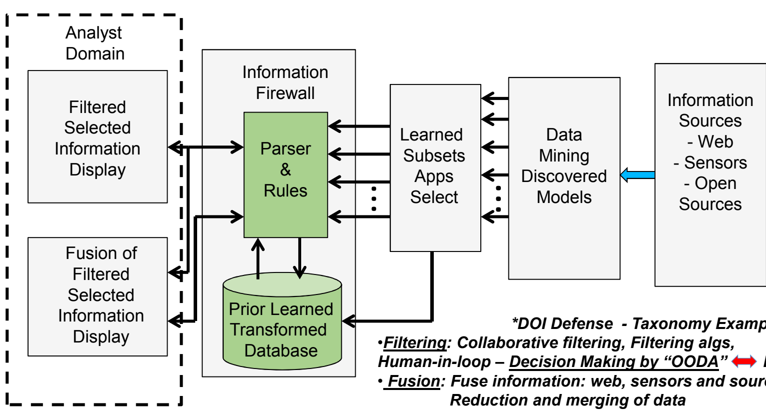
CATEGORIES			APPLICATIONS	REFERENCES	
Monitoring and control	against adversaries	computer security	intrusion detection	[91, 104, 77]	
		telecommunications	intrusion detection, fraud	[106, 66]	
		finance	fraud, insider trading	[20, 40]	
	for management	transportation	traffic management	[32, 109]	
		positioning	place, activity recognition	[164, 102, 100]	**
		industrial mon.	boiler control, telecom mon.	[6, 120]	***
Assistance and information	personal assistance	textual information	news, document classification	[156, 15, 99, 82, 111]	
			spam categorization	[36, 46]	Spam Detect
		web	web personalization	[158, 135, 33, 23]	
			libraries, media	[64, 48]	
	customer profiling	marketing	customer segmentation	[32, 16, 93, 134]	
		recommender systems	movie recommendations	[84, 8, 39]	
	information	document organization	articles, mail	[18, 149, 161, 78]	
		economics	macroeconomics, forecasting	[58, 80, 62]	
		project management	software project mgmt.	[43]	RM
Decision making	finance	creditworthiness	bankruptcy prediction	[144, 67, 165]	
	biomedicine	drug research	antibiotic res., drug disc.	[148, 49, 69]	
		clinical research	disease monitoring	[89, 54, 17]	
	security	authentication	biometrics	[159, 122]	
AI and robotics		mobile systems	robots, vehicles	[146, 124, 94]	
		intelligent systems	'smart' home, appliances	[126, 34]	
		virtual reality	computer games, flight sim.	[28, 63]	

*I. Zliobaite, "Learning under Concept Drift: an Overview" 2010, CoRR abs/1010.4784

Traffic management: drift detection to detect dynamic traffic states, patterns & context dependent changes

*** Positioning: 1- Remote Sensing in fixed geographic locations; 2- Interactive Road Tracking in Imagery (e.g.,WAMI) assist cartographer with contextual info annotating road segments & change detection (context ID & change); 3-place recognition; 4- activity recognition. For example, dynamics of the surroundings (context) causes drift in the learned models of transportation routes.

Example: A Cyber Info Processing System Concept for DOI Defense and Data Analysis



*DOI Defense - Taxonomy Example

•*Filtering*: *Collaborative filtering, Filtering algs,*
Human-in-loop – Decision Making by "OODA" ⟺ *DFIG Model*

• *Fusion*: *Fuse information: web, sensors and sources*
Reduction and merging of data
Enhanced analyst's decision making ability

•*Transform Data:* *Converting data into preferred forms*

*G. Conti and M. Ahamad; "A Taxonomy and Framework for Countering Denial of Information Attacks" *IEEE Security and Privacy*. November/December 2005.

G. Conti, M. Ahamad and R. Norback; "Filtering, Fusion and Dynamic Information Presentation: Towards a General Information Firewall; "*IEEE International Conference on Intelligence and Security Informatics (IEEE-ISI)*; May 2005. Talk PPT Slides(2.0M))

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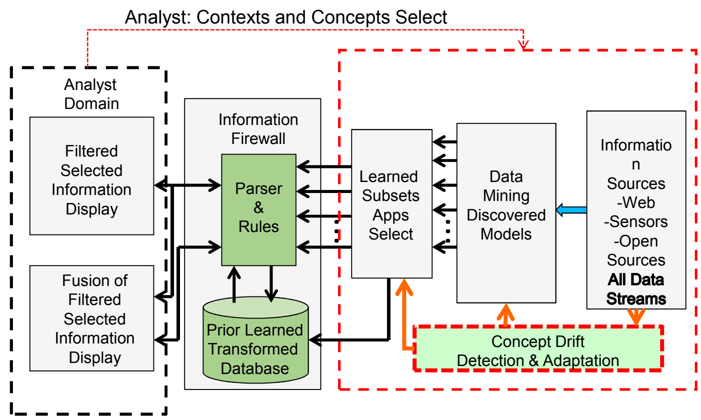
Example: A Cyber Info Processing System Concept for DOI Defense - Intent Detect, Domain Select

Issues and Challenges



Adapted from and Modified from: I .Kadar, "Perspectives on and Applications of Information Fusion in Contested Environments", Invited Panel Discussion, *Signal Processing, Sensor Fusion and Target Recognition XXIII,* edited by Ivan Kadar, Proc. SPIE Vol. 9091 Baltimore MD., May 2014.

Example: Cognitive Models of Intent

Issues and Challenges

The capability to "sense/observe, mine/*access*" data, learn, *associate*, recall, anticipate and predict/act" are key ingredients of ***human perceptual reasoning*****.** These attributes are necessary constructs in ***cognitive modeling.***

Example: Cognitive Models of Intent

The key ingredient is timely information access in modeling intent.**

Cognitive models
Predictive Models
Objectives of models

Imbedded in large family of methods called **Predictive Analytics/Modeling** (techniques to predict future entities) including: sensing/collecting, data mining, sorting, organizing, aligning, associating, fusing, and using a-priori and learned, SME based and current data

Example: Cognitive Models of Intent

The key ingredient is timely information access in modeling intent.**

Cognitive models
Predictive models
Objectives of models

Use algorithms, such as: machine adaptive learning, SVMs, regression, neural and abductive networks, classifiers, feature selection, distance measures, Bayes-nets/ influence diagrams, logic, decision making under uncertainty,…, *have been used in intent modeling, but did not use a cognition framework, which uses above methods/algorithms,* the ***cognitive PRM paradigm***:

The ***Perceptual Reasoning Machine (PRM)*** [1-3]: a "meta-level information management system", for adaptive information gathering/assessment, learning, anticipation, and prediction – ***emulating/modeling the analyst***

[1] I. Kadar, "Perceptual Reasoning In Adaptive Fusion Processing", *Signal Processing, Sensor Fusion and Target Recognition XI,* Ivan Kadar Editor, Proc. SPIE 4729, Orlando, FL., April 2002.
[2] E. 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 Advances in Information Fusion* '06
[3] I .Kadar, "Perspectives on and Applications of Information Fusion in Contested Environments", Invited Panel Discussion, *Signal Processing, Sensor Fusion and Target Recognition XXIII,* Ivan Kadar Editor, Proc. SPIE Vol. 9091, Baltimore MD., May 2014.

Example: Cognitive Models of Intent

The key ingredient is timely information access in modeling intent.**

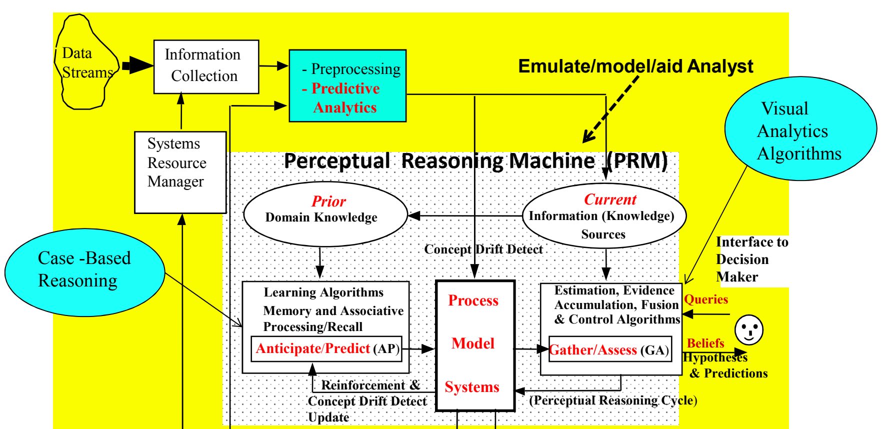
Cognitive models

Predictive models

Objectives of models

Minimize uncertainty and maximize the value of deduced information to *detect/identify potential intent*, and to act in a real-time environment with time constraints – (by modeling/aiding analyst by PRM)

Information "Process Model System" (PMS) / PRM Adaptive Information Gathering, Assessment, Prediction and Control



Issues addressed

- Use of *Knowledge* – Priori, Learned and Current
- Use of *Process* – gather facts - anticipate/predict
- User queries and Fusion System presents Beliefs
  - Provides feedback to gather information to satisfy MOMs

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Cognitive Models of Intent – Issues and Challenges in Social Networking Over Enormous Data

Social Networks data intent modeling in PMS/PRM framework

Social Networks (SNs) **provide access to real-time information exchange** [derived* **context (e.g., sentiments, emotions…**), extracted from cultural/social interactions - messages with location and time stamped data] to be used as input to the model

* Note: The preprocessing of linguistic messages to learn, classify and group various context is assumed a given herein.

Cognitive Models of Intent – Issues and Challenges in Social Networking Over Enormous Data

Potential Issues and Challenges

1. Is the extracted "big data" based on consensus of the population or only from "outliers"? ("outliers" can exert ***influence,* coalesce and become significant intent indicators). Furthermore, how to handle potential data sparsity (per individual) vs. enormity (web) of data; and *contextual validity* into emotional aspects?
2. Is information exchange restricted globally by particular entities? (potential direct intent indicators)
3. How to "*associate"* massive information from multiple SNs as input to PMS/PRM ?

**W. Pan, W. Dong, M. Cebrian, T. Kim, J. H. Fowler and A. (Sandy) Pentland, "Modeling Dynamical Influence in Human Interaction", *IEEE Signal Processing Magazine,* March 2012

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Cognitive Models of Intent – Issues and Challenges in Social Networking Over Enormous Data

Information access is crucial as an input both for real-time assessment, prediction and to data bases (learning) & for *message "change detection"* impending intent?

Example: Ben Zimmer, "Twitterology: A New Science?", *The New York Times,* October 30, 2011. The article illustrated the degree of relevant real-time information that can be derived from social/cultural interactions expressed in Twitter: (e.g., monitoring tweets to track on-the-ground *sentiment* over the course of the Arab Spring in Egypt & Libya to detect changes in *sentiments-contexts*)

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For example: Machine Learning* & linguistically extracted Twitter *context* information from messages can be used as **input to intent modeling:** sentiments, emotions - moods, opinions* etc. extracted context data (including *locations, time, consensus types, groups and number of constituting elements or computed probabilities)* used as input with other data sources to detect/ID *potential intent* via the cognitive PRM model –emulates/models interface to and role of Analyst

Use Concept Drift "Change" Detection to aide identification of impending context change inferring intent.

*A.Pak, and P. Paroubek, "Twitter as a Corpus for Sentiment Analysis and Opinion Mining", *Proceedings of the Seventh Conference on International Language Resources and Evaluation (LREC 2010)*, Valletta, Malta.

Summary

There are many issues and challenges that remain requiring research, implementation and testing to validate the proposed methods.
Any Questions in Addressed?

- Problem Settings and Challenges
- Challenges in Context Definitions, Modeling and Learning
- Challenges in Physics & Human Derived Data/Contextual Information Fusion
- Integrated Data Mining and Fusion System Example
- Big Data Analytics
- Concept Drift Evolution
- A Generic Schema for an Online Adaptive Learning System
- Data Pattern Changes and Data Stream Learning System/Recurrent concepts
- Summary of Applications of Concept Drift
- A Cyber Information Processing System DOI Defense -Analyst Selects *Contexts and Concepts*
- Cognitive Models of Intent – Perception, and a Perceptual System
- The Process Model System (PMS) and Perceptual Reasoning Machine (PRM) paradigm - emulate/model/aid Analyst
- Cognitive Models of Intent in Social Networks over enormous data

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Perspectives on the Applications of Context to Enhance Information Fusion

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1. INTRODUCTION

This succinct position paper, coupled with the associated viewgraphs, is to provide: (1) a short historical background, and recent research efforts and challenges in context definitions, modeling, extraction and use; and (2) most importantly, introduce the fusion community to unexplored research areas and challenges by Big Data Predictive Analytics machine adaptive learning processing methods to predict context, and concept dependent performance information, and detect/identify contextual and concept changes, "concept drifts" (CDs) [1] in enormous volume and speed online data streams information exchange in cyber and fusion systems. The balance of the paper illustrates the evolution of CD, adaptive machine learning, application of context, and concept/context change in hard/soft fusion, cyber and social networking applications along showing analogy between generalized adaptive machine learning, and the PMS/PRM process model system/perceptual reasoning machine scheme [2].

2. PROBLEM SETTING AND CHALLENGES

2.1 Succinct Background and Review

Over the past few years, the definition, identification, selection, management, adaptation and use of contextual information has been addressed at several fusion levels and systems applications by researchers in the USA, in Italy and Spain, and elsewhere as depicted in the slides along with applications. For example, X. Shi et al. [3] depict vehicle detection from wide area motion imagery (WAMI) by extracting contextual information about roads from vehicle trajectories and fed back this information to reduce false alarms. A machine learning approach to an analogous problem will be discussed in subsequent paragraphs as an application of the machine learning.

2.2 Challenges and New Perspectives by Predictive Analytics Processing

In Information Fusion (IF) applications high volume and speed data flows in, e.g., collaborating platforms, sensor networks and communications, cyber or program news feeds/communications via e-mail; needs to be explored, which is in the form of online data streams: "*Enormous"/"Big Data"* processed in real-time.
Due to *dynamically changing and non-stationary environments*, the pattern and probability distributions of data streams can change over time yielding the phenomenon of Concept Drift (CD): a term introduced in 1986 Schlimmer et al., [4] in the machine learning/predictive analytics area. At Fusion 2014 was the first time the topic of CD detection was addressed and used for spam filtering using a novel machine-learning algorithm by Abad et al. [5]. Yet Concept Drift detection has broad applications in Predictive Analytics/Information Fusion area (context ID, use and change).

2.3 Challenges in Context Definitions, Modeling and Learning

The reader is referred for details to subject slides providing numerous definitions of context. For example, Dey, et al., [6] in mobile computing environment characterized "entity" contexts and "context-awareness" referring to surroundings, and use of available context to provide relevant information respectively. For IF applications Phoba, etal. [7] investigated the notion of context in the DDDAS framework [8], viz., (1) context is "*required"* to be machine-understandable in order to allow machines to autonomously extract it from sensor data, implying the use of physical context, such as sensor models and, (2) use fusion of contextual complementarity of heterogeneous sensors from multiple sources, viz., "cross-sensory fusion", and avoid fusing inaccurate independent declaration level data. Phoba et al. [7] also identified two different types of contexts based on their influence on the sensor data, *"Intrinsic Context"* e.g., environment changes that effect sensor response, and "*Extrinsic Context*" e.g., operator doesn't trust sensor, a common occurrence.

2.4 Example of Context Rich Human Data Collection for Physics and Human Derived Information Fusion

The corresponding slide depicts issues and advantages of human derived information, and human information behavior in common/shared situations related to hard and soft information fusion [9]. The issue of "contested collaboration" arises when team members maintain an outward stance of cooperation but work to further their own interests, at times sabotaging the collective effort [for reference see corresponding slide]. However, at the same time provide *context rich information* otherwise not available directly from sensor data.

3. CONCEPT DRIFT EVOLUTION

3.1 Machine learning

Machine learning uses supervised learning, which is stated with parameters defined, and exemplified in the slides.

As well known by Bayesian decision theory [10] classification can be described by prior probabilities of the classes p(y) and the class conditional probability density functions of p(X/y) for all classes y=1, …,c, where c is the number of classes. The classification decision is made according to the posterior probabilities of the classes, which for class y can be computed from Bayes' formula $p(y/X) = \frac{p(y)p(X/y)}{p(X)}$, where p(X)= $\sum_{y=1}^{c} p(y)p(X/y)$ equal costs of misclassifications are assumed**.**

Given a non-stationary environment, the underlying distribution of the data stream can change unexpectedly (in real world situation could be predicted in association with the occurrence of an expected event).

As defined in the slides, formally *concept drift occurs* when the *joint distribution p(X, y) between two time points are not equal,* where X is a set of input variables and y is the target variable [1, 10]. This can occur when:

- Prior probabilities of the classes p(y) may change
- Class conditional probabilities p(X/y) may change, and

as a result the posterior probabilities of classes p(y/X) may change affecting prediction.

3.2 Learning Problems, Concept Drift Detection and System Adaptation

While monitoring a data stream, several CDs are of interest when p(y/X), the posterior distribution changes: when the user's or analyst's interests (concepts) changes (that is not interesting information or document is displayed (i.e., content changed about the same subject) while viewing it on a display, changes the conditional distribution p(X/y) from interesting concept to not interesting concept, and CD occurs. Changes can also be caused when: a sensor wears off and becomes less accurate, and replaced with one with a different calibration (i.e., incremental or sudden CD).

The overall effect induces **learning problems** [11] associated with the changed distributions because the learned reference is no longer a match. Predictive Processing/Analytics models [1], given enormous data streams can only be trained and process data in an online mode. There are several methods available, whose selection depends on the drift type. Frequently used are: incremental learning/adaptation, and retraining using recent batches of data that discards the current model and builds a new model from scratch using recent buffered data [1]. Therefore, novel algorithms are needed to **learn** and **adapt** to the changes in the process, and to **detect** the occurrence of a CD. Slides show examples of drifts type plots with expected pattern changes in the mean value over time. A drift can happen suddenly {e.g., (1) sensor failure p(X/y) changes, (2) analyst viewing e-mail news-feeds or Twitter feeds changes context and changes to new concept, p(y), y=1, ….c, changes}. There are many types of drifts. Only changes in p(y/X) that effect the prediction decision require adaptation.

Related to learning issues the drifts have to be detected as they provide significant system related information by: e.g., change detection/use (scene, roads; viz., contexts), spam, malware, anomaly, novelty, sentiments/emotion/context intent in Twitter feeds, unanticipated events, changes and many other applications illustrated in subsequent sections.

There are three basic methods to detect the occurrence of CD: (1) monitor incoming raw data stream, (2) monitor learner system parameters, (3) monitor output learning error rates by setting thresholds [11]. For (1) there have been several algorithms explored with various efficacies, viz., detecting shift of location (Mann-Whitney-Wilcoxon test), Wald's SPRT, Hotteling-T^2 (amplitude change), Change in Entropy between different time samples/batches of the data stream, Kullback-Leibler (distributions change), Moving Averages and Time Windows [1,11].

The slide entitled "Generic Schema for an Online Adaptive Learning Algorithm" depicts in the block diagram four elements of the adaptive learning system: (1) "Memory Type Select and Control", designates how and which data should be sent to what component of learning algorithm (2) "Learning: Type and Control"; (3) "Loss Estimation" algorithm tracks performance of Learning algorithm and sends information to (4) "Change Detection" to update if necessary, and can indicate alarm of occurrence of possible CD; the true value of the "target" variable (we are trying to predict) feedback path shown may come with a delay or may not available, because Prediction (output) may arrive before one gets feedback for data has been processed. So model update would be delayed [1].

Note that concept drift has been recognized and addressed in broad applications areas, such as medicine, business, information fusion, spam detection, WAMI applications, education, strategic planning, complex adaptive systems for defense in Australia [12], industrial, resource management, monitoring/control, personal assistance, ubiquitous computing [1,11] and all these applications require a type of generic learning schema. As a matter of fact the schema is analogous to the PMS/PRM process model system/perceptual reasoning machine scheme [2], as shown in subsequent paragraphs.

Another illustration of "Data Pattern Changes" (due to CDs), and an example of a "Data Stream Learning System for Recurring Drifts" are shown in a slide with subject title. The key ingredient of the learning system shown is that the learning algorithm utilizes association between contexts and concepts (interests). It assumes based on common knowledge or experimental observations, in reference to human behavior as example, that peoples' interests are different in various contexts and within each context the interests (concepts) recur.
For example, one has different interests at work, at home, at a sport event, on vacation, in a theater, etc., which are also a function of or depend on and subject to weather, seasons, etc.; that is, interests (concepts) can be locations-environments-time-seasons (context) dependent and recur. Furthermore, ones interests (concepts) are usually the same in each context setting given either periodic contexts or even in not periodic contexts (e.g., fashion changes, economic trends, unanticipated events) [13].

Based on the above assumption, association metrics between contexts and concepts are developed. Given the associations, the algorithm re-uses learned information for a given context that was stored from previous data stream incremental learning. A base-learner learns underlying concept and becomes the class model. A meta-level algorithm is used to warn anticipated occurrence of CD based on monitoring learning error rate threshold, and to subsequently declare detection of CD as shown in the figure. That is, concept-context relationship learned is re-used. Therefore, there is no need to relearn observed concepts. Of course the system requires storing models in its depository, and it can become memory limited. It can be used to advantage if recurrent concepts can be anticipated, such is the case for spam detection [5]. The algorithm utilizes the well know Naïve Bayes Learning scheme [10], which maximizes the a-posteriori distribution. Naïve Bayes assumes independence between classes, which, is often violated in practice, and yet does not appear to effect the performance of the algorithm [10].

Note that while "contexts and concepts (interests)" and related CDs were exemplified by using analogies in human domain, the same methods are easily generalized and applied to practical real-world systems by simple mappings to physical systems and parameters. A good example is "spam" detection, since it is known that spam is a recurrent process [13]. The table "summary of applications of CDs" shown in subject slide, illustrates a large set of applications using CD detection, addressing many information fusion related problems. Examples include GMTI tracking, traffic management: drift detection to detect dynamic traffic states, patterns and context dependent changes. Positioning problems: 1- remote sensing in fixed geographic locations; 2- interactive road tracking in Imagery (e.g., WAMI) assist cartographer with contextual information annotating road segments and change detection (context ID & change), 3-place recognition; 4-activity recognition. For example, dynamics of the surroundings (context) causes drift in the learned models of transportation routes. The subject method could be directly applied to the problem noted in previous paragraphs by X. Shi et al. [3].

3.3 Examples of CD Applications

3.3.1 Cyber related applications of CD are illustrated in**:** Cyber Information Processing System for DOI Defense-"Data Analysis" [9] and "Intent Detect, Domain Select" slides specifically addressing needs of intelligence analysts via filtering and information fusion, while highlighting the applications and role of context and concept control via the use of CD by analyst to enhance the performance of the overall system and to serve as an aid the analyst.

3.3.2 Cognitive Models of Intent/Context Issues and Challenges
Associated slides detail the analogous relationships between human perceptual reasoning, viz., the capability to "sense/observe, mine/*access* data, learn, *associate*, recall, anticipate and predict/act", cognitive modeling of context to assess intent, and algorithms used in Predictive Analytics/Machine learning. The predictive analytics associated algorithms are shown to be components of the *cognitive PRM paradigm*: the *Perceptual Reasoning Machine (PRM)* [2]:
a "meta-level information management system", for adaptive information gathering/assessment, learning, anticipation, and prediction – *emulating/modeling the analyst***,** with objectives to minimize uncertainty and maximize the value of context deduced information to *detect/identify potential intent,* and to act in a real-time environment with time constraints – (by modeling/aiding analyst by PRM). The slide "Information Process Model System (PMS)/PRM Adaptive Information Gathering, Assessment, Prediction and Control" depicts the interaction between PMS, the information "Process Model System" to PRM, and to Big Data Predictive Processing. Process modeling is defined as a set of procedures and algorithms that capture the functional and required (temporal and spatial) dependency relationships of tasks (e. g., needed for context/intent assessment) and/or processes, which are being modeled.
The associated slides, Cognitive Models of Intent "Issues and Challenges in Social Networking Over Enormous Data", depict social networks as basis for information exchange, identify potential issues and challenges in a social-cultural setting, allowing exchange/expression of information and enabling extraction of context, such as: ideas, concerns, sentiments, emotions, and opinions. Furthermore, address the role of PMS/PRM by the use of extracted context information, and use of CD to assess the potential of impending intent collected in real-time via the Web or from other sources.

SUMMARY

The background, application, definition, modeling, extraction and use of contextual information was described addressing issues and challenges. New perspectives were introduced to the fusion community by highlighting unexplored research areas and challenges by the use of Big Data Predictive Analytics machine adaptive learning processing methods to predict context and concept dependent performance information, and detect/identify contextual and concept changes, "concept drifts" (CDs) [1,11] in enormous volume and speed online data streams information exchange in cyber and fusion systems. The evolution of CD, adaptive machine learning, application of context, and concept/context change in hard/soft fusion, cyber and social networking applications along with showing analogy between generalized adaptive machine learning, and the PMS/PRM process model system/perceptual reasoning machine scheme were illustrated.

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Defining and Using Context

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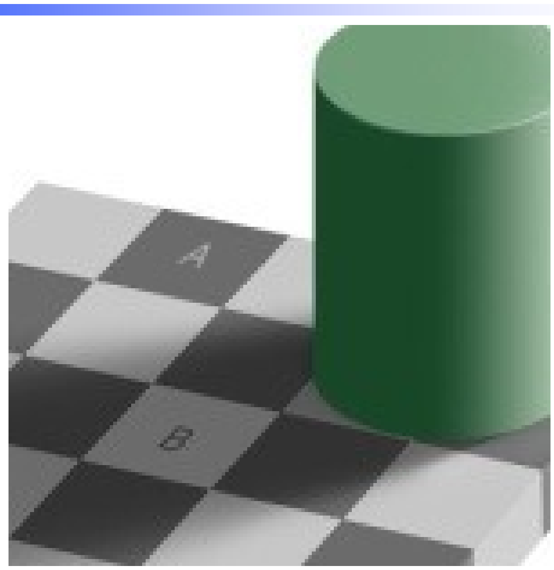
SPIE Conference 9474

"Signal Processing, Sensor/Information Fusion and Target Recognition Conference XIV"

20-22 April 2015
Baltimore, MD

Use of Context in Human Perception



Adapted from *Scientific American MIND*, 25 November 2013, p.6

[2]

Context-related Challenges in Information Exploitation

- **How to define and represent context?**
- **How to determine contexts that are relevant for particular applications?**
- **How to use contextual information in inferencing?**

These are issues in

> Data Fusion
> Natural Language Understanding
> Human Cognition
> Artificial Intelligence

[3]

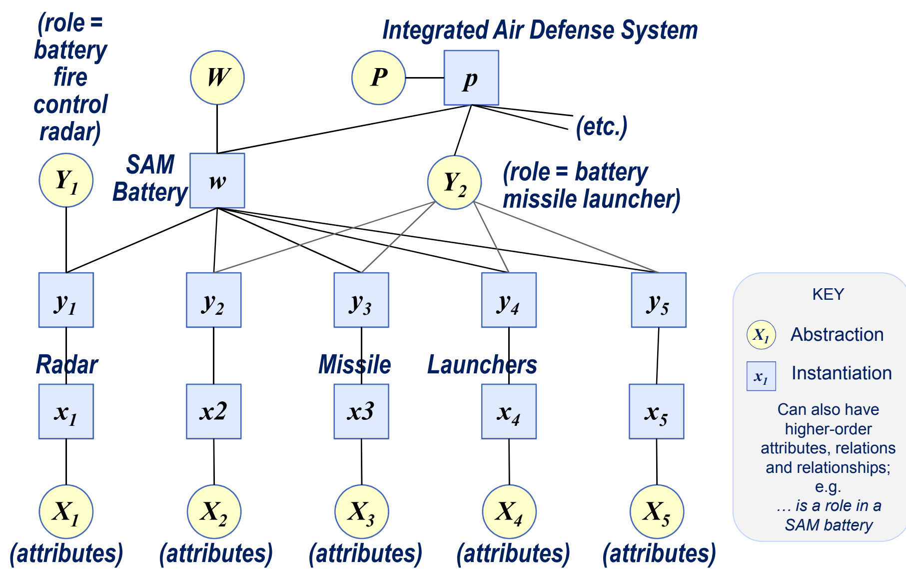
Informal Definitions

- **Contexts are relevant situations**
- **Situations are networks of relationships**
- **Relationships are instantiations of relations**

It is convenient to reify relations, relationships and situations (i.e. treat them as values of random variables)

[4]

Factor Graph Situation Representation



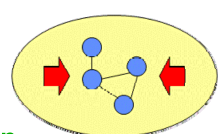
[5]

Define Context as Relevant Situation

- **To provide expectations**

  Situation → Expected entity states

  "In the context of the present economic situation, we expect an increase in property crime"

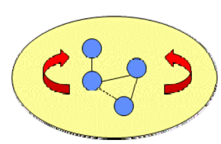


Inference

- **To resolve uncertainties**

  Problem → Relevant Situation → Problem Resolution

  "The town's economic situation provides a context for understanding this crime"



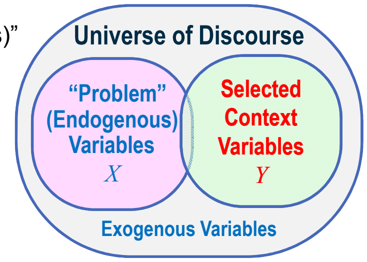
Discovery + Inference

Adapted from L. Gong, "Contextual modeling and applications," *Proc. IEEE International Conference on SMC*, V1, 2005.

[6]

Context Exploitation in Data Fusion

- **Define an inference problem in terms of**
  - An explicit set of "**problem variables**" X
    - "Endogenous variables"
    - "Essential Elements of Information (EEIs)"
  - A utility function on the resolution of these variables $\omega: \sigma_X \longrightarrow \Omega$
- **Allow the system to select additional *"context variables"* Y on the basis of**
  - **Utility:** of a given resolution of problem variables
  - **Probability:** correlation between the problem and context variable
  - **Cost:** of the applicable information acquisition/inferencing process

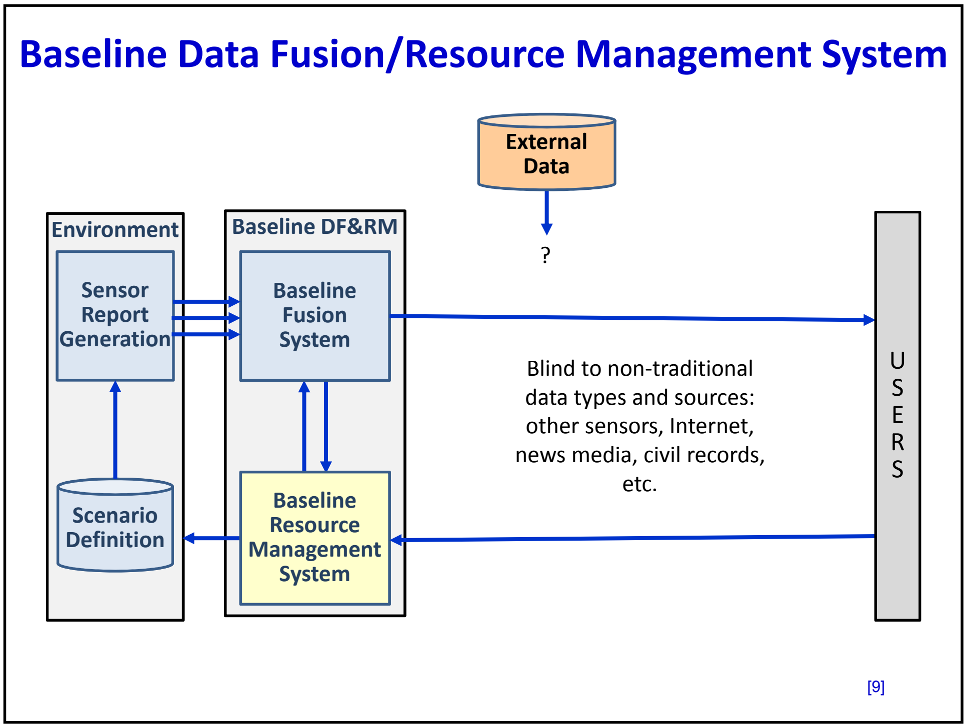


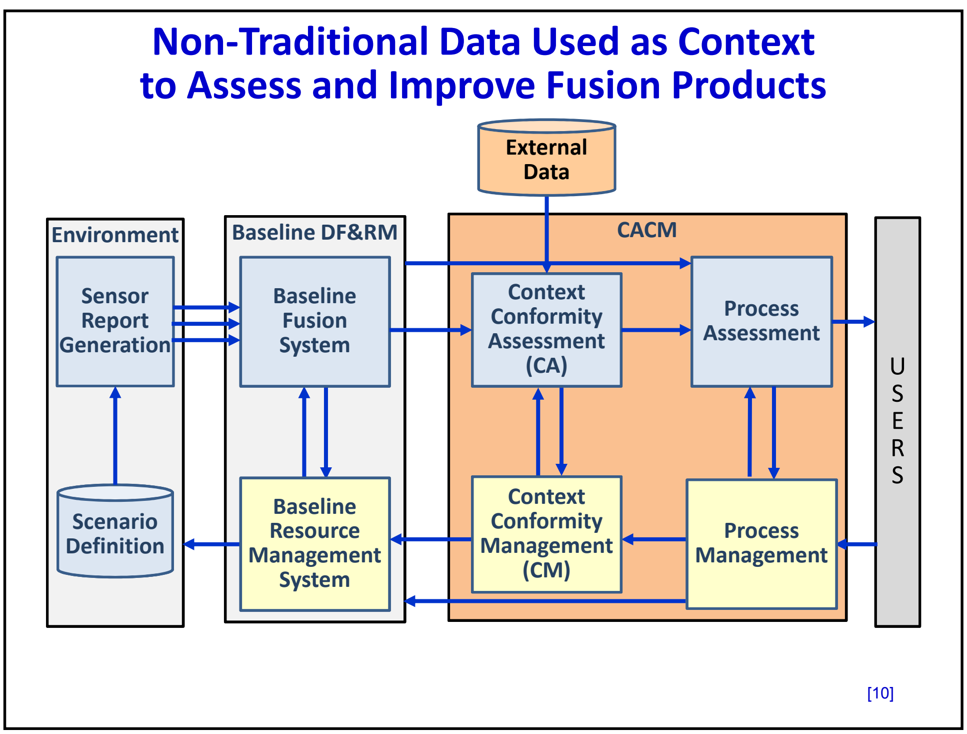
[7]

CACM: Context-Augmented Information Exploitation

- **Goal: exploit non-traditional data types and sources to boost the performance of Data Fusion/ Resource Management systems**
  - > Goal-driven context discovery and exploitation
  - > Ambiguity resolution
  - > Model refinement
- **Context Assessment**
  - > Automatically detects significant nonconformities with information found in other information systems or in large "external" databases
  - > Detects correlations in data with either known or unknown patterns
  - > Learns patterns of activity to discover new patterns of interest
- **Context Management directs adjustments:**
  - > Flagging and alerting
  - > Refined fusion
  - > Focused data collection
  - > Model refinement

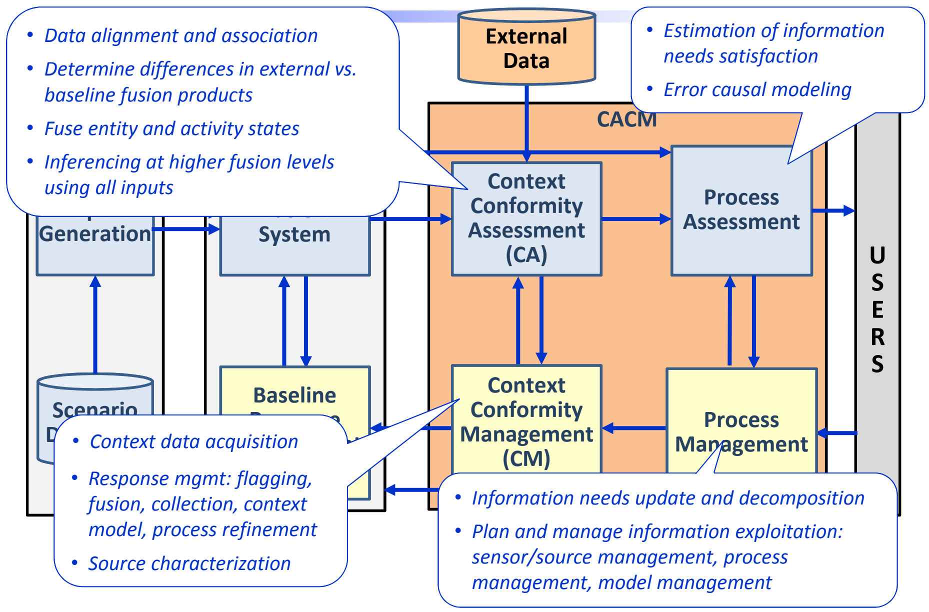
[8]


Baseline Data Fusion/Resource Management System
External Data
?
Environment
Sensor Report Generation
Scenario Definition
Baseline DF&RM
Baseline Fusion System
Baseline Resource Management System
Blind to non-traditional data types and sources: other sensors, Internet, news media, civil records, etc.
USERS
[9]


Non-Traditional Data Used as Context to Assess and Improve Fusion Products
External Data
Environment
Sensor Report Generation
Scenario Definition
Baseline DF&RM
Baseline Fusion System
Baseline Resource Management System
CACM
Context Conformity Assessment (CA)
Process Assessment
Context Conformity Management (CM)
Process Management
USERS
[10]

xli

Non-Traditional Data Used as Context to Assess and Improve Fusion Products



Why Not Just Fuse All Baseline and External Data?

- **Large investments in trusted legacy fusion systems**
  - > Not easily modified and tested to fuse new source data, especially "big data"
- **Not always advisable to redo the fusion process at run-time with added source data**
  - > Quality control of external, non-traditional data can be very difficult
  - > Often not cost-effective
  - > Often not allowed due to security, lack of domain expertise, or bandwidth
  - > May not be acceptable to baseline system users
- **CACM takes a flexible approach: graduated range of context-based responses**
  - > Alerts, flags
  - > New data acquisition
  - > Fusion of selected external and baseline data

[12]

Categories of Inference Problems

Adapted from E. Waltz, *Knowledge Management in the Intelligence Enterprise*, Artech House, 2003

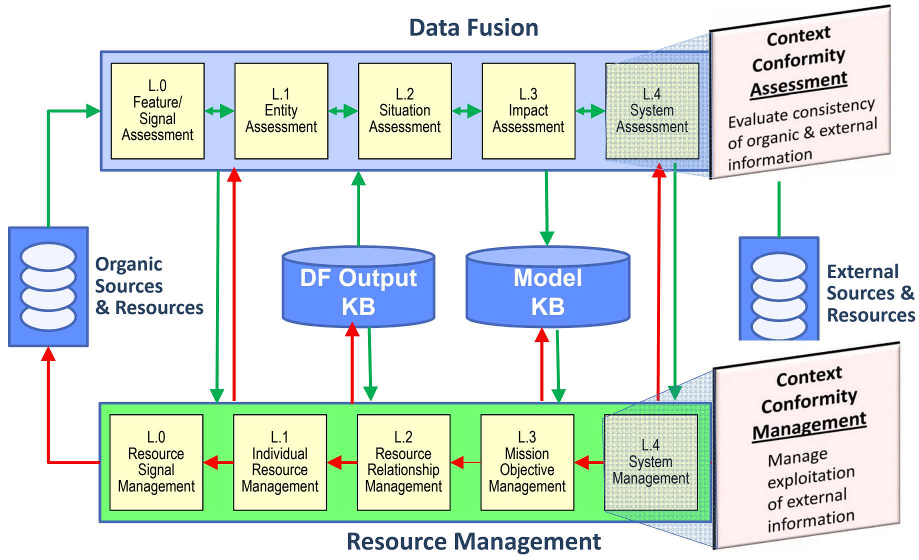
Problem Category/ Issue	Approach	Use of Context
CAT-0: Recognition	• Data-driven target model • Signature/behavior recognition	• Induced phenomenology in scene structure (shadows, wakes, contrails, plumes, etc.)
CAT-1: Detection	• Data-driven normalcy model • Anomaly detection/ diagnosis	• Use backgrounds (normalcy) are contexts for detecting
CAT-2: Discrimi-nation	• Patterns-of-life analysis • Detect/diagnose subtle underlying workflows	• Reason about the interactions of targets and contexts in postulating patterns of life
CAT-3: Discovery	• Theorize target state • Predict differential observables • Build and test theory (probe)	• Infer target state and expected signature/behavior largely from contextual constraints: capability, opportunity, intent

[13]

Back-Up

[14]

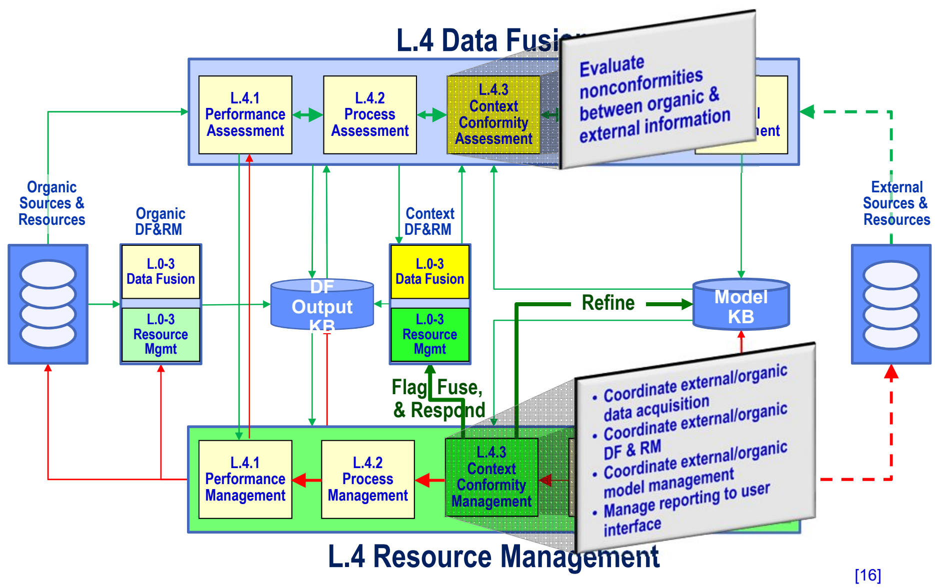
Ultimately Designing CACM Functionality into an Existing Information Exploitation System



[15]

Sample Level 4 DF&RM Node Decomposition

(showing the DF Output KB storing both organic and external fusion products)



[16]

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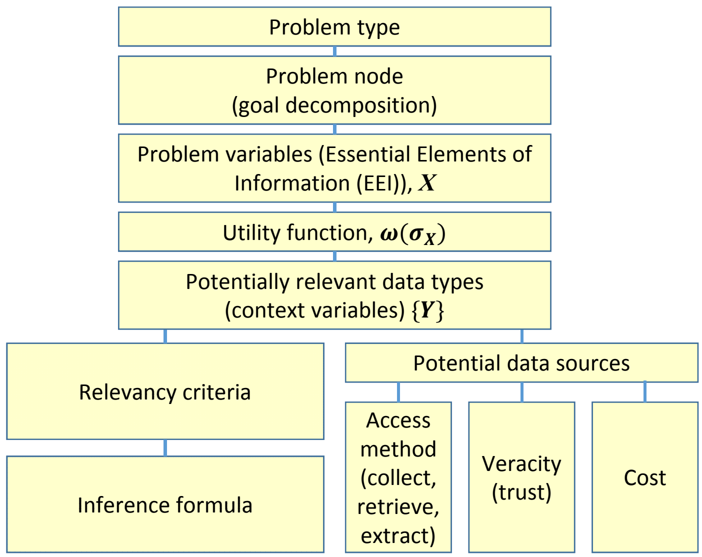
Context Management Model Structure



[17]

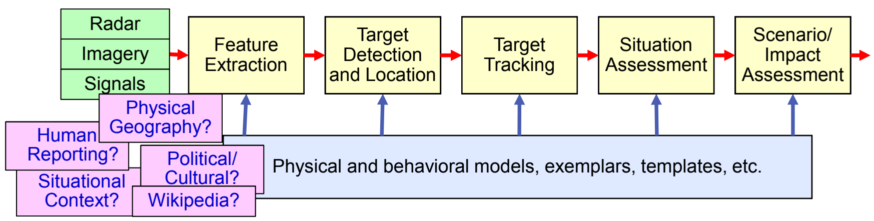
Model Assessment/Model Management

- **Classical data fusion involves estimation of *instantiated states* of L.0-4 entities: features, individuals, complexes, scenarios, system resources: *Recognition***
- **Model Assessment/Model Management: *Explanation and prediction***
  - > **Estimation of *possible states* of L.0-4 entities: conditional distributions**
    - – Characterize variability in a particular entity over time
    - – Characterize variability within a class of entities
    - – Causal and other dependencies
  - > **Involves classical data fusion functions:**
    - – **Data alignment:** for consistency in format, spatio-temporal/ measurement framework and confidence
    - – **Data association:** generating, evaluating and selecting hypotheses of model scope, i.e. of the range of phenomena to be explained by the model)
    - – **State estimation:** estimating and predicting the conditional distributions of characteristics and behavior of given (classes of) entities

[18]

“Dirty Secrets” of Current Fusion Systems

- **Data Push:** Do the best you can with whatever information is provided
  - > “We’ve started at the wrong end and continue to focus on the wrong end”
- **Model-Dependent:** Recognition/prediction process
  - > Fails with poorly modeled problems: sparse sampling, heavy-tail distributions, countermeasures/concealment/deception
- **Closed World:** Restricted ontology/model set
  - > Unable to exploit additional types of data from additional sources



[19]

Better: Adaptive Goal-Driven Information Exploitation

- **Recursively determine current information needs**
- **Compose a model that explains the data:** ***Explanation*** **rather than** ***Recognition*** **paradigm**
- **Tightly-coupled information exploitation**
  - Data Fusion
  - Resource Management
    - Data Acquisition Management: sensing, mining
    - Process Management
    - Model Management

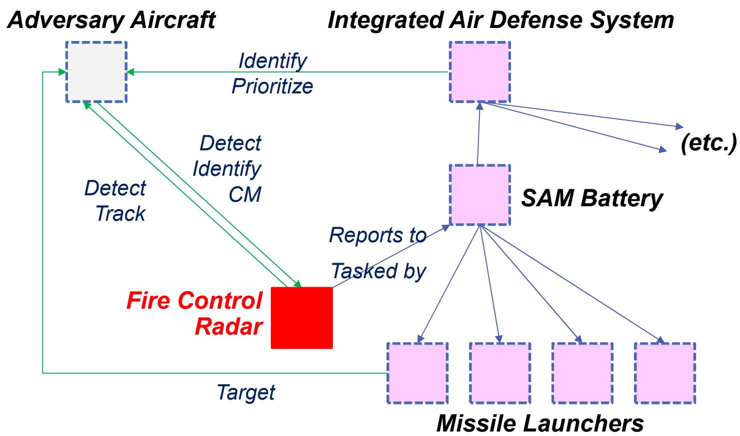
[20]

Entity State, Data Fusion and Resource Management "Levels"

Level	Entity Class	Example Continuous State Variables	Example Discrete State Variables	Data Fusion (Inference) Level	Resource Management Level
0	Patterns; e.g. features or signals	Temporal/ spatial/ spectral extent, amplitude and shape/ modulations	Signal/feature class, type, attributes	Signal/ Feature Assessment	Signal/ Feature Management
1	Individuals; e.g. physical objects or events	Location, velocity, size, weight, event time	Object class, type, identity, activity or attributes	(Individual) Entity Assessment	Individual Resource Management
2	Structures; e.g. relationships and situations	Distance, force/energy/ information transfer	Class, type, identity or attributes of relations, slots, arguments, situations	Situation Assessment	Resource Relationship Management (coordination)
3	Processes; e.g. courses of action, scenarios and outcomes	State utility, duration, transition conditions	State transitions; Class, type, identity, attributes of processes, scenarios or impacts	Scenario/ Outcome Assessment	Mission Objective Management
4	System resources	(all of the above, applied to system resources)	(all of the above, applied to system resources)	System Assessment	System Management

[21]

Situation Example



[22]

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Evidence Propagation in Situation Hypotheses

A belief propagation algorithm will determine the belief concerning the state of an entity (or, more precisely, of the vector of state variables associated with that entity) in terms of

- "local" evidence $\phi_i(x_i)$ – i.e. information about the particular entity (more accurately, about the particular the entity state variables of concern) – and
- evidence $\psi_{i,j}(x_i,x_j)$ concerning the entity from other situation elements used as context.

$$b_i(x_i) = k\phi_i(x_i) \prod_{j \in N(i)} m_{ji}(x_i);$$

Joint probability distribution of the set of state variables x_i corresponding to the set of N nodes in such a graph

$$p(\{x\}) = \frac{1}{N} \prod_{(ij)} \psi_{ij}(x_i, x_j) \prod_i \phi_i(x_i);$$

Messages are updated recursively through the graph as

$$m_{ij}(x_j) \leftarrow \sum_{x_i} \phi_i(x_i) \psi_{ij}(x_i, x_j) \prod_{k \in N(i) \backslash j} m_{ki}(x_i);$$

Data is passed from all nodes that are in the immediate neighbors of X but not from X itself. Such restriction on message passing maintains consistency and convergence in any singly-connected (i.e. non-looping) graph {Yedida et al]

[23]

Defining and Using Context

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ABSTRACT

Context-related challenges in Information Fusion – as well as in natural language understanding, human cognition and artificial intelligence – include (a) how to define and represent context; (b) how to determine contexts that are relevant for particular applications; and (c) how to make use of contextual information in inferencing. We adopt a working definition that is applicable in a wide variety of problem domains, defining a context as a *relevant situation*; i.e., a situation that provides information that can be used either a) to condition expectations or b) to improve the understanding of a given inference or planning/control problem. Notions of data association that are familiar in level 1 fusion can be extended to level 2 to determine the contextual relevance of various situations and situation elements as "contexts for" a given problem. Determining reliability, relevance, and utility of contextual information has specific implications for Information Fusion systems.

Keywords: context-sensitivity, situation assessment, higher-level fusion, factor graphs, induction, situation theory

1. RELATIONS, RELATIONSHIPS, SITUATIONS AND CONTEXTS

In [1,2] we adopted a useful working definition that is applicable in a wide variety of problem domains. We define a *context* as a *situation* that provides information that can be used either a) to condition expectations or b) to improve the understanding of a given inference or planning/control problem. These two ways in which a situation can be used as context relate to a formulation by Gong [3] as elaborated in [2,4,5], contrasting notions of "context-of" (C-O) and "context-for" (C-F):

a) C-O: We can have certain expectations based on situations; e.g. "in the *context of* the present economic situation, we should expect an increase in property crime";

b) C-F: Alternatively, we can assess reference items – whether individual entities or situations – in context: "the economic provides a *context for* understanding this crime."[1]

A situation can be a "Context-Of" or a "Context-For", depending on how it is used in reasoning. C-O-driven reasoning starts with a perceived situation to derive expectations about constituent entities, relationships and activities.

In contrast, C-F-driven reasoning starts with a particular problem – which might be an inferencing problem (what's happening?) or a control problem (what's to be done?) – and seeks to discover additional information that can resolve uncertainties in the problem solution.

Reasoning about attributes, relations, relationships and situations is facilitated if these concepts are "reified"; that is to say, attributes, relations and situations are admitted as entities in our working ontology. Attributes of entities are conveniently treated as one-place relationships.

Explicitly defined, a *relation* is a mapping from n-tuples of entities ($n \geq 1$) to a relational state r. A *relationship* r is an instantiation of a relation. Given this realist stance, we can take an expression like '$R(x_1, \dots, x_n)$' as an abbreviation for 'relation R applies to $< x_1, \dots, x_n >$'. The mapping from n+1-tuples to relationships can be many-one, because the same entities $<x_1, \dots, x_n>$ may be related multiply by the same relation.

We define a *situation* as a *network of relationships*, such as depicted in Figure 1. A *concrete situation S* is a set of a set of fully anchored relations relationships $\{\rho | \rho \text{ is true in } S\}$. Sets of relations of which some are not fully anchored are

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1 We dispense with Gong's term 'reference item' as it presupposes the existence of a referent. In many inference problems encountered in data fusion, entity existence is itself treated as a random variable, such that state estimation is of the states of *postulated* or *perceived* entities. Therefore, we interpret a "reference item" as a set of variables of concern in the given problem (endogenous or, equivalently, "problem variables"). Explicitly, a problem context (C-F) is a *relevant* situation for evaluating problem variables.

a*bstract situations*. The particular concerns of some agent determine which situations are under consideration as contexts for those concerns [6]. Like a relationship, a situation S may be real, or it might be hypothetical, fictitious or otherwise counterfactual in some encompassing situation $T \supseteq S$ (T may be the universe at large).

2. THE USE OF CONTEXT IN INFERENCE

We can define an *inference problem* such as encountered in data fusion as a utility function over a set of error terms (residuals)

$$\omega\colon \tilde{x}_1, \ldots, \tilde{x}_n \rightarrow \Omega$$

for residuals $\tilde{x}_i = |\hat{x}_i - x_i|$; $\hat{x}_i$being an estimated value of the variable whose true value is $\hat{x}_i$ (where truth can be conditional, as described above).

A *problem variable* is a variable x_i that is endogenous to a given inference problem.

A solution to an inference problem can be defined in terms of a utility threshold: an inference problem is solved by resolving (reducing the uncertainty of) associated problem variables such that $\omega(\tilde{x}_1, \ldots, \tilde{x}_n) > \theta$.

A *context for an inference problem* is a situation that is selected (by some agent) for use in solving the problem.

The relevance of contextual information can be stated in terms of the contribution of such information in resolving the values of endogenous problem variables. Relevance is not binary, nor is there generally one unique context for any given problem. Rather, some contextual information – and therefore, some contexts – can be more relevant than others.

A *context variable* is a variable *which the system or its users select to evaluate or refine an estimate of one or more problem variables*. Accordingly, we can define a *problem context* as a situation, comprising a set of entities and their relationships involving context variables and problem variables. A problem context is typically selected by a problem-solving agent (e.g. a fusion system or its user). Situations are selected as problem contexts for their presumed usefulness in solving the particular problem. Two systems or two users may select different contexts (i.e. in terms of different sets of context variables) in resolving a particular inference problem.

When a situation is used as a "Context-Of", these are simply situational variables (ranging over relationships and relational complexes); when used as a "Context-For", these are variables that are other than a given set of problem variables.

Note that, by this definition, one problem variable can serve as a context variable for resolving another problem variable. For example, an aircraft's observed speed may be used as a context for resolving its type and, conversely, its estimated type can be used for resolving its speed (e.g. in bearings-only target tracking). Context variables are ideally chosen on the basis of their utility in solving a given problem. Utility, of course, depends on the type of problem and on the agent posing the problem. In inferencing, context variables can be selected on the basis of the information their evaluation provides in resolving the given problem variables to some degree of accuracy and the net utility of that resolution, given an agent-provided (or assumed) utility function on such resolution and the cost of the planned action.

The problem of selecting context variables is complicated by the fact that any or all of these three factors can be time-variable. The agent's goal-driven information needs and inference processes are often dynamic; making the utility of information (e.g. of refining a problem variable) time-variable. Relevant situations are often dynamic, such that the availability of any sought data may also be time-variable. Also, the cost of data acquisition and processing varies with resource and situation state. Determining these relevance, likelihood, utility and cost factors is one of the challenges of contextual reasoning.

Belief networks can be used to propagate information from entities, relations and the relationships in which they participate. Given our reification of relation and relationships, we can depict a level 2 hypothesis after the pattern of Figure 1. This figure is in the form of a factor graph, in which variables are represented as circles and functions on these variables are represented as squares [7]. We model a network of relationships as a factor graph having nodes for attributes/relations and attributed/related entities. Each node in a level 2 hypothesis combines the effects of evidence

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from its immediate neighbors and distributes its own evidence to them, ensuring however that information is not circulated back to an originating node.[2]

A belief propagation algorithm will determine the belief concerning the state of an entity (or, more precisely, of the vector of state variables associated with that entity) in terms of

- "local" evidence $\phi_i(x_i)$ – i.e. information about the particular entity (more accurately, about the particular the entity state variables of concern) – and
- evidence $\psi_{i,j}(x_i, x_j)$ concerning the entity from other situation elements used as context.

The joint probability distribution of the set of state variables x_i corresponding to the set of *N* nodes in such a graph is

$$p(\{x\}) = \frac{1}{N}\prod_{(ij)}\psi_{ij}(x_i, x_j)\prod_i \phi_i(x_i);$$

The function $\psi_{i,j}(x_i, x_j)$ is an undirected compatibility function – say, Pearson product moment correlation – as a generalization from the directed conditional probability $p(x_i|x_j)$ [8].

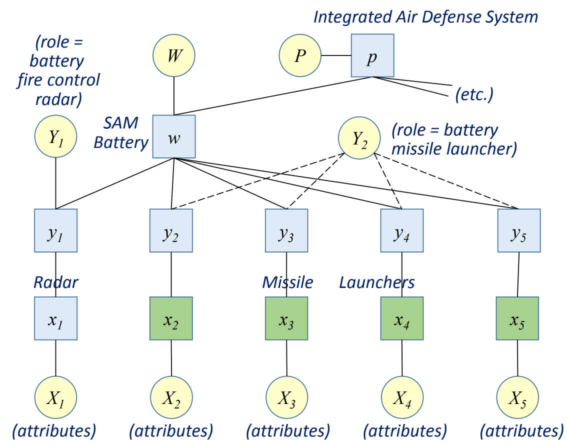

Figure 1. Factor graph representation of example situation

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[2] Note that we could extend this graph in many ways. For example, a round node for the second-order attribute '(is a) role' or '(is a) role in a SAM battery' could added with links to two square instantiation nodes linked to nodes Y_1 and Y_2. Any set of such links and nodes can represent a "situation" and any such situation may be used as a context (C-F or C-O).

Probabilistic Model for Context in Fusion

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Independent Consultant

Panel on Issues and Challenges of the Applications of Context to Enhance Information Fusion
SPIE DSS, Baltimore, Maryland
April 20, 2015

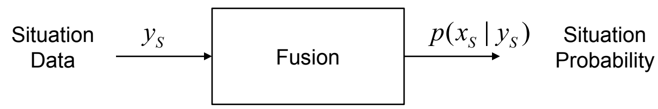
1

What is Context

- Context is (prior or posterior) domain knowledge on setting of fusion problem
  - Operational context
    - Use goal, e.g., situation assessment, fire control
    - Situation of interest, e.g., object class, target tracks, anomalous behaviors, network ID
    - Performance requirements, e.g., classification accuracy, location error, track life, detection probability/false alarm rate
    - Implementation constraints, e.g., available computing resources
  - Situation context
    - Entity environment, e.g., weather, terrain, traffic routes
    - Entity objectives ,behaviors, and relationships
  - Sensing context
    - Sensing environment, e.g., weather, terrain, clutter
    - Sensing objectives and behaviors
- Context is used in all fusion solutions but frequently not represented explicitly
  - Many tracking algorithms assume independent target motion without terrain or road constraints
  - Many sensor models assume clean sensing environments

2

Fusion Without Context Does Not Really Exist



$$p(x_S)$$
$$p(y_S \mid x_S)$$

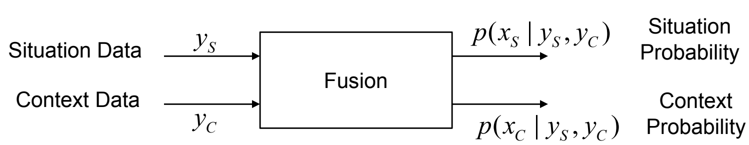
- Posterior situation probability is computed by Bayes rule from $p(x_S)$ and $p(y_S \mid x_S)$

$$p(x_S \mid y_S) = \frac{p(y_S \mid x_S)\, p(x_S)}{p(y_S)}$$

- Actually all fusion systems are based on explicit or implicit context

3

Fusion with Both Situation and Context



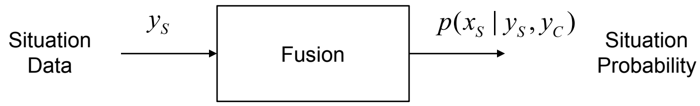
$$p(x_S, x_C) = p(x_S \mid x_C)\, p(x_C)$$
$$p(y_S, y_C \mid x_S, x_C) = p(y_S \mid x_S, x_C)\, p(y_C \mid x_C)$$

- Context data include prior knowledge and real-time data
- Fusion involves both situation and context estimation

$$p(x_S, x_C \mid y_S, y_C) = \frac{p(y_S \mid x_S, x_C)\, p(y_C \mid x_C)\, p(x_S \mid x_C)\, p(x_C)}{p(y_S, y_C)}$$
$$= \frac{p(y_S \mid x_S, x_C)\, p(x_S \mid x_C)\, p(x_C \mid y_C)\, p(y_C)}{p(y_S, y_C)}$$

4

Fusion Given Prior Context Data



$$p(x_S \mid y_C)$$
$$p(y_S \mid x_S, y_C)$$

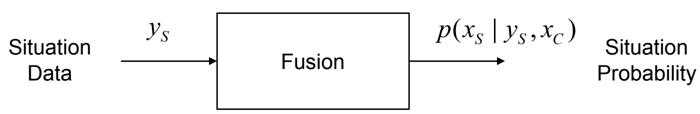
- Context x_C is not represented explicitly
- Fusion uses context-dependent models learned from prior context data

$$p(x_S \mid y_S, y_C) = \frac{p(y_S \mid x_S, y_C)\, p(x_S \mid y_C)}{p(y_S \mid y_C)}$$

- Fusion will have poor performance if y_C used in developing models is different from current y_C

5

Fusion Given Context



$$p(x_S \mid x_C)$$
$$p(y_S \mid x_S, x_C)$$

- Fusion uses context-dependent models developed with given context x_C

$$p(x_S \mid y_S, x_C) = \frac{p(y_S \mid x_S, x_C)\, p(x_S \mid x_C)}{p(y_S \mid x_C)}$$

- Fusion will have poor performance if x_C in developing models is different from current x_C

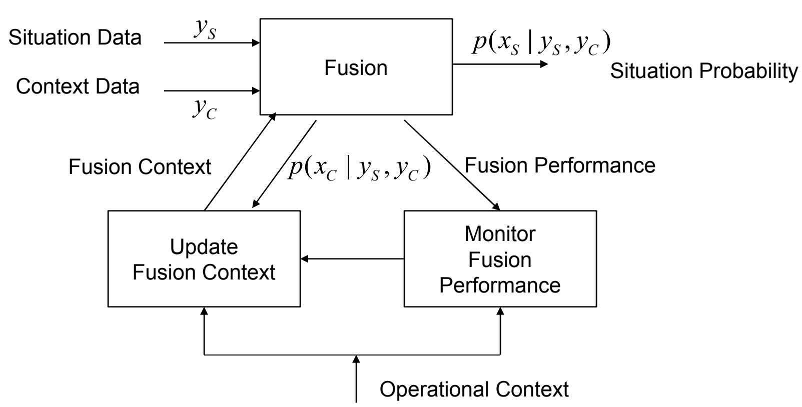
6

Fusion Performance Is Sensitive to Context

- Operational context
  - User goal, e.g., situation assessment, fire control – **define fusion objectives**
  - Situation of interest, e.g., object class, target tracks, anomalous behaviors, network ID – **define situation variables and algorithms**
  - Performance requirements, e.g., classification accuracy, location error, track life, detection probability/false alarm rate – **select algorithms that meet performance requirements**
  - Implementation constraints, e.g., computing resources – **select algorithms that satisfy resource requirements**
- Situation context
  - Entity environment, e.g., weather, terrain, traffic routes – **support prediction for association and estimation**
  - Entity objectives ,behaviors, and relationships – **support prediction for association and estimation**
- Sensing context
  - Sensing environment, e.g., weather, terrain, sensor locations – **support association and estimation**
  - Sensing objectives and behaviors – **support association and estimation**

7

Context Management Can Improve Fusion Performance



- Fusion context includes
  - Context x_C and context data y_C
  - Models with context: $p(x_C)$, $p(x_S \mid x_C)$, $p(y_C \mid x_C)$, $p(y_S \mid x_S, x_C)$

8

lv

Context Management Is Challenging

- Appropriate context and data for fusion problem
  - Determined by operational context, e.g., terrain is not necessary for tracking space objects
  - Available context data for estimating context
- Performance models for context-based fusion
  - Performance given current context
  - Predicted performance with different context
- Resource models for context-based fusion
  - Resource utilization given current context
  - Predicted resource requirements with different context
- Fusion algorithms for different contexts
  - Most implementable algorithms assume simple context
  - Realistic context usually leads to complicated algorithms

9

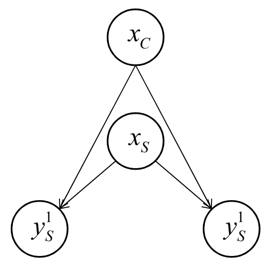
Realistic Context Leads to Complicated Algorithms

- Situation context
  - Motion environment
    - Unconstrained: linear prediction of estimate and error covariance
    - Terrain: prediction of probability distributions
  - Target behavior
    - Independent motion: decoupled filters
    - Group motion: coupled filters
  - Number of targets
    - Poisson distribution: association hypothesis probability decomposes into product of track likelihoods
    - Non-Poisson distribution: complicated hypothesis probability that may not be practical
- Sensing context
  - Sensing environment
    - Unconstrained: Gaussian update of estimate and error covariance
    - Terrain: update with detection probability distribution

Simple context is assumed unless fusion performance is really unsatisfactory

10

Distribution Fusion Is More Difficult with Context



- Since $p(y_S^1, y_S^2 \mid x_S) \neq p(y_S^1 \mid x_S)\, p(y_S^2 \mid x_S)$
  $p(x_S \mid y_S^1, y_S^2)$ cannot be reconstructed from $p(x_S \mid y_S^1)$ and $p(x_S \mid y_S^2)$
- Context information has to be included for optimal fusion

$$p(x_S, x_C \mid y_S^1, y_S^2) = C^{-1} p(x_S, x_C \mid y_S^1)\, p(x_S, x_C \mid y_S^2)$$

11

Summary

- Operational context defines fusion algorithms
  - Situation variables , data, models
  - Performance requirements, resource constraints
- All fusion algorithms assume some context
  - Explicit, e.g., in algorithm specification or description
  - Implicit, e.g., from models used or context data used to generate models
- Context should be explicit in all fusion algorithms
  - Selection of best algorithm from operational context, e.g., in service-oriented architecture
  - Real-time adaptation to changing context
- Context management requires
  - Fusion algorithm performance and resource modeling
  - Algorithms that exploit context

12

Probabilistic models for context in fusion

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ABSTRACT

Context-based fusion can be represented by a probabilistic model that contains both situation and context data, as well as conditional probabilities for the random variables. Context management selects context variables and probabilities to improve fusion performance in real time.

Keywords: Fusion, context, probabilistic model, context management

1. INTRODUCTION

As information fusion systems are used in more problems, it is important that the appropriate context information is used for the particular problem. While there is no standard definition for context[1], we can view context as the prior or posterior domain knowledge of the fusion problem. There are at least three types of context. Operational context includes: fusion goals such as situation assessment or fire control; situations of interests such as object class, target tracks, anomalous behaviors, or network identities; performance requirements such as classification accuracy, location error, track life, detection probability and false alarm rate; and implementation constraints such as available computing resources. Situation context includes: entity environment such as weather, terrain, and traffic routes; and entity objectives, behaviors, and relationships. Sensing context includes: sensing environment such as weather, terrain, and clutter; and sensing objectives and behaviors.

Context is used in all fusion solutions or systems but frequently not represented explicitly. For example, many target tracking algorithms assume independent target motion without terrain or road constraints. Also, most sensor models assume clean sensing environments. Since fusion can be formulated as the problem of computing the posterior conditional probability of the situation given the data, it is useful to develop a probabilistic model of using context in fusion.

2. PROBABILISTICS MODELS

Let x_S be the situation of interest and y_S be the situation data for the fusion problem. Then the objective of fusion is computing the posterior situation probability $p(x_S \mid y_S)$ given $p(x_S)$ and $p(y_S \mid x_S)$ (Figure 1). Even though context is not explicitly represented, all fusion problems assume some context that is modeled in the conditional probability $p(y_S \mid x_S)$. The posterior probability of the situation is computed by Bayes rule as

$$p(x_S \mid y_S) = \frac{p(y_S \mid x_S)p(x_S)}{p(y_S)} \tag{1}$$

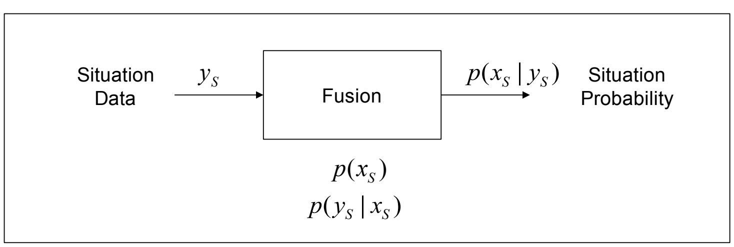

Figure 1. Fusion without explicit context.

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Figure 2 shows a probabilistic model that includes context x_C, context data y_C, and the probabilities $p(x_S, x_C)$ and $p(y_S, y_C \mid x_S, x_C)$. The context data may involve both prior knowledge and real time data. The posterior probability of the situation and context given the data is computed by Bayes rule as

$$
\begin{aligned}
p(x_S, x_C \mid y_S, y_C) &= \frac{p(y_S \mid x_S, x_C)\, p(y_C \mid x_C)\, p(x_S \mid x_C)\, p(x_C)}{p(y_S, y_C)} \\
&= \frac{p(y_S \mid x_S, x_C)\, p(x_S \mid x_C)\, p(x_C \mid y_C)\, p(y_C)}{p(y_S, y_C)}
\end{aligned}
\tag{2}
$$

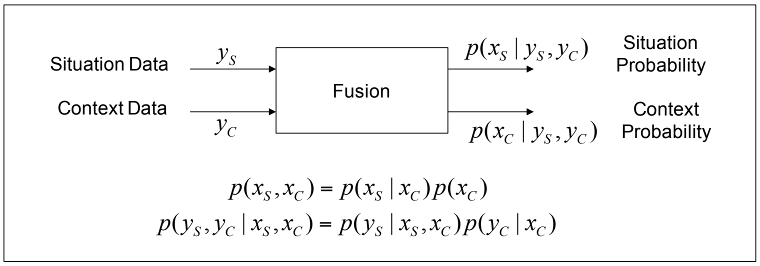

Figure 2. Fusion with both situation and context

In fusion given prior context data y_C, the context x_C is not represented explicitly. However, $p(x_S \mid y_C)$ and $p(y_S \mid x_S, y_C)$ are context-dependent models learned from prior context data y_C (Figure 3).

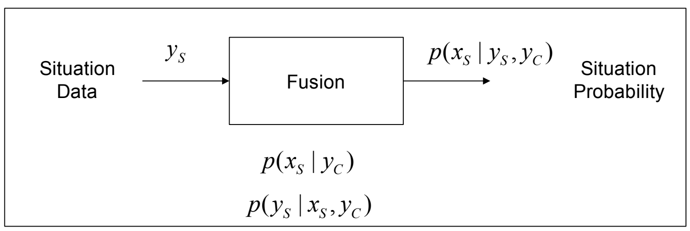

Figure 3: Fusion given prior context data

The posterior situation probability is computed by Bayes rule as

$$
p(x_S \mid y_S, y_C) = \frac{p(y_S \mid x_S, y_C)\, p(x_S \mid y_C)}{p(y_S \mid y_C)} \tag{3}
$$

Fusion will have poor performance if y_C used in developing models is different from current y_C.

In fusion given context, $p(x_S \mid x_C)$ and $p(y_S \mid x_S, x_C)$ are developed given explicit context x_C (Figure 4).

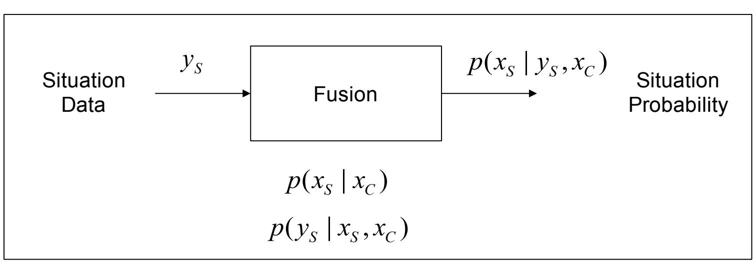

Figure 4. Fusion given context

The posterior situation probability is computed by Bayes rule as

$$p(x_S \mid y_S, x_C) = \frac{p(y_S \mid x_S, x_C)\, p(x_S \mid x_C)}{p(y_S \mid x_C)} \tag{4}$$

Fusion will again have poor performance if x_C in developing the models is different from the actual x_C.

3. CONTEXT MANAGEMENT

Context management[2] can improve the performance of fusion systems. Figure 5 shows an adaptive context management system that monitors fusion performance to modify the fusion context in real time. The fusion context can include the context x_C, context data y_C, and the probabilities $p(x_C)$, $p(x_S \mid x_C)$, $p(y_C \mid x_C)$, and $p(y_S \mid x_S, x_C)$.

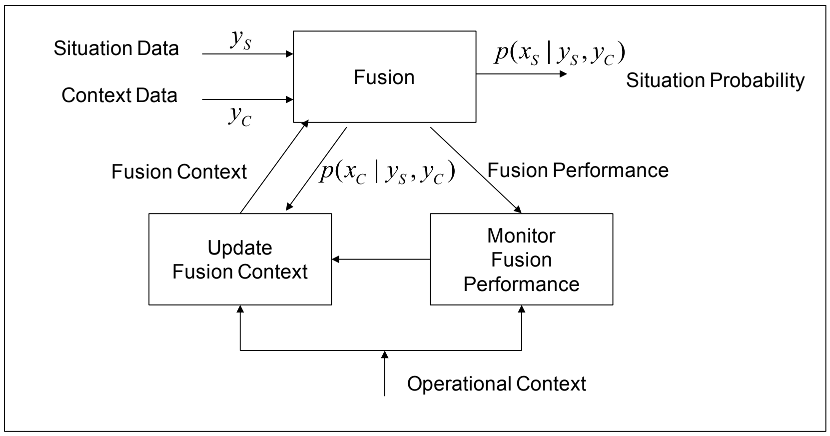

Figure 5. Context management

The challenges to context management include:

- Determining the appropriate context and data from the operational context. For example, terrain is not necessary for tracking space objects.
- Developing models to estimate performance given current context and predict performance with different context
- Developing models to estimate resource utilization given current context and predict resource requirements with different context
- Developing fusion algorithms for different contexts. Most implementable algorithms assume simple context and realistic context usually leads to complicated algorithms that are difficult to implement.

4. SUMMARY

Context management is essential for fusion problems. The operational context defines fusion algorithms, situation variables, data, models, performance requirements, and resource constraints. All fusion algorithms assume some context. The context may be explicit and documented in the algorithm specification or description. It may be implicit and inferable from the models in the algorithms or context data used to generate the models. Explicit representation of context in fusion algorithms allows selection of the best algorithm given operational context in service-oriented architectures and real-time adaptation to changing context. Context management requires modeling of fusion algorithm performance and resource utilization, as well as algorithms that exploit context.

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RANDOM SETS LLC
Cutting-Edge Information Fusion Innovation

The Fundamental Statistics of Contextual Information

Panel on “Issues and challenges of the applications of context to enhance information fusion”

Ronald Mahler
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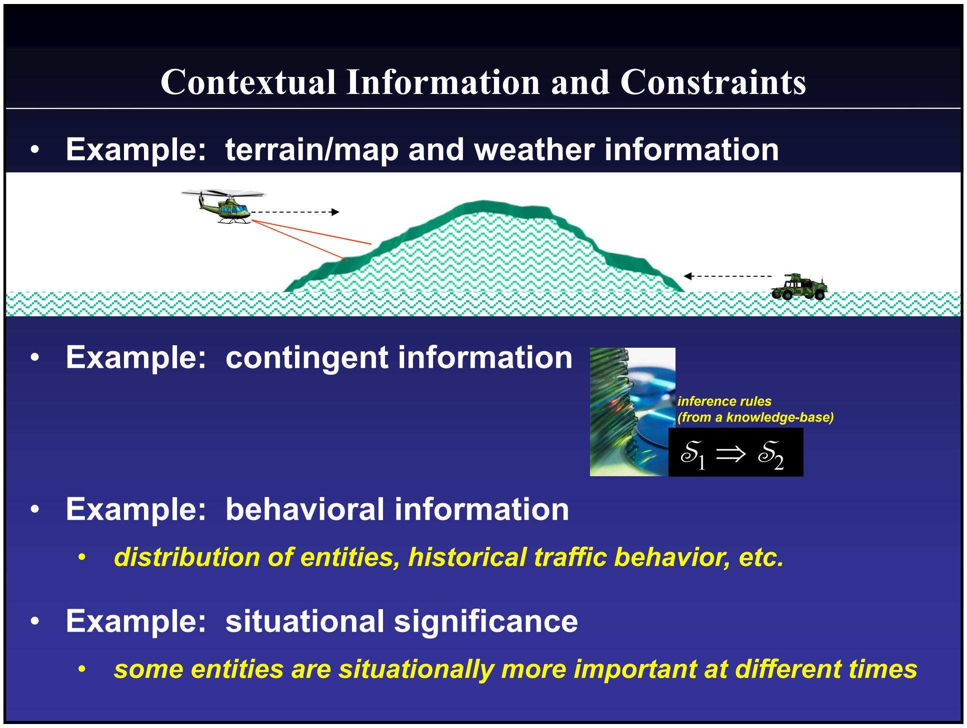
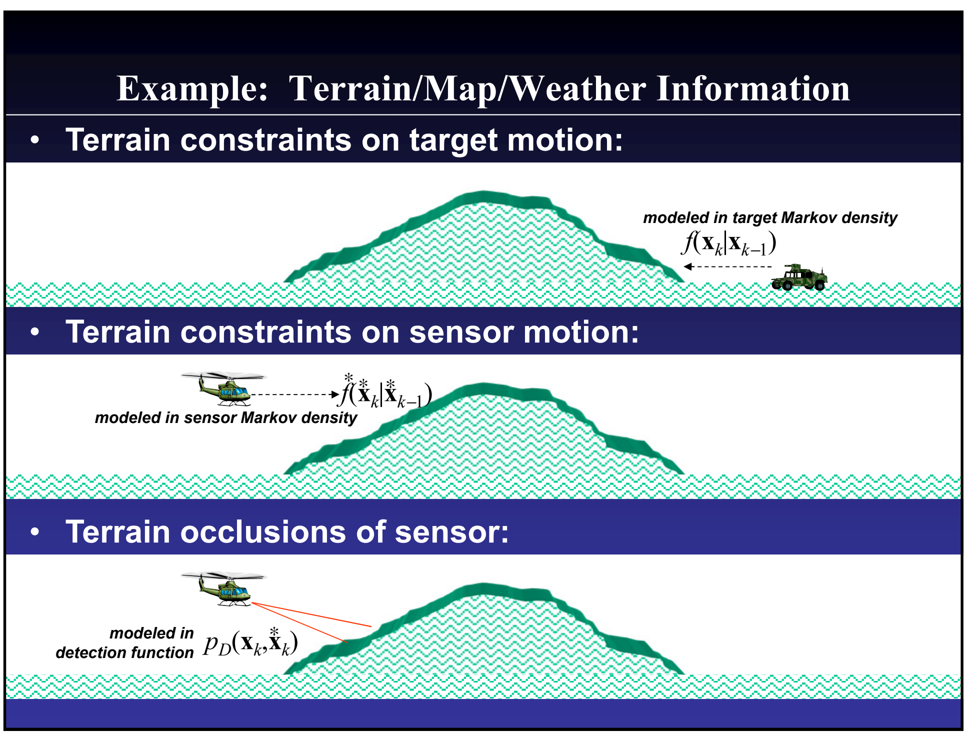
2015 SPIE Defense & Security Symposium
Baltimore MD, April 20, 2015

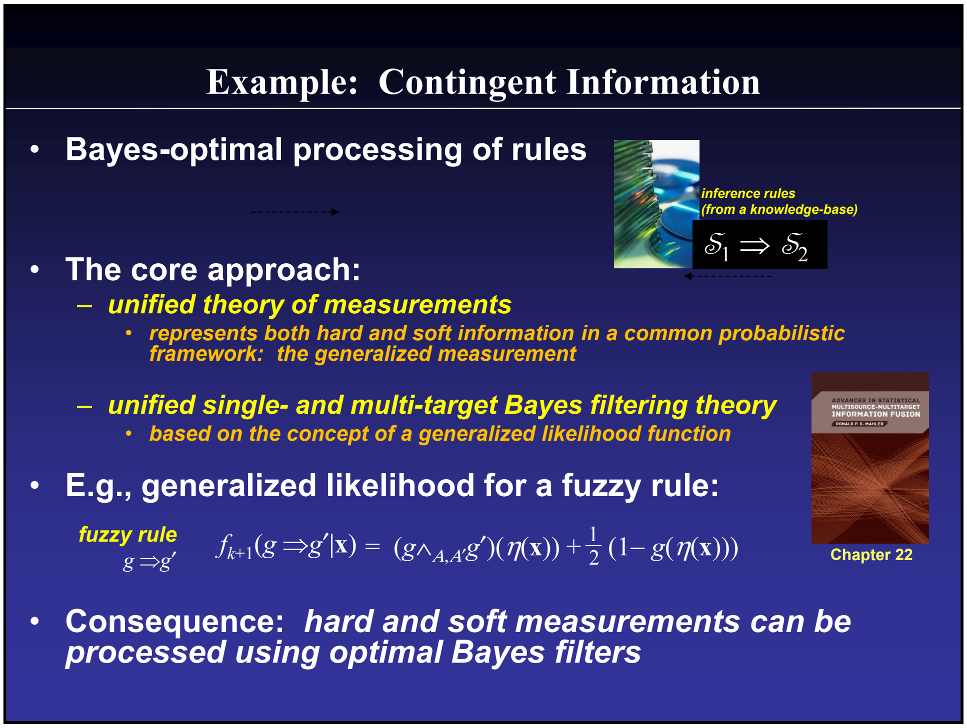
Intrinsic vs. Extrinsic Information

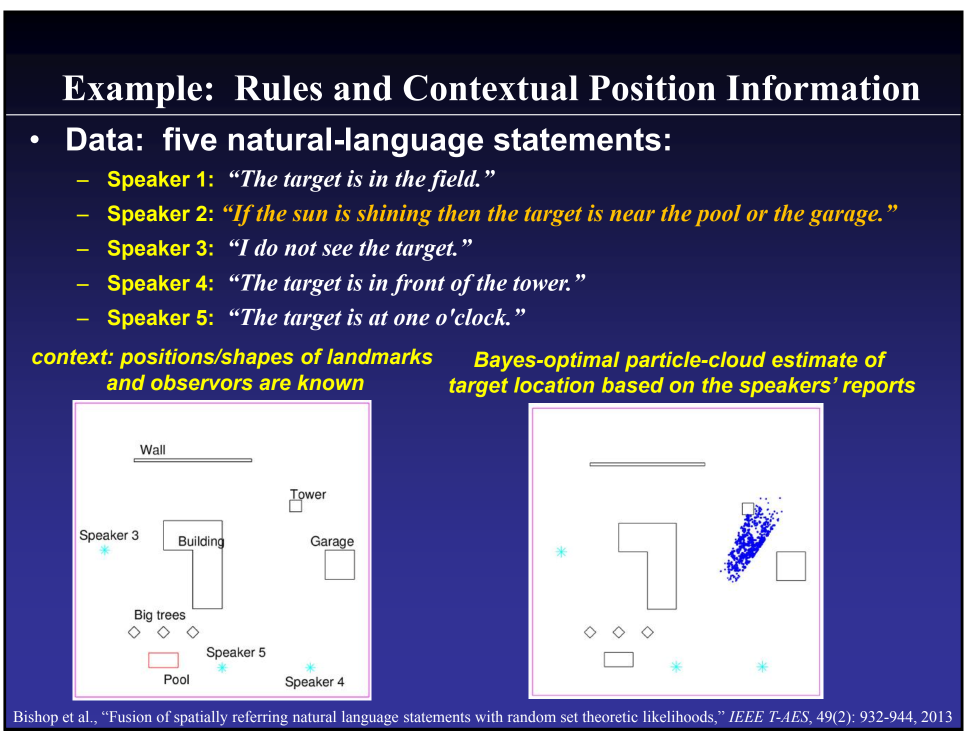
- **Intrinsic information** is information that can be gleaned from “hard” or “soft” measurements, collected from entities by various sources, in **real time**
- **Contextual information** is **extrinsic**—it consists of static and/or dynamic knowledge about the **background constraints** in which the entities and sources operate
- Whether static or dynamic, these constraints must be pre-loaded into algorithms before any effective intrinsic information collection cycle can occur
- Contextual information can be expressed as **constraint models** in the **fundamental statistics** of multiplatform-multisensor-multitarget systems


Contextual Information and Constraints
• Example: terrain/map and weather information
• Example: contingent information
inference rules
(from a knowledge-base)
$\mathcal{S}_1 \Rightarrow \mathcal{S}_2$
• Example: behavioral information
• distribution of entities, historical traffic behavior, etc.
• Example: situational significance
• some entities are situationally more important at different times


Example: Terrain/Map/Weather Information
• Terrain constraints on target motion:
modeled in target Markov density
$f(\mathbf{x}_k|\mathbf{x}_{k-1})$
• Terrain constraints on sensor motion:
$\overset{*}{f}(\overset{*}{\mathbf{x}}_k|\overset{*}{\mathbf{x}}_{k-1})$
modeled in sensor Markov density
• Terrain occlusions of sensor:
modeled in
detection function
$p_D(\mathbf{x}_k,\overset{*}{\mathbf{x}}_k)$

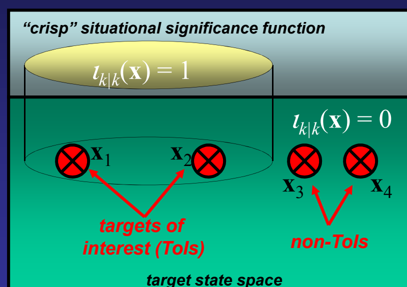
lxiii

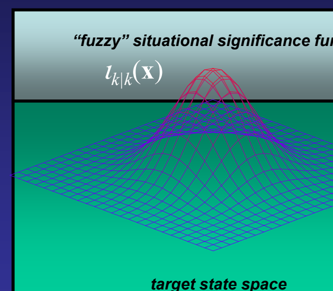

Example: Contingent Information
• Bayes-optimal processing of rules
inference rules
(from a knowledge-base)
$\mathcal{S}_1 \Rightarrow \mathcal{S}_2$
• The core approach:
– unified theory of measurements
• represents both hard and soft information in a common probabilistic framework: the generalized measurement
– unified single- and multi-target Bayes filtering theory
• based on the concept of a generalized likelihood function
• E.g., generalized likelihood for a fuzzy rule:
fuzzy rule
$g \Rightarrow g'$
$f_{k+1}(g \Rightarrow g' | \mathbf{x}) = (g \wedge_{A,A'} g')(\eta(\mathbf{x})) + \frac{1}{2}(1 - g(\eta(\mathbf{x})))$
Chapter 22
• Consequence: hard and soft measurements can be processed using optimal Bayes filters

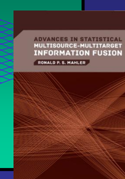

Example: Rules and Contextual Position Information
• Data: five natural-language statements:
– Speaker 1: "The target is in the field."
– Speaker 2: "If the sun is shining then the target is near the pool or the garage."
– Speaker 3: "I do not see the target."
– Speaker 4: "The target is in front of the tower."
– Speaker 5: "The target is at one o'clock."
context: positions/shapes of landmarks and observors are known
Bayes-optimal particle-cloud estimate of target location based on the speakers' reports
Wall
Tower
Speaker 3
Building
Garage
Big trees
Speaker 5
Pool
Speaker 4
Bishop et al., "Fusion of spatially referring natural language statements with random set theoretic likelihoods," IEEE T-AES, 49(2): 932-944, 2013

Example: Situational Information

- One could wait to take an action until accumulated information suggests importance of a particular entity
- Approach: situational significance functions (SIFs) can be incorporated into fundamental multitarget statistics





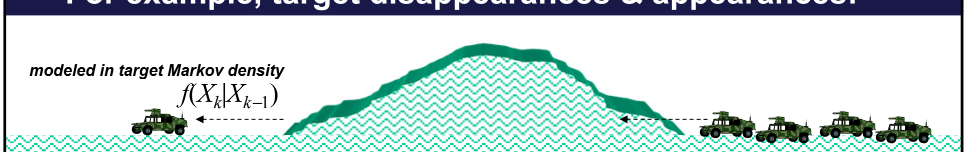


Section 25.14

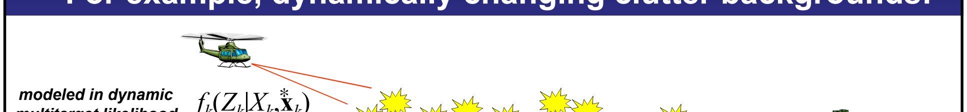
- For example: platform / sensor manager (SMgr)
  - *use a SIF to rank targets by situational importance at given time*
  - *SMgr focuses on most important targets while not losing others*

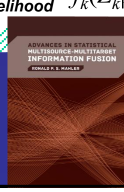
Example: Behavioral / Historical Information

- Can be incorporated into multitarget models
- For example, target disappearances & appearances:



- For example, dynamically changing clutter backgrounds:





Chapter 18

Conclusions

- Contextual information: the background constraints under which sensors, platforms, and targets operate
- Constraint information can be incorporated in the form of "constraint models"
- These can be incorporated into the fundamental statistics of multiplatform-multisensor-multitarget systems: multitarget and multiplatform Markov densities, and multisensor-multitarget likelihood functions

The fundamental statistics of contextual information

Position Paper: Panel on "Issues and challenges
of the applications of context to enhance information fusion

Ronald Mahler
Consultant

"Intrinsic information" is information about entities that can be gleaned from "hard" or "soft" measurements collected from those entities by various sources. Contextual information, by way of contrast, is *extrinsic*. It consists of knowledge, whether static or dynamic, about the *background constraints* in which the entities and sources operate. Whether static or dynamic, these constraints must be "pre-loaded" into algorithms before any effective intrinsic information collection cycle can occur.

In this sense, contextual information is *a priori information*, and a priori information can be expressed statistically in the form of *constraint models*. Map and weather constraints, for example, can be loaded into Markov motion models for both targets and sensors, and into sensor likelihood function models. So can historical information about the behavior of specific entities or entity types at any given time.

Situational significance provides another example of contextual constraints. Platforms, and the sensors carried by them, should be directed to entities of interest. In principle, one could address situational significance by waiting until accumulated intrinsic information strongly suggests that particular entities have high situational interest. Unfortunately, deterministic techniques of this kind have inherent weaknesses. Information about entity type accumulates incrementally, not suddenly, and thus preferential biasing of sensors should likewise be accomplished incrementally, and only to the degree supported by accumulated evidence. Also, hard-and-fast deterministic decisions to ignore some entities may be ill-conceived, since information about target type may erroneous and reversed by later, better data.

Consequently, it is better to have a theoretically principled way of incorporating situational significance—and all other contextual information—into the fundamental statistical representation of multisensor-multiplatform-multitarget systems. This is the approach described in this paper, based on the theory of finite-set statistics.[1,2,3]

Example 1: Terrain Constraints on Target Motion. The motion of ground targets is constrained by the terrain through which they move. They cannot scale cliffs. They cannot, aside from a small number of amphibious types, cross rivers. Many are restricted to roads. Similarly, many airborne target types cannot penetrate bad weather or fly over mountains. These kinds of constraints can be incorporated into *single-target motion models*, in the form of Markov transition densities $f(\mathbf{x}_k|\mathbf{x}_{k-1})$. This is the probability (density) that a target with state $\mathbf{x}_{k-1}$ at time t_{k-1} will transition to state $\mathbf{x}_k$ at time t_k. If $\mathbf{x}_{k-1}$ corresponds to a position on one side of a river, for example, and $\mathbf{x}_k$ corresponds to a position on the other side, the value of $f(\mathbf{x}_k|\mathbf{x}_{k-1})$ will be very small. Because the states $\mathbf{x}_k, \mathbf{x}_{k-1}$ can contain a target-class state variable, $f(\mathbf{x}_k|\mathbf{x}_{k-1})$ can have different forms for different target types. Particle methods are required to accuracy describe $f(\mathbf{x}_k|\mathbf{x}_{k-1})$ for more complex constraint types.

Example 2: Dynamical Constraints on Targets. Targets are physical objects which cannot move arbitrarily. Jet aircraft can execute far more stressful turns than passenger jets. Trucks moving through intersections are restricted to a small number of possible turns. Such motions can, once again, be described by Markov densities $f(\mathbf{x}_k|\mathbf{x}_{k-1})$.

Example 3: Dynamical Constraints on Platforms. Similar comments apply to sensor-carrying and/or weapon-carrying platforms. The Markov density $\overset{*}{f}(\overset{*}{\mathbf{x}}_k|\overset{*}{\mathbf{x}}_{k-1})$ describes the probability that a platform with state $\overset{*}{\mathbf{x}}_{k-1}$ at time t_{k-1} can transition to state $\overset{*}{\mathbf{x}}_k$ at time t_k.

Example 4: Terrain Occlusions of a Sensor. An airborne sensor will often be unable to observe a target if the latter is located on the other side of a wall or hill, or if it is obscured by weather. Constraints of this type can be incorporated into *single-target detection models*, in the form of detection functions $p_D(\mathbf{x}_k, \overset{*}{\mathbf{x}}_k)$. This is the probability that, at time t_k, a target with state $\mathbf{x}_k$ can be detected by a sensor if the sensor has state $\overset{*}{\mathbf{x}}_k$. The probability that the sensor will detect the target *and* collect measurement $\mathbf{z}_k$ from it, is $p_D(\mathbf{x}_k, \overset{*}{\mathbf{x}}_k) \cdot f(\mathbf{z}_k|\mathbf{x}_k, \overset{*}{\mathbf{x}}_k)$. Here $L_{\mathbf{z}_k, \overset{*}{\mathbf{x}}_k}(\mathbf{x}_k) = f(\mathbf{z}_k|\mathbf{x}_k, \overset{*}{\mathbf{x}}_k)$, the sensor likelihood function, is the probability (density) that $\mathbf{x}_k$ will generate $\mathbf{z}_k$ if the sensor has state $\overset{*}{\mathbf{x}}_k$. Typically, $f(\mathbf{z}_k|\mathbf{x}_k, \overset{*}{\mathbf{x}}_k) = f_{\mathbf{V}_k}(\mathbf{z}_k - \eta(\mathbf{x}_k, \overset{*}{\mathbf{x}}_k))$ where $\eta(\mathbf{x}_k, \overset{*}{\mathbf{x}}_k)$ is the sensor measurement function.

Example 5: Contingent Information. Much contextual information is codified in the form of *inference rules*. That is, if event A is true then so is event A', denoted $A \Rightarrow A'$. A typical example is a natural-language statement such as "If the sun is shining then the target is near the pool or the garage." However, events are typically ambiguous in nature. In the approach advocated in this paper, ambiguous events are modeled as the random set realizations of fuzzy membership functions g, g'. Likewise, rules involving ambiguous events are modeled as the random set realization of *fuzzy rules* of the form $g \Rightarrow g'$.

The core approach consists of three parts.[1,Chapter22] First, a *unified theory of measurements*, in which both hard and soft information is mathematically modeled using a common probabilistic framework: the *generalized measurement* (a random closed subset Θ_k of a measurement space). Second, *generalized likelihood functions* (GLFs) $L_{\Theta_k}(\mathbf{x}_k, \overset{*}{\mathbf{x}}_k) = \rho(\Theta_k|\mathbf{x}_k, \overset{*}{\mathbf{x}}_k)$, which is the probability that generalized measurement Θ_k will be collected from a target with state $\mathbf{x}_k$. Third, *provably Bayes-optimal fusion of both "hard" and "soft" fusion*, via Bayes filtering using GLFs.

As an example, the GLF of the fuzzy rule $g \Rightarrow g'$ is

$$\rho(g_k \Rightarrow g'_k|\mathbf{x}_k, \overset{*}{\mathbf{x}}_k) = (g_k \wedge_{A,A'} g'_k)(\eta(\mathbf{x}_k, \overset{*}{\mathbf{x}}_k)) + \frac{1}{2}(1 - g'_k(\eta(\mathbf{x}_k, \overset{*}{\mathbf{x}}_k))) \tag{1}$$

where "$\wedge$" denotes a certain kind of fuzzy conjunction operator. Provably Bayes-optimal processing of $g_k \Rightarrow g'_k$ is accomplished via Bayes' rule:

$$f(\mathbf{x}_k|g_k \Rightarrow g'_k, \overset{*}{\mathbf{x}}_k) \propto \rho(g_k \Rightarrow g'_k|\mathbf{x}_k, \overset{*}{\mathbf{x}}_k) \cdot f(\mathbf{x}_{k-1}) \tag{2}$$

where $f(\mathbf{x}_{k-1})$ is the target track distribution at time t_{k-1} (the prior distribution) and $f(\mathbf{x}_k|g_k \Rightarrow g'_k, \overset{*}{\mathbf{x}}_k)$ is the updated track distribution at time t_k. A particle Bayes filter for the optimal processing of natural-language statements has been implemented.[4]

Example 6: Behavioral/Historical Information. Most real-world applications involve not a single target, but many. Much contextual information about them can be inferred from historical analysis. Some target types are likely to be present at particular times, whereas other types will be rare ("order of battle"). Such information can be represented in the form of a *multitarget prior distribution* $f(X_k)$. Here, $X_k = \{\mathbf{x}_{k,1}, ..., \mathbf{x}_{k,n_k}\}$ is a multitarget state-set. It indicates that $|X_k| = n_k \geq 0$ targets are present, and that their respective states are $\mathbf{x}_{k,1}, ..., \mathbf{x}_{k,n_k}$. Also, $f(X_k)$ is the probability that targets with state-set X_k will be present at time t_k. Because these states can contain a target-type state variable, order-of-battle information can be incorporated into $f(X_k)$.

Similarly, targets can appear within a scene without warning, and they can disappear from a scene without warning. Targets can be sparsely distributed at certain times but can "bunch up" at others. Information of this type can be incorporated into *multitarget motion models*, in the form of multitarget Markov transition densities $f(X_k|X_{k-1})$. This is the probability (density) that targets with state-set X_{k-1} at time t_{k-1} will transition to state-set X_k at time t_k. Thus, for example, if X_{k-1} corresponds to target positions on one side of a terrain bottleneck and X_k corresponds to their positions on the other side, $f(X_k|X_{k-1})$ selects for those X_k that are in a more linear configuration. Similarly, $f(X_k|X_{k-1})$ can be used to model target appearances and disappearances (for example, at the different ends of an airport runway).

Example 7: Complex Terrain Information. In real-world application, a set $Z_k = \{\mathbf{z}_{k,1}, ..., \mathbf{z}_{k,m_k}\}$ of measurements will be collected from targets with state-set X_k. These targets will have different probabilities of detection, and will be obscured within background clutter measurements. Such information can be modeled as *multitarget measurement models*, in the form of multitarget likelihood functions $L_{Z_k, \overset{*}{\mathbf{x}}_k}(X_k) = f(Z_k|X_k, \overset{*}{\mathbf{x}}_k)$. This density gives the probability that measurement-set Z_k will be collected from targets with state-set X_k, if the sensor's state is $\overset{*}{\mathbf{x}}_k$.

However, the statistics of the background clutter process will be unknown in general. Filters that can detect and track multiple targets, while simultaneously estimating the clutter process, have been devised.[1,Chapter18]

Example 8: Situational Significance. *Target importance* is the simplest form of situational significance. Tanks and mobile missile launchers are usually tactically more "interesting" than transport trucks, for example. Target importance is crucial for sensor and platform management, since scarce sensing resources must be continually reassigned to prosecute important targets under constantly changing conditions.

Target importance can be incorporated into the fundamental statistics $f(X_k)$ of a scene using *situational significance functions* (SIFs).[1,Section25.14] A SIF is a fuzzy membership function $\iota(\mathbf{x}_k)$ that indicates the *relative tactical importance* of a target with state $\mathbf{x}_k$ at time t_k. If $\iota(\mathbf{x}_k) = 0$ then $\mathbf{x}_k$ is of no importance whatsoever, whereas if $\iota(\mathbf{x}_k) = 1$ it is of utmost importance. Intermediate values of $\iota(\mathbf{x}_k)$ indicate intermediate degrees of significance.

Far more complex forms of situational significance can be modeled using SIFs. For example, $\mathbf{x}_k$ becomes "interesting" if it rapidly approaches a friendly asset; or if it is near a friendly asset and has been discovered to be a probable unfriendly. In its most general form, a SIF $\iota(\mathbf{x}_k)$ can be visualized as a "heat map" of a scene, with "red" areas (larger values of $\iota(\mathbf{x}_k)$) indicating regions of potential threat and "blue" areas (smaller values of $\iota(\mathbf{x}_k)$) indicating regions of little threat. By incorporating semi-automated procedures for time-updating SIFs, SIFs can be regarded as a systematic foundation for situation and threat modeling and assessment.

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Panel Discussion Context

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SPIE
20 April 2015

Sponsor
AFRL/AFOSR

Collaborators: Snidaro, Garcia, Llinas, Israel, Aved, Seetharaman

OUTLINE

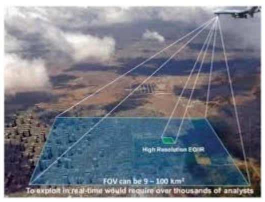
- **Context Complexity – Many levels of context**
  - Could be a benefit or hindrance over varying complexity (data context)
- **Information Fusion – Systems Developments**
  - Requires different solutions over applications (business context)
- **Dynamic Data Driven Application System – System**
  - Requires models for object assessment (object context)
- **User Defined Operating Picture – Visualization**
  - Situational awareness (SAW) tailored to user needs (user context)
  - Could be a benefit or hindrance over user perspectives
- **Example for Multi-INT Fusion**
  - Association of chats to tracks (ACT) - (application use of context)
- **Summary: Context Assessment/Context Mgt (HLIF)**

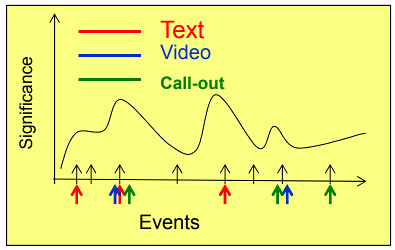
Erik Blasch – SPIE15

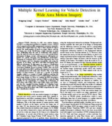
Four V’s of Big Data

Volume
(Scale of Data)

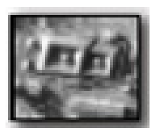
Variety
(Types of Data)







Velocity
(Speed of Data)



Veracity
(Uncertainty of Data)

Erik Blasch – SPIE15

OUTLINE

- **Context Complexity – Many levels of context**
  - Could be a benefit or hindrance over varying complexity (data context)
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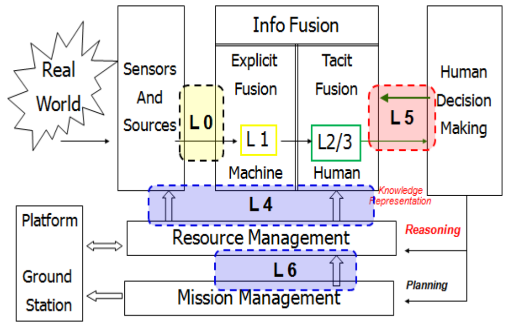
- **Summary: Context Assessment/Context Mgt (HLIF)**

Erik Blasch – SPIE15

Information Fusion and DDDAS

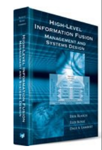
E. P. Blasch, E. Bosse, and D. A. Lambert, *High-Level Information Fusion Management and Systems Design*, Artech House, Norwood, MA, 2012.

- **Information Fusion**
  - **Processing Levels** :
    L0 data registration,
    L1 object assessment, (tracking, classification)
    L2 situation awareness
    L3 impact assessment (threat).
    L4 process refinement,
    L5 user refinement
    L6 mission management



- **DDDAS and Information Fusion**
  - **Environmental modeling** for object assessment, situation and impact assessment over mission needs

E. P. Blasch, E. Bosse, and D. A. Lambert, ***High-Level Information Fusion Management and Systems Design,*** Artech House, Norwood, MA, 2012.

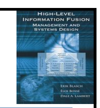


- **Applications :** *various applications need different context analysis were there is no universal solution*

Erik Blasch – SPIE15

High-Level Information Fusion Design

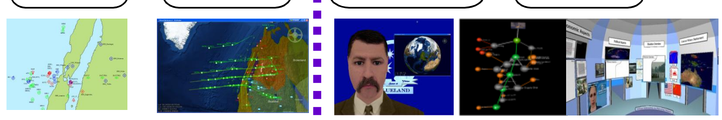
E. P. Blasch, E. Bosse, and D. A. Lambert, *High-Level Information Fusion Management and Systems Design*, Artech House, Norwood, MA, 2012.



Low-level Information Fusion | High-level Information Fusion

Human: Level 0 SAW SENSATION; Level 1 SAW PERCEPTION; Level 2 SAW COMPREHENSION; Level 3 SAW PROJECTION — Situation Awareness (SAW)

Interface Visualization (Evaluation)



Observables (dots on maps); Objects (lines on maps); Situations (storytelling); Scenarios (forecasting)

≈

Machine: Level 0 MIF SUB-OBJECT ASSESSMENT; Level 1 MIF OBJECT ASSESSMENT; Level 2 MIF SITUATION ASSESSMENT; Level 3 MIF IMPACT ASSESSMENT — Machine Information Fusion (MIF)

Decompose problem into elements of LLIF and HLIF

Determine the user (situation awareness) and machine (computation)

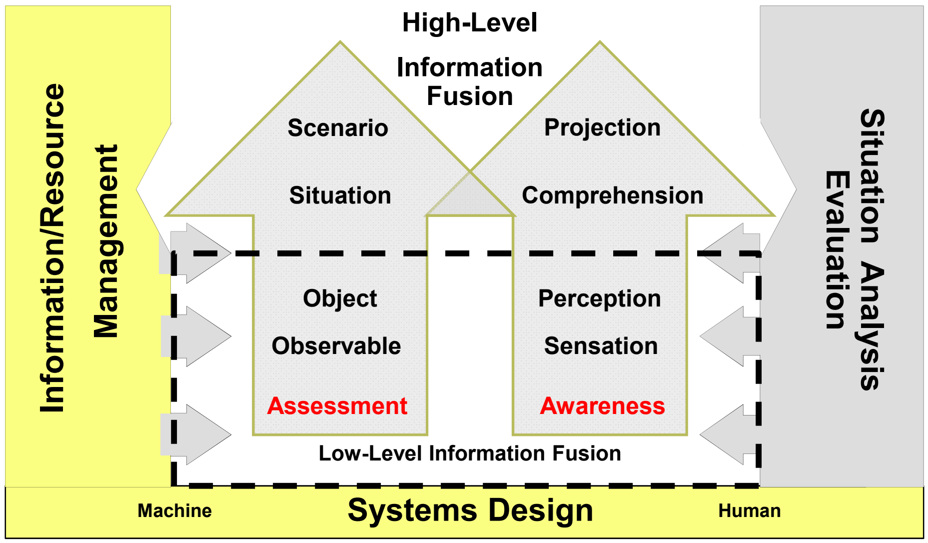
Discussion on evaluation/visualization and projection

6

Erik Blasch – SPIE15

High-Level Information Fusion

E. P. Blasch, E. Bosse, and D. A. Lambert, *High-Level Information Fusion Management and Systems Design*, Artech House, Norwood, MA, 2012.



Erik Blasch – SPIE15 7

High Level Information Fusion Challenges

Focus of the text

Paradigm Challenge: How should the interdependency between the sensor fusion and information fusion paradigms be managed?

Semantic Challenge: What symbols should be used and how do those symbols acquire meaning?

Epistemic Challenge: What information should we represent and how should it be represented and processed within the machine?

Interface Challenge: How do we interface people to complex symbolic information stored within machines to provide decision support?

System Challenge: How should we manage information fusion systems formed from combinations of people and machines?

Design Challenge: How should we design information fusion systems formed from combinations of people and machines?

Evaluation Challenge: How should we evaluate the effectiveness of information fusion systems?

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HLIF Compare and Contrast (4)

Interface Challenge: How do we interface people to complex symbolic information stored within machines to provide decision support?

Linking: Human Situation Awareness with Machines

COMMON:

- **Pairing** involves **interfaces across** the different levels of fusion
- **Interface technology** moves beyond the traditional "dots on maps" and "lines on maps" technology of LLIF (UDOP in Ch 9, command and control graphical user interface in Ch 7 and HiCOP in [4, 12, 13]).

CONTEXT

- **Physical Modeling**:
  - How to integrated the different perspectives with different collection times
  - How to provide decision support over the evolving situation
- **Human/Social Modelling**:
  - How to integrated the different bias, perceptions, and analysis
  - How to use cultural models from different scenarios for context
  - How to refine context based on the user requests

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OUTLINE

- **Context Complexity – Many levels of context**
  - Could be a benefit or hindrance over varying complexity (data context)
- **Information Fusion – Systems Developments**
  - Requires different solutions over applications (business context)
- **Dynamic Data Driven Application System – System**
  - Requires models for object assessment (object context)
- **User Defined Operating Picture – Visualization**
  - Situational awareness (SAW) tailored to user needs (user context)
  - Could be a benefit or hindrance over user perspectives
- **Example for Multi-INT Fusion**
  - Association of chats to tracks (ACT) - (application use of context)
- **Summary: Context Assessment/Context Mgt (HLIF)**

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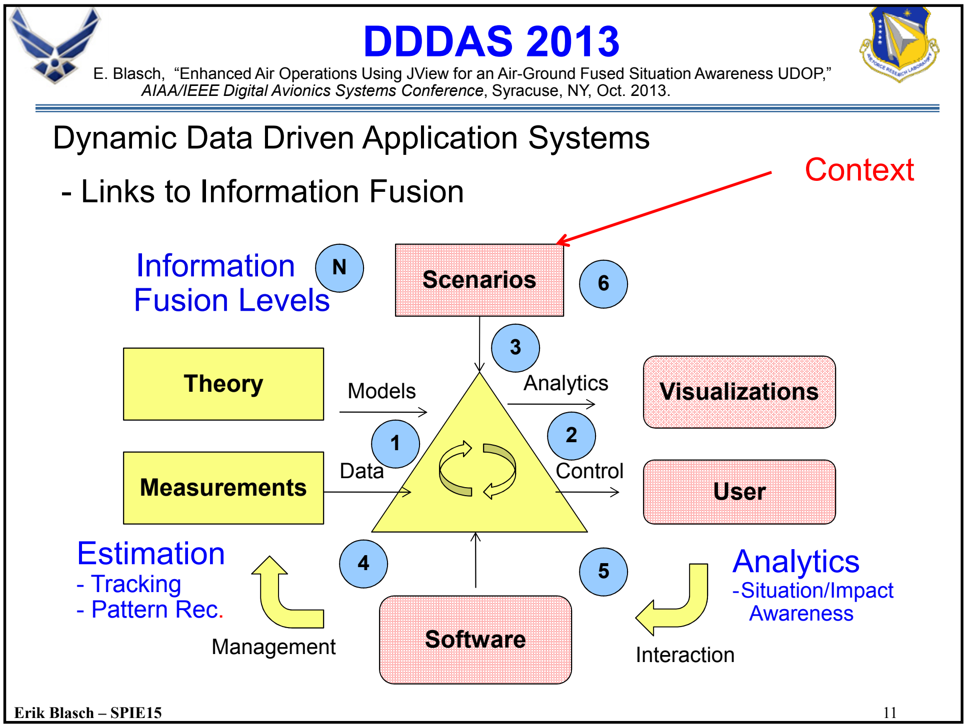
DDDAS 2013
E. Blasch, "Enhanced Air Operations Using JView for an Air-Ground Fused Situation Awareness UDOP,"
AIAA/IEEE Digital Avionics Systems Conference, Syracuse, NY, Oct. 2013.
Dynamic Data Driven Application Systems
- Links to Information Fusion
Context
Information Fusion Levels
N
Scenarios
6
3
Theory
Models
Analytics
Visualizations
1
2
Data
Control
Measurements
User
Estimation
- Tracking
- Pattern Rec.
4
5
Analytics
-Situation/Impact Awareness
Management
Software
Interaction
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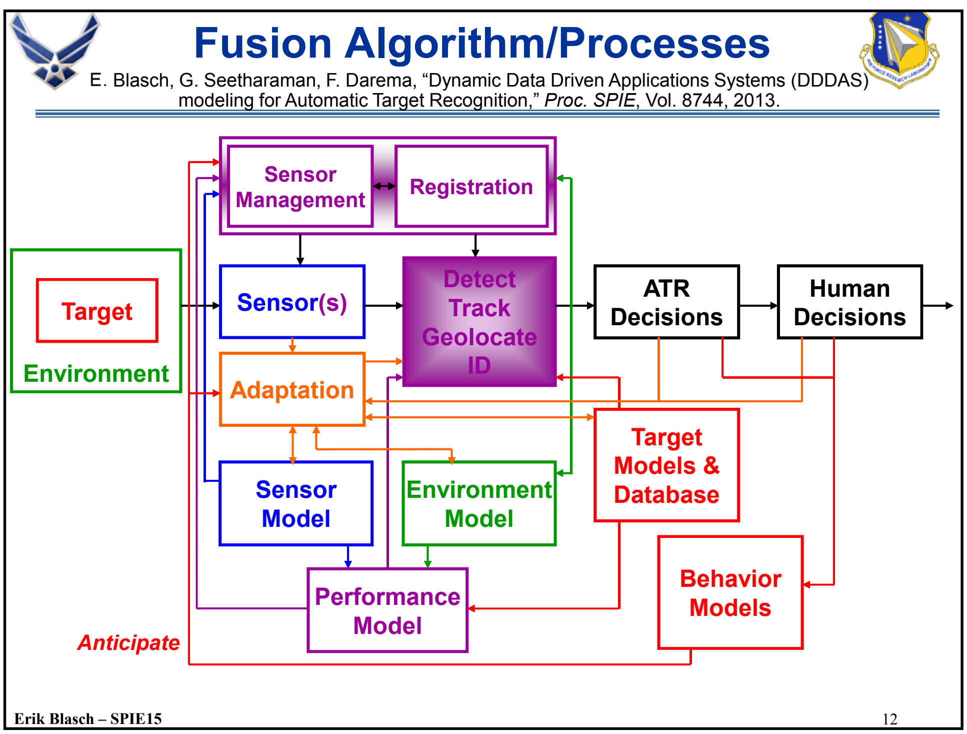
11


Fusion Algorithm/Processes
E. Blasch, G. Seetharaman, F. Darema, "Dynamic Data Driven Applications Systems (DDDAS) modeling for Automatic Target Recognition," Proc. SPIE, Vol. 8744, 2013.
Sensor Management
Registration
Target
Environment
Sensor(s)
Detect
Track
Geolocate
ID
ATR Decisions
Human Decisions
Adaptation
Target Models & Database
Sensor Model
Environment Model
Behavior Models
Performance Model
Anticipate
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12

OUTLINE

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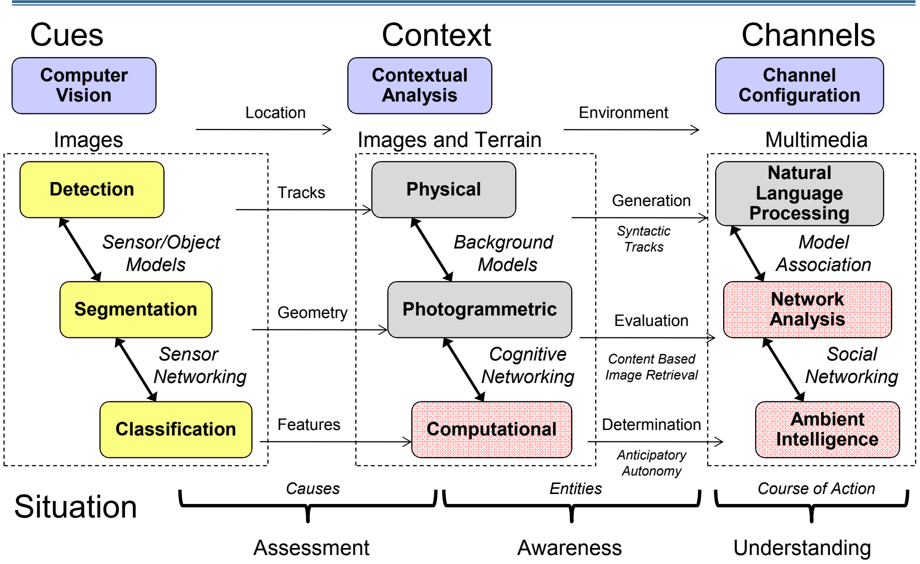
Contextual Analysis

(over large sensory data)



E. Blasch, "Book Review: 3C Vision: Cues, Context, and Channels," *IEEE Aerospace and Electronic Systems Magazine,* Vol. 28, No. 2, Feb. 2013.

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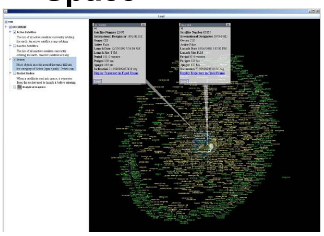
JView - User Defined Operating Picture

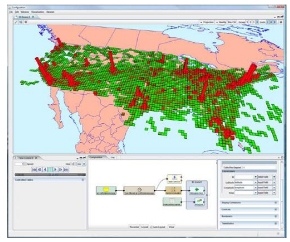
E. Blasch, "Enhanced Air Operations Using JView for an Air-Ground Fused Situation Awareness UDOP," *AIAA/IEEE Digital Avionics Systems Conference*, Syracuse, NY, Oct. 2013.

- **User Define Operating Picture**

Space

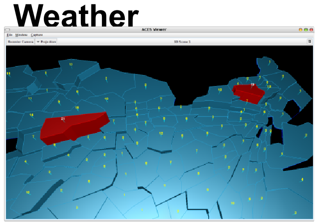


Air



Land

Weather



- **Layered Visualization**
  For Large Data Terrain Context

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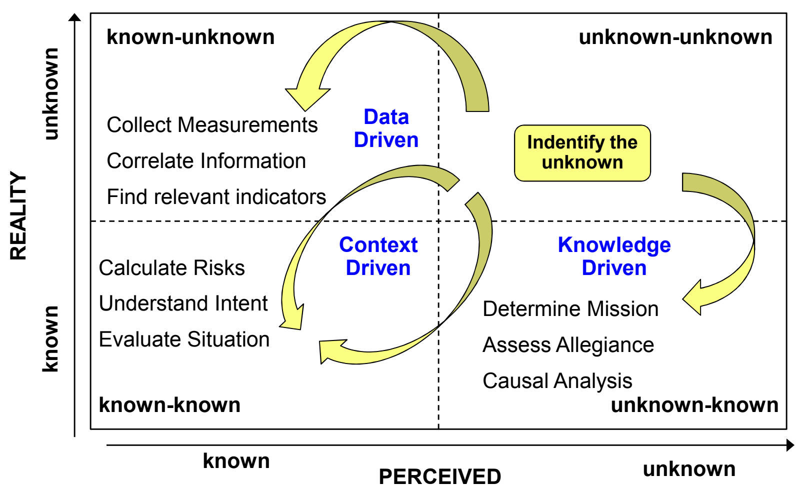
Contextual Threat Assessment

E. Blasch, S. Israel "Context Threat Assessment," *Int. Conf on Information Fusion,* 2015.

E. Blasch, S. Israel for *Context Enhanced Information Fusion*.



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OUTLINE

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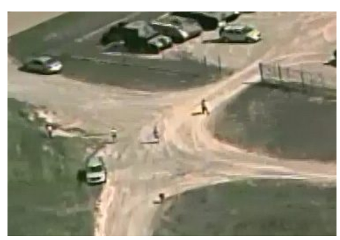
Spiral 1 Demo

E. Blasch, G. Chen, J. Gao, H. Ling, D. Shen, K. Palaniappan, G. Seetharaman, A. Aved, "Video-Based Activity Analysis Using the L1 tracker on VIRAT data," *IEEE Applied Image Patter Recognition*, 2013.

- **Scenario Options [VIRAT]- Aerial DataSet 2**

Story

Identified bombing suspect followed back to compound and meets with his friends



09152008flight2tape1_3

0:08-0:18 People walking in parking lot

1:55-1:96 People milling around a building

2:39-2:50 Person Running

2:56-3:15 Person gets into a parked car (near base entrance)

3:22-4:26 Person gets out of car, but all kinds of movers

5:05-5:08 Black car drives away

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L1 Video Processing

E. Blasch, G. Chen, J. Gao, H. Ling, D. Shen, K. Palaniappan, G. Seetharaman, A. Aved, "Video-Based Activity Analysis Using the L1 tracker on VIRAT data," *IEEE Applied Image Patter Recognition*, 2013.

- **Aerial Surveillance (**Simultaneous Track and Identification)
  - Combine with other sensors (HUMINT), context (terrain) data

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Video-2-Chat Messages Fusion

E. Blasch, J. Nagy, A. Aved, W. M. Pottenger, M. Schneider, R. Hammoud, E. K. Jones, A. Basharat, A. Hoogs, G. Chen, D. Shen, H. Ling, "Context aided Video-to-Text Information Fusion," *Int'l.. Conf. on Information Fusion*, 2014.

Combinations for text to video fusion

CHAT	Relevant	Non-Relevant	Clutter
Call-Outs	Car, Truck (ALL recorded)	--	When is bathroom break
Internal	Clarifications	Other tasks	Where to go for dinner
External	AOI	Other missions	Other missions

VIDEOS	Relevant	Non-Relevant	Clutter
Detections (objs, facilities)	Car, Truck A priori bldgs	Animals Passer-bys	Spurious signals inducing change detection
Tracks	In AOI	Other hgwys	Many short tracks
Classifications (POV/HVAC)	High Prob.	"Other"	Low prob classifications, false alarms
Identifications (FFN)	High Prob in AOI, threat	Friendly (but then the dist)	Neutral

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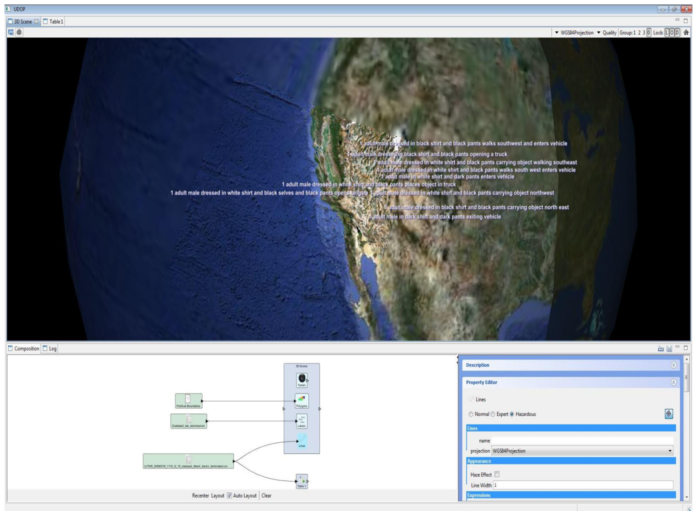
JView – Mutli-INT Fusion

E. Blasch, J. Nagy, A. Aved, W. M. Pottenger, M. Schneider, R. Hammoud, E. K. Jones, A. Basharat, A. Hoogs, G. Chen, D. Shen, H. Ling, "Context aided Video-to-Text Information Fusion," *Int'l.. Conf. on Information Fusion*, 2014.

- **Situation Awareness UDOP**



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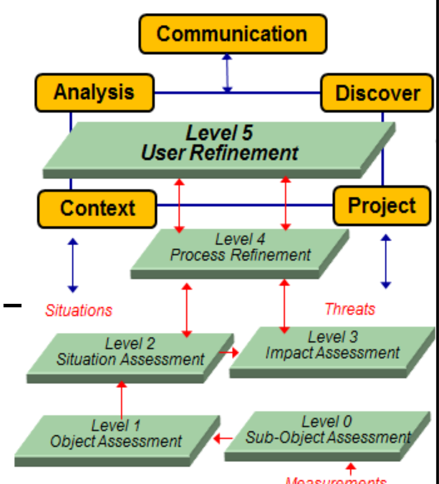
Context Summary

- **Many levels of context**
  - Big Data (data context)
- **Information Fusion – Systems**
  - Applications (business context)
- **Dynamic Data Driven Apps Sys**
  - Models (object context)
- **User Defined Operating Picture –**
  - Situational awareness (user context)
- **Example for Multi-INT Fusion**
  - Discovery needs context
- **Context Assessment/Context Management**
  - High Level Information Fusion (situation, threat, user, mission)



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Finding Context In a Complex World

Erik Blasch

Air Force Research Laboratory, Information Directorate, Rome, NY, 13441

ABSTRACT

Information fusion typically includes methods such as Bayesian and belief reasoning which utilizes a prior information and current measurements to update the state estimate. Thus, in one sense contextual information is everywhere through a prior information. On the other hand, there is so much data that finding the appropriate context to align with the measurement information is subject to many challenges and issues. The challenges associated with contextual reasoning include: (0) sub-object data assessment access, (1) object assessment models, (2) situation awareness comprehension, (2) impact assessment magnitude, (4) process refinement opportunity cost, (5) user refinement subjectivity, and (6) mission refinement attitudes. While these elements follow the traditional Data Fusion Information Group model, the challenge includes the complexity of the situation which provides an endless perspective of context processing.

Keywords: Context enhanced information fusion, DFIG modeling, big data

1. CONTEXT PROCESSING

Where to begin (as a point of context)? Given the big data problems of volume, variety, velocity, and veracity; there exists a vast array of complexity with real world opportunities. Figure 1 presents the levels of information fusion processing [1] with a focus on user decision making [2, 3, 4, 5] as well as the Dynamic Data-Driven Applications System (DDDAS) [6]. As part of high-level information fusion [7], the subjective nature of perspective influences the context processing [8]. DDDAS brings together theory, measurements, and software; requiring the dynamic interaction data, models, control, and analytics. To accomplish the context analysis requires the interaction of signals of opportunity [9], social/cultural networks [10, 11], situation assessment [12], impact assessment [13, 14], and sensor management over operating conditions of the sensor, target, and the environment [15].

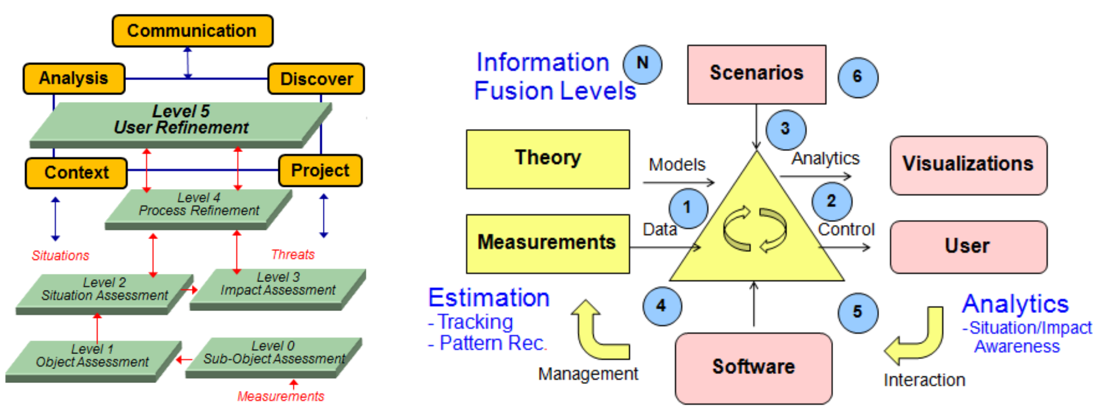

Figure 1: User refinement (left) of data to find context in a Dynamic Data-Driven Applications System (right).

The key issues are then the types, fidelity, and relevance of *models* of context against the constantly changing nature of the situation. Likewise, the distribution nature of multiple *users* operating over different visualizations and computational tools affects the contemporary understanding of the evolving scenario. Various *data sources* from physical sensors [16] and human sensors [17] need to be combined for a complete contextual analysis [18]. Last, the software architecture [19] influences the information management [20]. The challenge is then of the unknown – does the data contextual analysis known the unknown?

2. CHALLENGES OF THE UNKNOWN: CUES, CONTEXTS, AND COMMUNICATIONS

The context understanding is shown in Figure 2. The ontology for uncertainty reduction [21] drives the movement from the unknown-unknown to the known-known. The data-driven approach helps in resolving the perceived unknown to the perceived known, whether or not it reflects reality. Likewise, knowledge of the world from contextual analysis moves from the unknown reality to the known reality whether all elements are perceived correct. Thus, context is the required combination to go from the unknown-unknown to the known-known. Doing the contextual analysis is thus a contemporary challenge. A paradigm of Figure 2 includes cues, contexts, and channels [22]; which uses data cues and knowledge channels to enhance the contextual analysis. Elements of Figure 2 show that the physical world (with theory and measurements) needs to be coordinated with the human world (as visualizations and user) to capture the scenario.

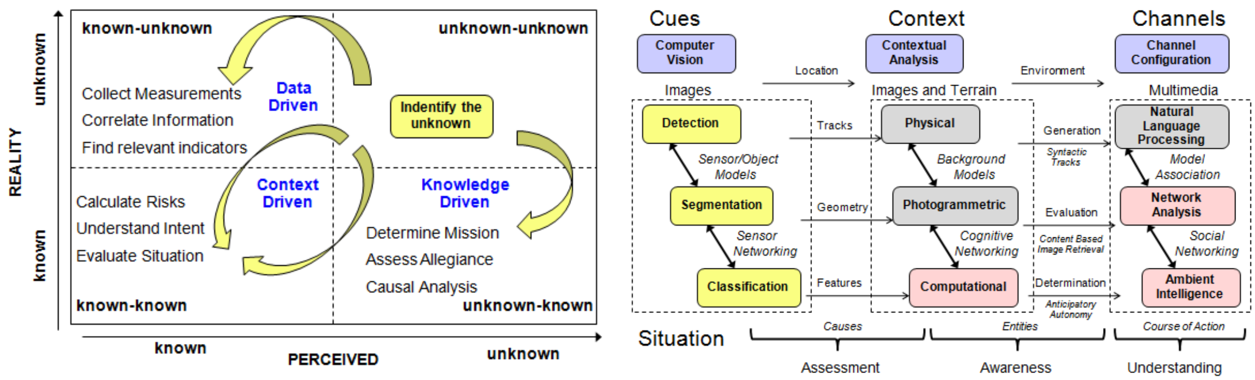

Figure 1 - Context-driven assessment, awareness, and understanding.

In summary, the issues are the cues: model building, dynamic data, and the unknown-unknown. The challenges are the channels: control, analytics and communication. Both data-driven and knowledge-driven approaches must be coordinated for future context-driven applications to find context in the complex world.

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DTRA Network Sciences

SPIE DSS 2015 Brief

CWMD Context and IF Issues

Paul Tandy, PhD
Basic & Applied Sciences Dept.
J9 Research & Development
April 20, 2015

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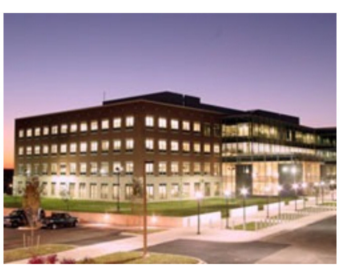
Network Sciences

What is Defense Threat Reduction Agency?



"Our focus is to keep WMD out of the hands of terrorists and other enemies by locking down, monitoring, and destroying weapons and weapons related materials. We also assist Combatant Commanders with their plans and responses to WMD events and develop and deliver cutting-edge technologies to assist with all of these endeavors.

There is no other country or government that is solely focused on combating weapons of mass destruction 24 hours a day, 7 days a week."

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Strengthen Global CWMD Situational Awareness

Strengthen Global CWMD Situational Awareness

- Obtain, analyze, and fuse intelligence and information about adversary WMD programs, proliferation activities, and dual-use technologies
- Access and share information on CWMD strategy, plans, operations, and activities across U.S. Government agencies
- Utilize open source, “non-classified” information to complement unclassified and classified information held by the U.S. Government
- Strengthen collaboration among interagency and international partners to build partner capacity and counter threats
- Increase capability and capacity for detecting, understanding, and forecasting threats
- Federate data and integrate advanced technologies to map knowledge, streamline analysis and planning, and support decision-making

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Minimal Context Space to Support Late Context Binding

- **Users are able to find, use, and share CWMD mission information across the DoD, USG, and other mission partners**
  - ***Get what you need, when you need it***
- **CWMD Combat Support capabilities are seamlessly integrated into next generation military tactical cloud environments**
  - ***Integrated force protection situational awareness***
- **Role-based, entity-level security and other cyber security features are “baked in” from the start, supporting automated ‘tear lines’ and marking**
  - ***Data ownership and access security managed for interagency and international collaboration***
- **Teams able to remain in communications with National Technical Reachback and utilize data and services/apps from the field**
  - ***Improved support to field teams***

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Importance of Contextual Knowledge

- Cost reduction
- Manpower reduction
- Computational efficiency
- Boundary condition definition
- Temporal conditions defined
- Sampling rate specification
- Increased data quality
- …and many more resource related savings. If we can get it!

What if we have no prior domain knowledge?
What if we have no way to train?

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Some issues important for DTRA

- High impact low probability context definition
- Finding automatic methods for identifying data sources that are relevant and in machine readable form.
- Resolving issues related to “do we have enough data?” vs. “we have too much data!”.
- Finding ways to combine simulation data with other data sources in a consistent manner
- Finding the “limits of use” synthetic data when real data is not available in a CWMD context
- Need to generalize fused information from rare events
- Fuse similar scenario data to mimic the case when no instances have occurred and it may be difficult to anticipate an occurrence

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Network Sciences Potential 6.1 Funding to Seek Innovative Approaches by DTRA

- **Semantic Representation of information**
  - Semantic representation schemes to unambiguously express meaning.
  - Automatic processing of corpora to identify both lexical semantics and semantic relationships involved in predicate-argument or some alternative to represent semantic structure for sentences.
- **Machine Learning Methods for Network Analysis**
  - Difficult detection due low observable and ambiguous
  - Relating observations and representing interactions
- **Development of Models for the Time Evolution of Realistic Multilayered Networks in Response to Large-Scale Damage**
  - Multiple time scales and sampling rates
  - Uncertainty, minimal dataset construction, control

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THE AIR FORCE RESEARCH LABORATORY
LEAD | DISCOVER | DEVELOP | DELIVER

The Importance of the "emic" Perspective

April 20 2015

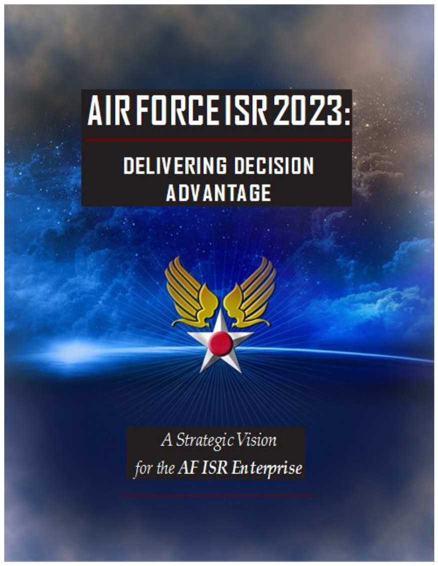
Laurie Fenstermacher
Air Force Research Laboratory, 711 HPW/RHXM
Human Centered ISR Research Division

Briefing Roadmap

- Challenges for ISR
- "emic" versus "etic"
- Discourse Analysis for "emic" perspective
    - •Methodology exemplar: Arabic
    - •Affect analysis
    - •Al Qaeda case study
- Information Fusion? Boko Haram case study
- Summary

2

Challenges for ISR*



ISR enterprise must:

- **Expand to support strategic intelligence in peacetime, Phase 0**
- **Provide multi- and all-source intelligence**
- **Support operations from humanitarian operations to major contingencies**

Goal of Air Force ISR is to be able to "*analyze, inform, and provide commanders at every level with the knowledge they need to prevent surprise*."

3

*** Intelligence, Surveillance and Recconaissance**

"emic" versus "etic" perspectives

"emic" – 1st perspective, native participant viewpoint

"etic" – 3rd perspective, observer viewpoint

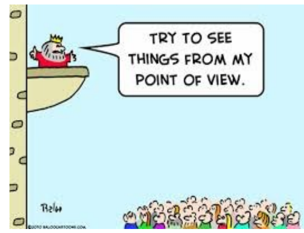
- **"emic" analysis – to support meaning making about sounds (or behaviors, or…) from the perspective of the native participant**
  - **Example: "wh": is it a sound or part of the language?**
  - **Example: "mischievous": is it harmless or not?**
- **Ethnographic analysis includes both the "etic" and "emic", just as writing a novel involves both 3rd and 1st person perspectives**

?

4

Multiple Perspectives

- ❖ Impossible to achieve a solely “emic” perspective due to past, experiences, ideas
- ❖ If only “etic” perspective, will overlook hidden nuances, meanings, concepts
- ❖ Storytellers naturally combine perspectives or “point of view”
- ❖ Depends on how they want to tell the story and how they want the reader to create meaning



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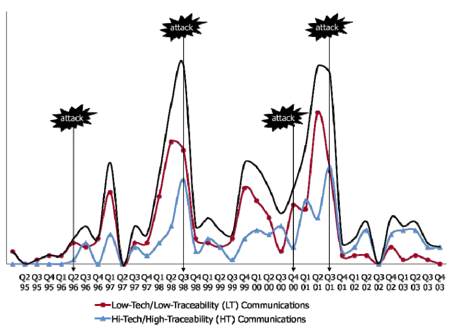
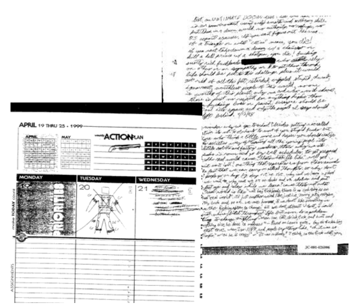
Motivation for “emic”



Ref: Drozdova and Samoilov, 2010



- ➢ There are “signals” prior to an individual or group acting out in behaviors (actions, speech/text)
- ➢ Provides important context for meaning making about situation, threat

6

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“emic” Discourse Analysis Strategy/Approach

- Develop social science theory based “lenses” through which to view discourse
  - Methodology development
  - Text analytics, forecasting models

Approach

- Focus on social identity, integrative complexity, worldview, trust
- Grounded theory approach
  - Focus groups
  - Case studies
- Text analytics – extend and develop new ways to code/proxies for social identity, integrative complexity

7

Arabic Discourse Analysis: Initial Methodology Development

Literature search identified key linguistic indicators of in-group/out-group discourse:

- Lexicalization
- Quotations
- References
- Allusion

Macro-level Phenomenon	Aspect	Rhetorical Phenomenon	Linguistic Indicators	English Examples	Automate?	Literature
Positive Self-Representation van Dijk (2006) van Dijk – is correlated with: mitigations, disclaimers, denials	Positive Representation	Glorification	• Themes of (national/other) pride	“no other country”	phrase counts	*Theory:* → van Dijk (2006) → Rahimi and Sahragard (2006)
		Positive Description	• Positive ideologically-laden terms • Foregrounded information/ themes • References to “good” historical characters/events	“amazing” God light civil rights movement	word counts (more complicated: sentiment analysis)	*Theory:* → Hopper and Thompson (1980) → Halliday (2004) → Fairclough (1992) → Rahimi and Sahragard (2006) → van Dijk (2006) → Meinhof and Galasinski (2005)

Effect	Phrase	Translation	Explanation	Citation
National Self-Glorification	الملك حمد بن عيسى آل خليفة عاهل البلاد المفدى	King Hamad bin Isa Al Khalifa, the king of the beloved country	Rather than using the name of the country, a possessive ending indicating “our country,” or omitting the word entirely, this phrase using مفدى informs the audience how precisely they should feel about the country – or, equally, how the “in-group” feels about the country and thus how the audience should feel if they desire to be a part of that in-group.	C17
	جلالة الملك المفدى	His beloved Majesty	Ditto, with regard to glorifying His Majesty.	C17
	صاحب الجلالة الملك	His Majesty (= the owner of reverence / magnificence)	This reference's terminology would be expected from only the king's own people, the in-group; in addition, it intensifies the awe and distance	C17

Coding (285 documents) study:

- Identified indicator examples
- Developed initial methodology for analysis of in-group/out-group, their sentiments

8

Arabic Discourse Analysis: A New Methodology

- Developed codebook based on results of 2 focus groups (37 Arabic speakers, 10 with discourse analysis background)
- Coding study with 34 Arabic speakers validated and augmented the codebook (1500 coded documents), identifying rhetorical phenomena for expressing in-group/out-group discourse

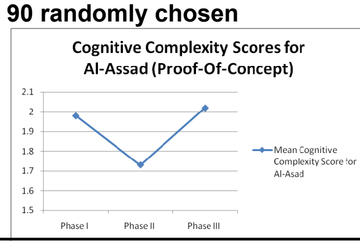
Rhetorical Phenomenon	In-Group	Out-Group
Amount of attention:	Much attention	Not represented
Opinions represented:	Fully represented	
Reference terminology:	Respectful terminology	Disrespectful terminology
Groupings:	With "good" entities, against "bad" entities	With "bad" entities, against "good" entities
Intimacy:	Close to "us"/the world	Distant from "us"
Attributed power:	Powerful/involved	Weak/useless
Attributed virtue:	Glorified/canonized	Immoral/irresponsible
Attributed motivations:	Neutral/cooperative	Non-neutral/has negative motivations
Attributed nature:	Bad attributes diminished, has fundamentally good nature	Good attributes diminished, has fundamentally bad nature
Victimization:	Victimized/sufferer	Victimizer/aggressor

9

Cognitive Complexity Case Study: Syrian Pres. Bashar al-Assad Speeches

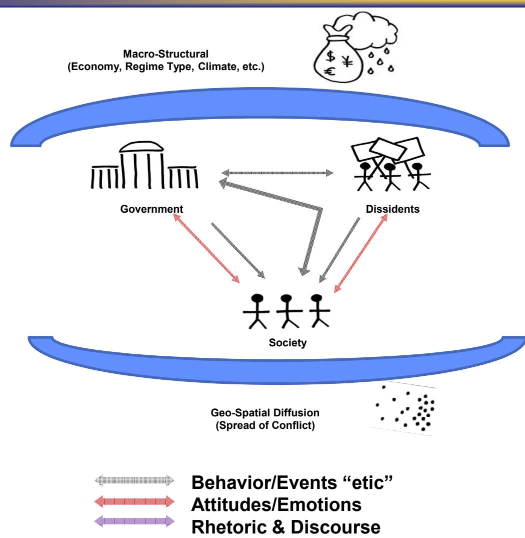
- Cognitive complexity analysis uses language-based cues to predict changes in actors' psychological posturing -- cognitive complexity of elites/leaders decreases between 3 weeks and 3 months prior to an attack, crisis, or violent action

- Analyzed discourse from period encompassing the 14 Feb 2005 assassination of former Lebanese Prime Minister Rafic Hariri
  - Lebanese and Syrian officials helped plan and execute Hariri, according to International Community investigation
- Hypothesis: al-Assad's cognitive complexity will decrease immediately prior to the assassination due to involvement, psychological investment in assassination
- Scored al-Assad's cognitive complexity in 90 randomly chosen paragraphs from political speeches
  - Texts were divided into three periods:
    - Phase I (Baseline) : 10/2003-5/2004
    - Phase II (Pre-Attack): 10/2004-1/2005
    - Phase III (Post-Attack): 2/2005-12/2005



10

Theoretical Framework for Text Analytic Based Analysis

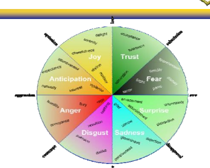


"We must rely on the force of the popular masses, for it is only thus that we can have a guarantee of success." Mao Tse Tung
Guerrillas must draw their "greatest force from the mass of the people." Che Guevara

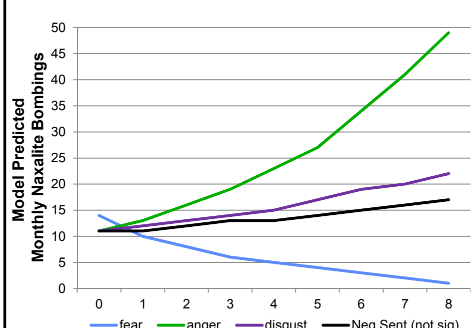
11

Modeling the Impacts of Emotions on Behavior

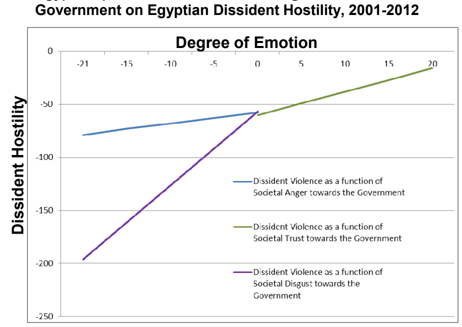
- Emotions linked to behavior
- Different events lead to different emotions and vice versa
- Fear and anger often result in opposite responses



Plutchik's Wheel of Emotions



Egypt: Impacts of Societal Fear & Anger Directed Towards Government on Egyptian Dissident Hostility, 2001-2012



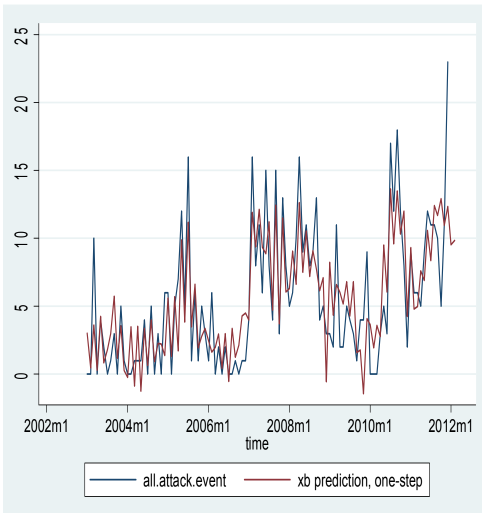
Increased trust towards the government decreases dissident violence

Increased disgust towards the government increases dissident violence

12

xcii

Al Qaeda Case Study



Insights:

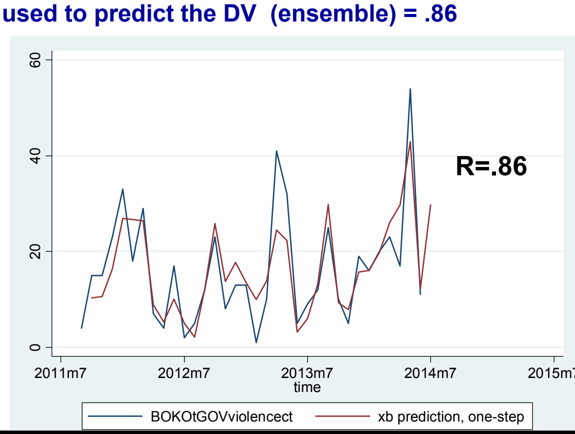
- **Content Analysis variables improve fit -- many are statistically significant**
  - **Use of *Islamic* and *Loyal* terms are strongly and positively associated with future violence**
- ***In to Out Disgust* strongly, positively related to future violence**
- **Differentiation and Integration reduce the frequency of future violence with integration (higher level) having a bigger effect**
- **Idea density related to increased frequency of future violence**

13

Boko Haram Case Study: Information Fusion(?)

Estimated 3 separate models:

- **Sentiment only (r between predicted and actual events =.49)**
- **Events only - INSIGNIFICANT (r between predicted and actual events = .36)**
- **Discourse only (r between predicted and actual events =.69)**
- **➢ Outputs used to predict the DV (ensemble) = .86**



Results suggest that HOW groups say things and WHAT they say is more important than what they've done in the past for forecasting what they will do next!

14

Summary

- To handle the complexities of the new security environment will require not only more information, but different information/perspectives
- “etic” data is the predominant focus of current data collection and analysis
- Inclusion of the “emic” perspective is important for looking at the “why” to augment the “what” and “how”
- “emic” perspective provides important clues about what is going to happen and context for meaning making, enabling hypothesis generation and better resource allocation, potential mitigation of event/violence
- Discourse analysis can provide “emic” (and “etic”) perspectives

➢ **Need to explore strategies to incorporate “emic” perspectives in information fusion!**

15

Questions?

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16

The Importance of the “emic” Perspective in Information Fusion

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ABSTRACT

In order to conduct “full-spectrum cross-domain operations in volatile, uncertain, complex, and ambiguous environments around the globe”[1], it is important to provide decision makers with the information they need, from traditional and non-traditional sources (open source, social media). The information needs to be fused and presented in a way to maximally support meaning making about not only “what” is happening but also “why”. To develop a more complete understanding of a current or future situation or event requires the ability to go beyond the fusion of “data”, or even information, to the fusion of perspectives -- the “etic”, or third person, and “emic”, or first person, perspectives. This is something that storytellers do naturally; for example, storytellers will often use first person when there is a strong protagonist or main character that they want the audience to focus on[2]. When a reader gets “inside a character’s head”, they can gain an understanding of their motivations and worldview. Integration or fusion of “emic” information provides important clues/insights critically needed by analysts and decision makers for forecasting behavior and a more nuanced understanding of the situation and threat.

AFRL has been engaged in research aimed at enabling meaning making based on the “emic” perspective from discourse (text from a variety of open sources, including social media) for several years. Early research focused on the development of multi-lingual methodologies (Arabic and Pashto), documented in primers transitioned to operational customers, including the National Air and Space Intelligence Center. The methodologies enable the detection and interpretation of the discourse patterns related to social identity (in-group/out-group)[3]. Identification of these patterns enables forecasting of events (e.g., violence). Subsequent research developed methodologies to identify and interpret characteristic patterns or themes used to express or detect trust, trustworthiness in Farsi discourse and explored the link/influence between affect expressed in discourse and behaviors[4]. Recent research has focused on the development of semiautomatic methods to assess intent based on discourse analysis, resulting in text analytic and forecasting algorithms based on discourse markers related to social identity and integrative complexity [5].

“Etic” and “emic” are essentially different ways to view the same thing[6], a “stereoscopic window on the world.”[7] In initial “fusion” experiments combining “etic” (events analysis) and “emic” information from discourse and sentiment analysis, the discourse markers were twice as powerful/accurate for forecasting violence as the previous forecasting “gold standard”, event analysis. This provides confirmation of the value of integrating/fusing “emic” information and perspectives and provides the motivation for further research.

Keywords: “etic”, “emic”, perspective, information fusion, fusion, open source information, social media, meaning making, sensemaking, text analytics, discourse analysis, social identity, integrative complexity

1. INTRODUCTION

A recent vision document about the future of Air Force Intelligence, Surveillance and Reconnaissance (ISR), “Air Force ISR 2023”, talked about the need to not only conduct tactical intelligence, but also strategic intelligence collection in peacetime, Phase 0. The ISR enterprise must provide multi- and all-source intelligence in operations ranging from humanitarian relief to major-contingency operations in contested environments. This will inherently require “better collectors, enablers, and integrators” of information from multiple sources, including space, cyberspace, human and open sources. The goal of Air Force ISR is ultimately to be able to “analyze, inform, and provide commanders at every level with the knowledge they need to prevent surprise.”[8] To do so across the spectrum of conflict and operational domains will require the collection, processing, analysis and interpretation of information from various sources and perspectives, building an integrated picture of people, places, events/situations. Developing the necessary depth of understanding required will demand a layered approach: people moving back and forth from the objective “etic” perspective they have been trained to utilize to a subjective or “emic” understanding of what the categories (events, people, organizations, behaviors, language, etc.) mean.[9]

2.0 The “Emic” Perspective

“Emic”, originally derived from “phonemic” by linguist Kenneth Pike, refers to the native participant viewpoint, the 1st person perspective. This is contrasted with the “etic” (derived from “phonetic”, the study of sounds universally used in language) perspective that refers to the detached observer, 3rd person viewpoint. Pike sought to create an “emic” analysis of his data in order to understand which set of sounds conveyed specific meaning to native speakers of a language[10]. A simple example of this is the articulation of the English << wh >>, pronounced as in the word “when” (as if blowing out a candle). In an unknown language/culture, it is unclear if the sound is just a sound or part of the language; thus, context and the situation must be considered, as well as all the other vocal sounds in that language, in order to determine the meaning of the sound[11].

When applied to the study of human behavior, “etic” viewpoint connotes studying behavior “as from outside of a particular system” whereas “emic” viewpoint results from studying behavior as from inside the system.”[12] The “emic” perspective attempts to “capture participant’s indigenous meanings of real-world events”[13] and look at “things through the eyes of member of the culture being studied”[14]. Etic perspective, encompassing the external view of a culture, language, meaning associations and real-world events, is based on “etic” constructs: accounts, descriptions, and analyses expressed in terms of the conceptual schemes and categories regarded as meaningful and appropriate by…observers.” [15] It is impossible to achieve a solely “emic” perspective due to the inescapable subjectivity a person applies to each study/analysis based on their past, experiences, ideas and perspectives. However, if only the “etic” perspective is included, there is the possibility of overlooking hidden nuances, meanings and concepts.[16] Agar argued that both “etic” and “emic” are “both part of any understanding.”[17] Both perspectives are important and necessary for a nuanced understanding of people and events.

Storytellers naturally combine both “etic” and “emic” perspectives. Perspective or point of view is very important to a story, how the story is told, and what point of view has a technical effect or result. First person (“emic”) is accessible to the reader, but limits the storyteller’s perspective. 3rd person (“etic”) has the ability to move both internally and externally, but only with regards to the character the “lens” is attached to. Storytellers switch between perspectives based on strategic choices informed by the craft of telling stories and the context, based on how they want the reader to create meaning.[18]

In the context of information fusion for situation awareness or threat understanding, the “etic” and “emic” terms contrast the subjective/worldview filtered view of a situation/event/issue with that of a more objective/scientific/measurement based view. While both perspectives are necessary for an explanation of human thought and behavior, the current balance of sensor data collection/processing/analysis is overwhelming toward the “etic” perspective. An “outsider’s (etic) perspective can never fully capture what it really means to be part of the culture.”[19] “Emic” information provides unique insights and important early indicators or signals of impending action/violence as well as important context to enable meaning making beyond target detection or identification.

3.0 Discourse Analysis for “emic” Perspective

The Air Force Research Laboratory (AFRL) has been engaged for several years in research aimed at enabling meaning making from discourse, particularly focusing on the “emic” perspective. Early research developed multi-lingual methodologies (Arabic and Pashto), documented in primers transitioned to operational customers, including the National Air and Space Intelligence Center (NASIC), which enable the identification, extraction and interpretation of discourse related to social identity (in-group/out-group)[20]. A grounded theory approach, using human coders, was used to identify relevant discursive practices and patterns (themes and rhetorical devices), including intensifiers used to express social identity (e.g., expression of glorification, victimization, derogation). Key themes expressed in both Arabic and Pashto included intimacy, power, virtue, honor/shame. Shaheed, or martyr, was also important for the expression of in-group identity in Pashto.[21]

Subsequent research used the grounded theory approach to develop a methodology to identify and interpret the language of trust, trustworthiness or distrust in Farsi. Key themes identified included: Islam, positive virtues, and advanced age and/or experience. Association with a trusted individual, expert citation, language related to intimacy and poetry were typically associated with trust. Conversely, distrust was conveyed in themes related to negative virtues and government agendas and by the use of figurative language such as metaphors and allusions.

A research effort to explore the link between affect and behaviors in a social system-of-system (government, dissidents, population) automatically coded eight classes of affect (trust, fear, surprise, sadness, disgust, anger, anticipation and joy). Quantitative models of the effects of emotions on behaviors of competing actors in Syria, Egypt and the Philippines illuminated similarities and differences in the influence of one group/organization on the other; for example, how affect (e.g., fear) expressed by the population influenced dissident behavior and government behaviors. In both Egypt and the Philippines, societal fear, anger and disgust expressed by the population/society toward dissidents resulted in increases in dissident hostility. Conversely, in Egypt, government hostility increased in response to societal disgust whereas in Philippines it decreased.[22]

Recent research has focused on the development of automated discourse analysis techniques to extract information related to group identity and intent in order to forecast violence, identifying computational methods to extract markers related to social identity and integrative complexity. The latter is a concept which measures the extent to which a person or group recognizes perspective(s) or dimension(s) of an issue/situation/problem (differentiation) and integrates them and has been shown to be a reliable predictor of cooperation (increase) or violence (decrease).[23] A pilot study identified several independent features: idea density and vocabulary diversity (proxies for integrative cognitive complexity) as well as affect expressed regarding in-group and out-group. Initial results on forecasting Naxalite (People's Party) bombings were promising (.92 in sample, .8 out of sample correlation between model and actual bombings).[24] Subsequent research has explored enhancements to the original discourse analysis algorithms with new metrics, independent complexity indicators, such as "differentiation" and "integration", and content analysis that identified characteristic words and phrases used before, during and after attacks (e.g., "us" versus "them", loaded language, loyalty rhetoric, hedging rhetoric). The content analysis essentially identifies the perspectives or alternatives that are being differentiated and integrated. The enhanced algorithms demonstrated similar performance in forecasting violence. The forecasting results on an Al Qaeda case study were similar to the People's Party results.

4.0 Information Fusion?

A recent case study investigated the use of three different text analytic algorithms for forecasting violence by Boko Haram, a violent extremist group in Nigeria. Separate statistical forecasting models were developed for the features/markers extracted from the three text analytic methods. The first was based on event analysis[25]; that is, coding events (kidnapping, coup, bombing, etc.). The second was based on sentiment/affect analysis and the third was based on discourse analysis, using the markers related to social identity and integrative complexity. The events analysis based forecasting resulted in the predicted events correlating with actual events 36% of the time. The result based on sentiment analysis was slightly higher, 49%. The result based on the discourse markers was 69%. The "fused" result (all three in a single forecasting model) was 86%. Clearly, the emic perspective (sentiment and discourse analysis) is useful for forecasting; although, the best forecasting performance overall resulted from combining the events analysis ("etic") and the "emic" perspectives, as one would expect. This is a small step towards information fusion incorporating both "etic" and "emic" perspectives and much more research is needed to develop methods which incorporate sources of information other than text; however, the prospects are promising.

4.0 Conclusions

In order to be able to make meaning about human behavior requires both "etic" and "emic" perspectives. Without the "emic" perspective, it is difficult to impossible to have a nuanced understanding of an individual or group/organization in order to make meaning about a situation or threat and forecast and/or influence behavior. With social media and open source information gaining increased attention in terms of their value for analysis, it will be important to have methodologies and text analytics to filter, cue an analyst's attention and inform analysis and decision making. AFRL has developed both methodologies and text analytic algorithms to enable meaning making from the "emic" perspective. A limited, text-only experiment demonstrated the potential of fusing both "etic" and "emic" perspectives" in order to more accurately forecast extremist violence. Clearly more research is necessary to fully explore how to incorporate an "emic" perspective in information fusion. The challenge will be to do so in a way that does justice to both perspectives. LGen

Flynn wrote, "…one thing is certain: without integration, the entire decision-making process is compromised…Context is king. Achieving an understanding of what is happening—or will happen—comes from a truly integrated picture of an area, the situation, and the various personalities in it…."[26]

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NETWORK ATTACK MODELING WITH AND WITHOUT CONTEXT FUSION

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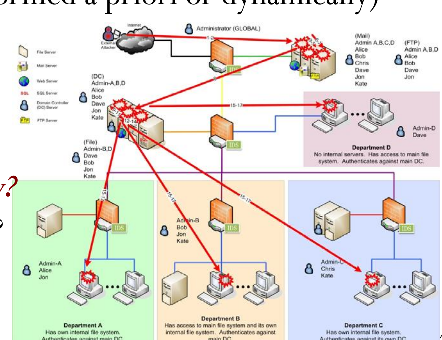
"Secure/reliable/resilient networks, systems &computation methods"

Network Attack Modeling

- Goal: to track, comprehend, synthesize, and predict network attacks (sequences of recons and exploitations)
  - Fusing large volume of incomplete, uncertain data from heterogeneous sources with potentially decoy and colluding activities.
- Without context: machine learning with basic features
  - E.g., host/flow clustering, alert correlation, and bot-net analysis, …
- With context: attack plans/paths (formed a priori or dynamically)
  - E.g., alert correlation, vulnerability analysis, attack prediction, and impact assessment, …
- ***How can computational models account for context automatically?***
  - Are context known w/ high fidelity?
    - Motivation/intent?
  - Can we extract context?

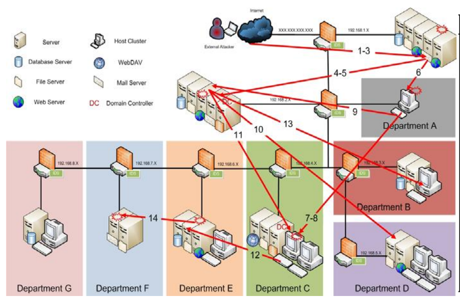


2

Fusing/Aggregating Predictions

- Fuzzy-VLMM combines predictions w.r.t. different attack attributes (attack methods, target IP, …) [Fava2008][Du2010]
- TBM combination of predictions based on Attacker Capability and Opportunity [Holsopple2008]
- Is one better than the other?
- Context or no context?
- Additional context?
- Should context part fusion process or as simply a way to interpret results?

	Net A	Net B Eff=0.8	Net B Eff=0.5	Net B Eff=0.3
TBM-CO	[75%,80%]	[59%,79%]	[55%,77%]	[54%,74%]
F-VLMM	[81%,88%]	[85%,88%]	[84%,88%]	[81%,84%]

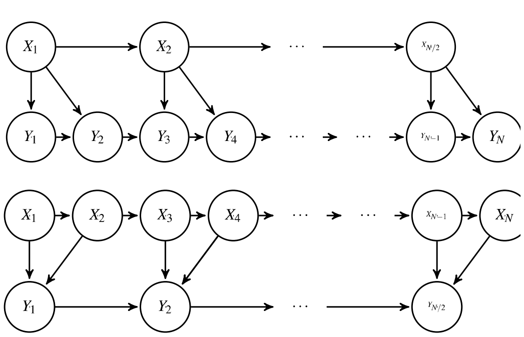


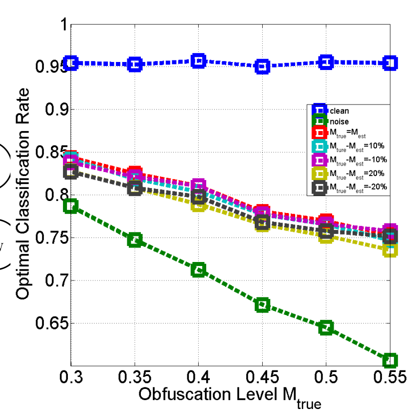
Step	Percentile Rank
1	N/A
2	[90.63%,93.75%]
3	[93.75%,96.88%]
4	[96.88%,100%]
5	[50.00%,53.13%]
6	[84.38%,87.50%]
7	[81.25%,84.38%]
8	[96.88%,100%]
9	[37.5%,40.63%]
10	[40.63%,43.75%]
11	[84.38%,87.5%]
12	[84.38%,87.5%]
13	[18.75%,21.88%]
14	[3.13%,6.25%]

3

Can context help de-obfuscate attack plans?

- From descriptive context (e.g., CAPEC, STIX) to computational models.
- Develop DBN Models to analyze the effect of attack obfuscation.
  - Noise Injection, Trace Removal, … [Du2014]





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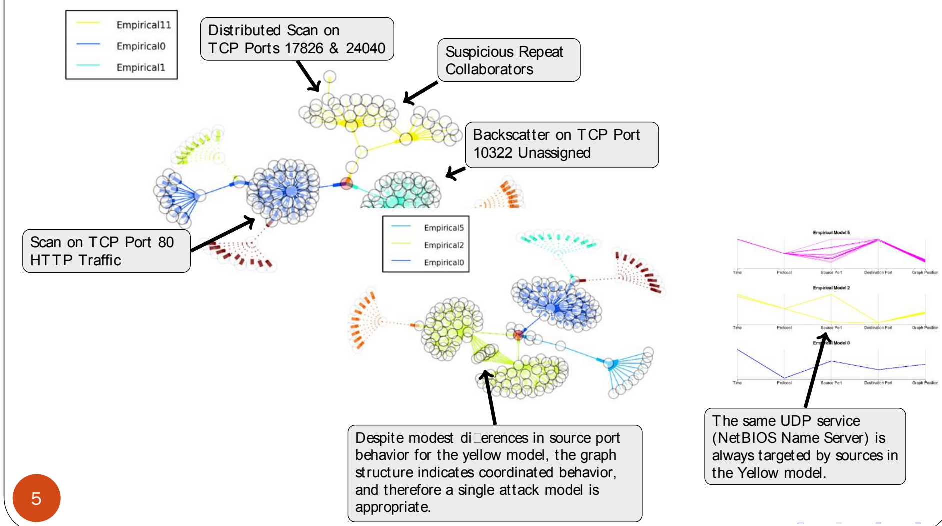
Can we extract context?

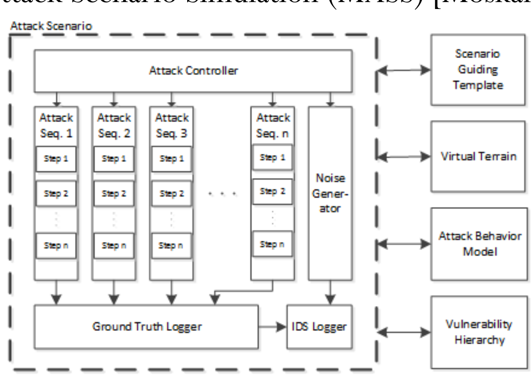
- Use semi-supervised learning to extract the spatial and temporal characteristics from real-world data [Strapp2014].



5

Can we generate attacks by fusing context?

- How to use extracted contexts, expert knowledge, and industry standards (e.g., CVE/CPE/CWE, CVSS, STIX, CAPEC), etc. to generate multistage network attacks?
  - Able to do it well means a success in context fusion – good contextual information and good way to combine the context.
- Multistage Attack Scenario Simulation (MASS) [Moskal2014]



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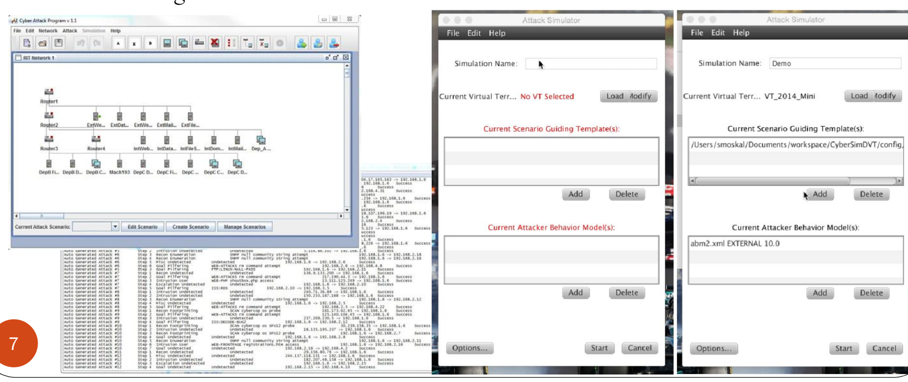
MASS: The Context Models

Scenario Guiding Template (SGT): defines the stages an attack sequence may include (observable or not) to reach the final goal of an attack scenario
Virtual Terrain (VT.2): defines the assets, their services, their vulnerabilities, the accessibilities between the assets, the sensors, and the sensor ranges.

Attack Behavior Models (ABM): each defines the preference of attackers, whereas the preference can be w.r.t. the SGT stages, VT asset/service types, specific attack actions, stealthy, decoy actions, etc.
Vulnerability Hierarchy (VH): Cyber VM: CWE-type, CWE, CPE, CVE, Alerts; (CWE-Type will map to SGT stages)



7

MASS: Sample Outputs

- Ground Truth: step-by-step attack actions

```
Attack 1, Stage 1, Step 0   SUCCESSFUL:     58.205.112.87   ->  192.168.95.150  (Reconnaissance->Network Scan->Generic
Attack 1, Stage 1, Step 1   SUCCESSFUL:     58.205.112.87   ->  192.168.95.150  (Reconnaissance->Service Scan->Generic
Attack 1, Stage 1, Step 2   SUCCESSFUL:     58.205.112.87   ->  192.168.95.150  (Read memory->20->lexmark:e240->CVE-20
Attack 1, Stage 1, Step 3   SUCCESSFUL:     58.205.112.87   ->  192.168.119.152 (Reconnaissance->Service Scan->Generic
Attack 1, Stage 1, Step 4   SUCCESSFUL:     58.205.112.87   ->  192.168.119.152 (Read memory->20->google:chrome:25.0.1
Attack 1, Stage 1, Step 5   UNSUCCESSFUL:   192.168.119.152 ->  192.168.25.26   (Reconnaissance->Network Scan->Generic
Attack 1, Stage 1, Step 5   SUCCESSFUL:     192.168.119.152 ->  192.168.25.26   (Reconnaissance->Network Scan->Generic
Attack 1, Stage 1, Step 6   SUCCESSFUL:     192.168.119.152 ->  192.168.25.26   (Reconnaissance->Service Scan->Generic
Attack 1, Stage 1, Step 7   SUCCESSFUL:     192.168.119.152 ->  192.168.25.26   (Read files or directories->20->mozill
Attack 1, Stage 2, Step 9   UNSUCCESSFUL:   192.168.25.26   ->  192.168.180.36  (Node Discovered)
Attack 1, Stage 2, Step 10  SUCCESSFUL:     192.168.119.152 ->  192.168.25.26   (Reconnaissance->Service Scan->Generic
Attack 1, Stage 3, Step 11  SUCCESSFUL:     192.168.119.152 ->  192.168.25.26   (DoS: resource consumption (memory)->2
```

- Sensor outputs: each sensor reports observed actions, including noise.

```
07/21-16:58:45.968466 [**] [1:23577:2] FILE-OTHER VLC mms hostname buffer overflow attempt [**] [Classification
07/21-17:49:55.567872 [**] [1:24283:1] FILE-MULTIMEDIA Microsoft Windows DirectX quartz.dll MJPEG content proce
07/21-18:29:34.596748 [**] [1:2049:7] SQL ping attempt [**] [Classification: Misc activity] [Priority: 3] {tcp}
07/21-20:29:30.814650 [**] [1:15432:9] SERVER-WEBAPP wordpress cat parameter arbitrary file execution attempt ['
07/21-21:07:57.189529 [**] [1:2049:7] SQL ping attempt [**] [Classification: Misc activity] [Priority: 3] {tcp}

     192.168.252.157 ->  192.168.147.124 sp5xdec.c in the Sunplus SP5X JPEG decoder in libavcodec in FFmpeg b
     192.168.191.90  ->  192.168.147.124 Stack-based buffer overflow in VideoLAN VLC media player before 2.0.
     192.168.203.13  ->  192.168.147.124 Race condition in the VRF-aware NAT feature in Cisco IOS 12.2 throug
     192.168.252.157 ->  192.168.147.124 demux/mkv/mkv.hpp in the MKV demuxer plugin in VideoLAN VLC media pl
     192.168.203.13  ->  192.168.147.124 SQL injection vulnerability in Best Practical Solutions RT 2.x and 3
     192.168.195.227 ->  192.168.147.124 Multiple cross-site scripting (XSS) vulnerabilities in Best Practica
     192.168.252.157 ->  192.168.147.124 Heap-based buffer overflow in the Ogg DecodePacket function in the O
```

8

So where do we stand?

- ✓ Context helps network attack modeling when we have it, or if we can generate it with high fidelity …
- ✓ A formal method to extract critical context (attribution) for computational models can be instrumental for Cyber SA …
- ✓ Formal simulation can be useful to test whether the context is important …

- ❖ Hard-soft fusion with contextual information is not covered here, but clearly important!

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Network Attack Modeling with and without Context

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ABSTRACT

Analyzing network attacks based on sensor observables has many similarities with other fusion problems where contextual information can benefit tracking and prediction of attack actions. This paper reviews a few existing context-based network attack modeling works and notes that only context with high fidelity should be used due to the diverse and constantly changing nature of network configurations and attack tactics. From there, this paper discusses the needs to extract critical attack features that can be used to synthesize or simulate attack scenarios comprehensively. Such approach may help reveal critical and rare attack scenarios by extrapolating from extracted attack features.

Keywords: Network Attack Analysis, Context Modeling, Cyber Situation Awareness

1. INTRODUCTION

Attacks onto enterprise networks often consist of multitudes of reconnaissance and/or exploitations, some of which may be observed and trigger one or more sensor outputs while others don't. The goal of network attack modeling is to track, comprehend, synthesize, and predict network attacks based upon these observables. Similar to other fusion problems, analyzing these observables faces the challenge of handling large volume and high velocity of incomplete, uncertain data from heterogeneous sources with potentially decoy and colluding activities. Over the past 15~20 years, the research community has analyzed network attacks with and without context, and both have shown success and limitations.

Generally speaking, one may categorize network attack modeling without context as those utilize machine learning techniques with basic features directed derived from raw data. These include host clustering, flow clustering, alert correlation, and bot-net analysis among others. On the other hand, many research works develop a priori models to represent how specific attacks may transpire using Bayesian Networks or other graph models, or how attacks may impact the mission of the network. Some have even attempted to dynamically update or generate attack models from sensor outputs. The effectiveness of using specific context to track, comprehend, synthesize, and predict network attacks depends heavily on whether the context is known with high fidelity. For example, obtaining up-to-date and accurate configuration and vulnerability information of a large-scale enterprise network is very challenging in practice. Likewise, the intent and tactics of advanced attackers is unlikely to be known a priori, and can change rapidly while the attack actions are being observed.

This paper summarizes a few existing works where context is applied in predicting attack actions and analyzing attack obfuscation techniques, as well as discusses whether context can be extracted and simulated.

2. APPLYING CONTEXT TO NETWORK ATTACK MODELING

Attack Prediction

Fava *et al.* [1], Du *et al.* [2], and Holsopple and Yang [3] have developed algorithms to predict attack actions based on observations of ongoing malicious activities. The Variable Length Markov Model (VLMM) Predictor developed by Fava *et al.* [1] is an adaptive learning algorithm that aggregates the joint effect of sequential patterns of different lengths from observables. Each attribute extracted from intrusion sensor observables produces one VLMM predictor, and Du *et al.* [2] combines the different predictors using Fuzzy rules. The resulting algorithm is called Fuzzy-VLMM or F-VLMM in short. Holsopple and Yang [3], on the other hand, developed a framework to analyze adversary capability and opportunity based on where the attacker has visited in the network. Du *et al.* [2] further expanded that approach and applied Transfer Belief Model (TBM) to combine the predictions based on capability and opportunity assessments. F-VLMM depends very little on context except the creation of the Fuzzy rules, while TBM-CO depends heavily on the

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network configuration to estimate the adversary's capability (what services can be exploited) and opportunity (what vulnerabilities are exposed).

Analyzing the two algorithms together, shows that F-VLMM outperforms TBM-CO in most cases. This is because 1) the attacker repeat certain attack patterns for much of the tested dataset, and 2) there are too many exposed vulnerabilities and the attackers are quite capable, resulting in a large prediction space with little differentiation using TBM-CO. While in most cases F-VLMM performs well, it suffers when the attacker changes behavior; in such cases, TBM-CO can ensure the exposed vulnerabilities that the attacker is capable of exploiting are not overlooked. The above observations suggest that applying context can sometimes helpful but misleading in other cases. Applying more advanced expert knowledge to combine various predictors, *e.g.,* dynamically adjusting weights to TBM-CO versus F-VLMM, as part of an ensemble approach is expected to enhance the overall performance.

De-obfuscating Network Attacks

A particularly challenging aspect of network attack analysis is to deal with the high noise or obfuscation level embedded in observables containing signals of critical attacks. Du and Yang [4] developed a set of Dynamic Bayesian Network (DBN) models to capture various types of obfuscation techniques, including noise insertion and trace removal. These models are developed based on expert knowledge, context provided through descriptions of how obfuscations may occur along side true objectives of network attacks. Using these models allow one to determine the optimal level of recovering true attack strategies in the presence of the different obfuscation techniques.

Extracting Context of Network Attacks

It is clear that context can help network attack analysis, if the context matches well to the scenario being analyzed. Unfortunately, both network configurations/vulnerabilities and attack tactics are changing rapidly and expert knowledge is often lagging behind to provide context with high fidelity. An interesting question then is whether one can extract context from data near real-time, and extrapolate from such context to generate comprehensive attack scenarios via simulation.

Strapp and Yang [5] developed a semi-supervised learning framework where attack data can be processed in near real-time to produce attack features for each cluster of observables. The observables are clustered to differentiate attack behaviors. Preliminary results have shown success in clustering observables and revealing distinct attack behaviors. This ongoing work will continue to develop effective means to extract critical attack features and context based on which network attack models can be built.

Simulating Network Attacks with Context

With sufficient contextual information, one is expected to synthesize or simulate network attacks. In fact, if critical attack features can be identified, simulating based on extrapolating values from these features can potentially reveal attack scenarios that are not easily observed. Moskal *et al.* [6] developed a simulation framework where four context models are fused to generate sequences of network attacks. The four context models are Network Virtual Terrain, Vulnerability Hierarchy, Scenario Guidance Template, and Attack Behavior Models. The separation of the context models allows the users to specify the contextual information without concerning the others. In fact, the simulation framework can generate attacks based on different combinations of the context models. It also helps to update the algorithms developed in one context model without requiring others to change. Sample results have been reported in [6], showing how an attacker can navigate through an enterprise network to compromise a SQL server.

3. CONCLUSION

This short paper summarizes some of the existing works that apply or extract context to analyze network attacks. These examples and others have demonstrated that network configurations and attack tactics can be helpful for network attack modeling, but only if the context is known with high fidelity. It is not an uncommon knowledge that network and system configurations / vulnerabilities is rapidly changing and thus very challenging to maintain and recorded. Furthermore, attack strategies are diverse and constantly evolving. Because of these, it is desirable to have a near real-time process that can extract critical attack features and apply such contextual information to a simulator where comprehensive attack scenarios, including the potentially rare yet critical ones, can be synthesized and analyzed.

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Impacts of Fusion and Context on Tracking and Anomaly Detection in Videos

Alex Lipchen Chan, Ph.D.
US Army Research Laboratory
20 Apr 2015

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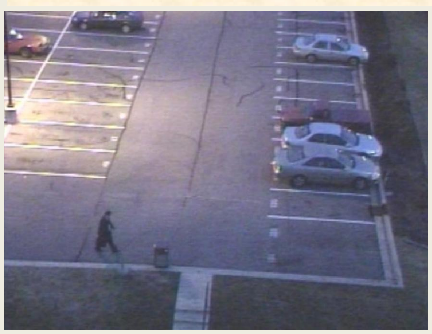
Impact of Fusion on Tracking

- **Data level fusion:** can EO-IR image fusion improve the tracking performance of a given tracker?
- **FPSS Dataset:** Coarsely co-registered, concurrent, and ground-truthed color-FLIR videos of staged activities are used as testing dataset.



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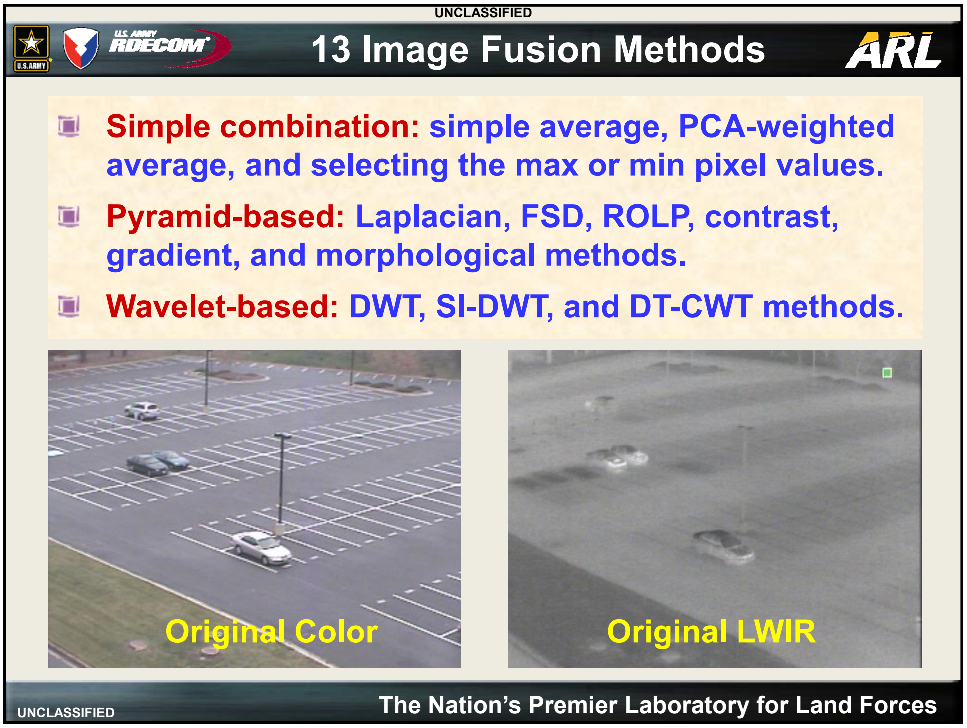
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U.S. ARMY
U.S. ARMY RDECOM
13 Image Fusion Methods
ARL
Simple combination: simple average, PCA-weighted average, and selecting the max or min pixel values.
Pyramid-based: Laplacian, FSD, ROLP, contrast, gradient, and morphological methods.
Wavelet-based: DWT, SI-DWT, and DT-CWT methods.
Original Color
Original LWIR
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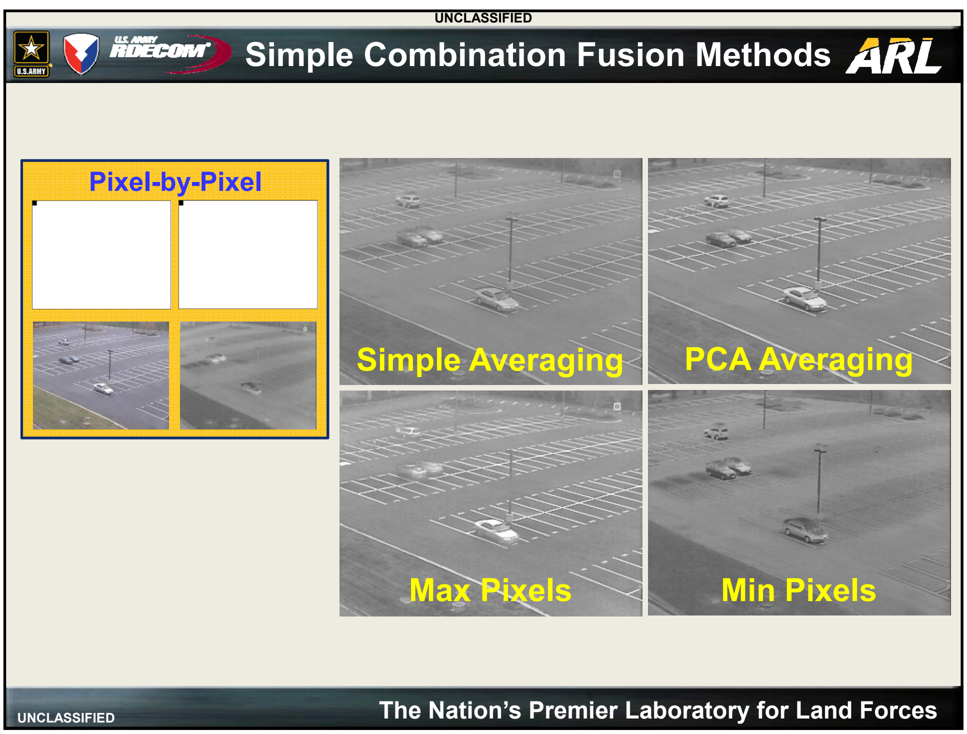
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Simple Combination Fusion Methods
ARL
Pixel-by-Pixel
Simple Averaging
PCA Averaging
Max Pixels
Min Pixels
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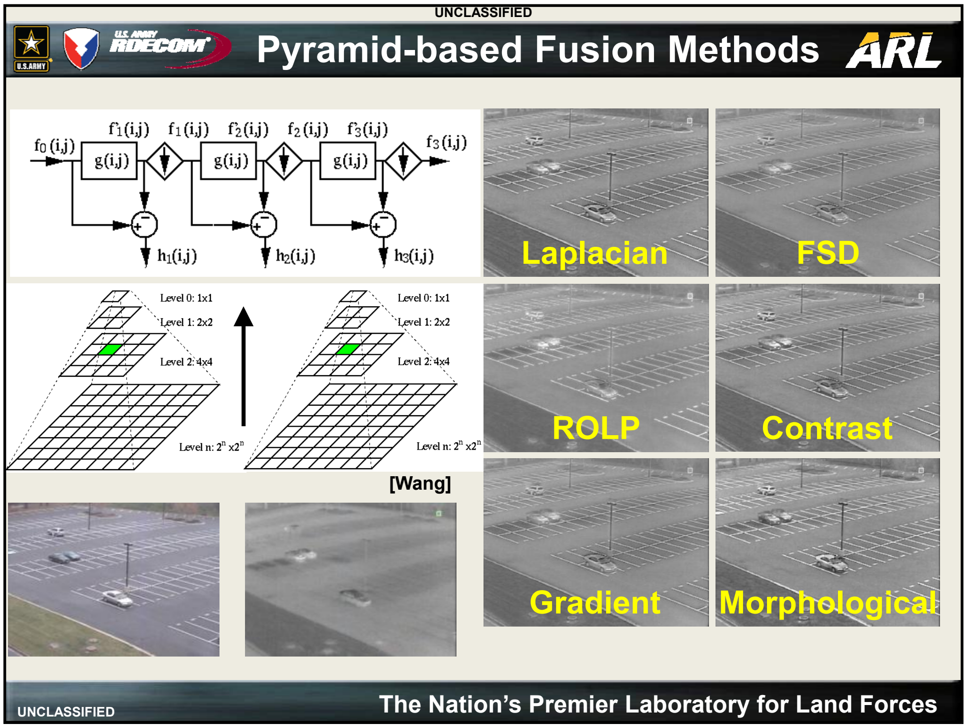
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Pyramid-based Fusion Methods
ARL
f0 (i,j)
f1(i,j)
f2(i,j)
f3(i,j)
g(i,j)
h1(i,j)
h2(i,j)
h3(i,j)
Level 0: 1x1
Level 1: 2x2
Level 2: 4x4
Level n: 2^n x2^n
[Wang]
Laplacian
FSD
ROLP
Contrast
Gradient
Morphological
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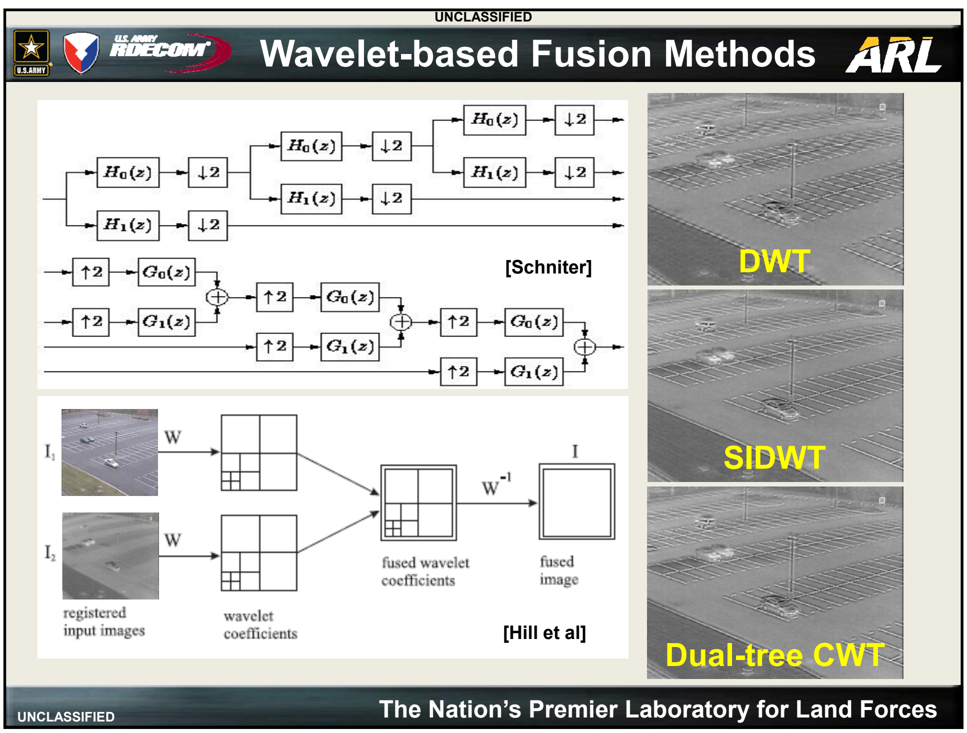
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Wavelet-based Fusion Methods
ARL
H0(z)
H1(z)
↓2
↑2
G0(z)
G1(z)
[Schniter]
I1
I2
W
W-1
I
registered input images
wavelet coefficients
fused wavelet coefficients
fused image
[Hill et al]
DWT
SIDWT
Dual-tree CWT
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Complexity of Fusion Methods

CPU seconds: needed to fuse 30 pairs of images on a Dell T7400 workstation using Matlab code.

Simple methods	CPU time	Pyramid methods	CPU time	Wavelet methods	CPU time
Average	1.280	FSD	21.670	DWT	22.740
PCA	2.030	ROLP	23.050	DT-CWT	49.940
Max pixel	1.560	Contrast	23.240	SIDWT	209.600
Min pixel	1.840	Laplacian	24.040		
		Morpho	62.530		
		Gradient	78.970		

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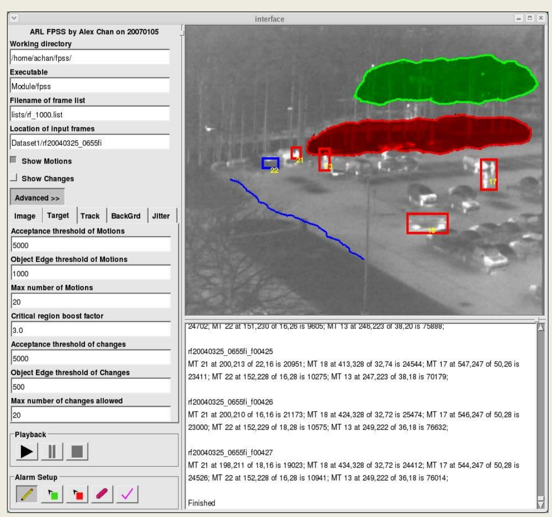
FPSS Target Tracking Algorithm

- **Algorithm:** FPSS is an efficient target tracking algorithm based on adaptive background modeling method.
- **Role:** to examine the impacts of different image fusion methods on target tracking performance.



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Hit Rates at 0.02 FAR

Simple methods	HR / FAR	Inferior pyramid / wavelet	HR / FAR	Superior pyramid / wavelet	HR / FAR
Average	56.14 / 0.02005	FSD	60.34 / 0.02008	Laplacian	73.51 / 0.02008
PCA	53.43 / 0.02008	Gradient	62.90 / 0.02005	ROLP	75.11 / 0.02005
Max pixel	55.71 / 0.02008	DWT	61.47 / 0.02008	Contrast	76.94 / 0.02005
Min pixel	56.17 / 0.02008	Morpho	40.27 / 0.02008	SIDWT	67.53 / 0.02005
				DT-CWT	73.80 / 0.02002

At 0.02 FAR, the hit rates for the original color and LWIR are 54.29% and 62.99%, respectively.

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Hit Rates at 0.8 FAR

Simple methods	HR / FAR	Inferior pyramid / wavelet	HR / FAR	Superior pyramid / wavelet	HR / FAR
Simple average	93.41 / 0.80183	FSD	91.93 / 0.80070	Laplacian	95.69 / 0.80087
PCA average	92.37 / 0.80025	Gradient	93.38 / 0.80343	ROLP	95.37 / 0.80040
Maximum pixel	94.77 / 0.80146	DWT	95.48 / 0.80023	Contrast	95.52 / 0.80048
Minimum pixel	90.92 / 0.80343	Morpho	94.88 / 0.80020	SIDWT	95.66 / 0.80068
				DT-CWT	95.69 / 0.80138

At 0.8 FAR, the hit rates for the original color and LWIR are 93.66% and 94.31%, respectively.

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Contextual Information

Question: can we improve the tracking performance if we know more than just pixel values?

- **Location:** Urban, rural, public, restricted, roadway, waterway? Any extra sensitive or don't care areas?
- **Time:** often affects traffic volume and direction, as well as efficacy of color and thermal cameras.
- **Day:** weekday, weekend, and holiday strongly influence the expected activities in many areas.
- **Season:** affects ambient temperature, vegetation, daylight hour, human clothing and activities, etc.
- **Weather:** linked to seasonal effects, but at shorter cycles and often produces drastic changes.

Effects of Location

- **Installation:** determine the gating and zoning needs, including privacy concerns.
- **Roadway:** determine the expected traffic types, volume, and direction.
- **Parking lot:** may have different traffic patterns depending where it is.
- **Wooded area:** affects traffic pattern and sensitivity; often the source of occlusions and false alarms.

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Effects of Time

- **Daylight effect:** color camera can't see well at night hours, but thermal camera is not affected much.
- **Tracker adaptations:** should give more weights to thermal camera as the darkness comes.

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Weekday-Weekend Effects

- **Big difference:** same parking lot, still packed on a Friday but almost deserted on next day.
- **Tracker adaptations:** different counting measure and sensitivity level may be needed.

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Seasonal Effects

ARL

- **Summer vs. Winter:** signatures of targets and environment often greatly changed or reversed.
- **Tracker adaptations:** different target and scene models may be needed for different seasons.

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Summer Storm Effects

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- **Drastic change:** two very different looks of the same scene within 1 hour of a summer afternoon.
- **Tracker adaptations:** different contrast and target silhouette settings may be needed.

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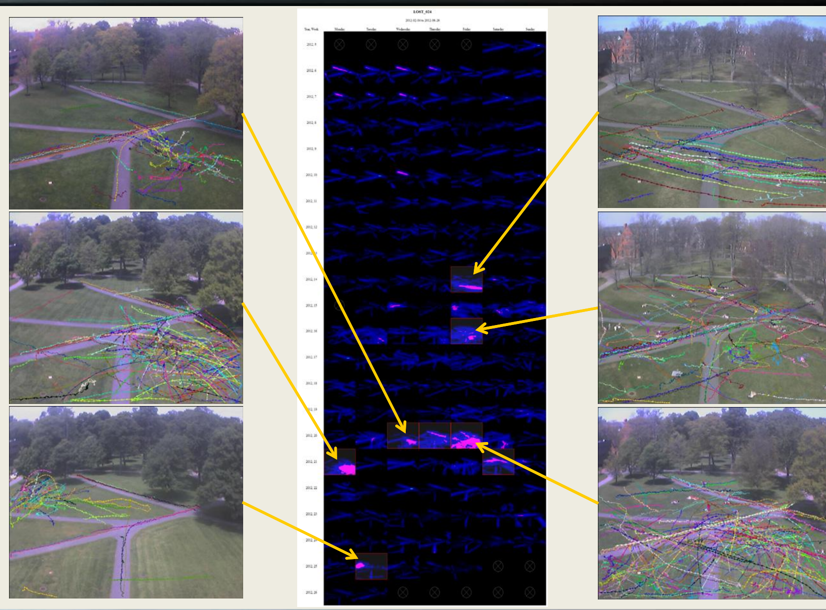
Long-term Anomaly Detection Example

ARL



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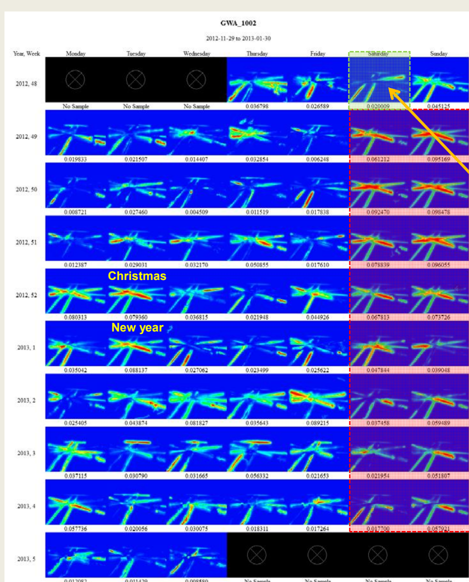
Problems With Global Comparison

ARL



- **Weekend anomalies:** Weekends often appear anomalous (red) due to lower activity, but this phenomenon is actually expected for weekends. One Saturday seems "less anomalous" since it's closer to the average.
- **Contextual adaptations:** need to separate the computation of weekends from that of weekdays, holidays from school days, etc.

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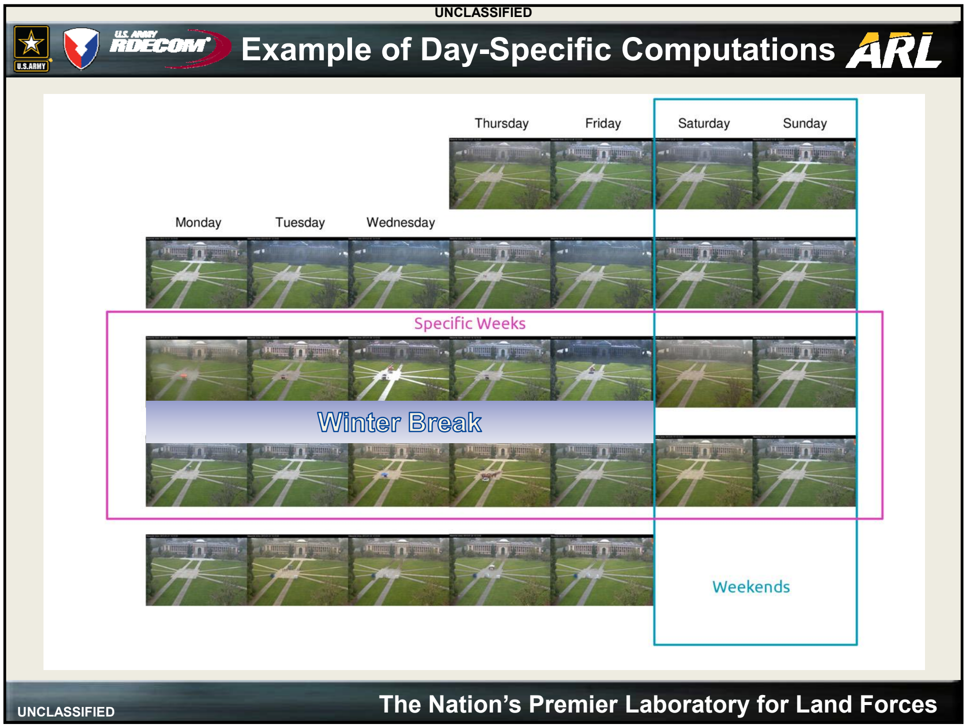
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Example of Day-Specific Computations
ARL
Thursday
Friday
Saturday
Sunday
Monday
Tuesday
Wednesday
Specific Weeks
Winter Break
Weekends
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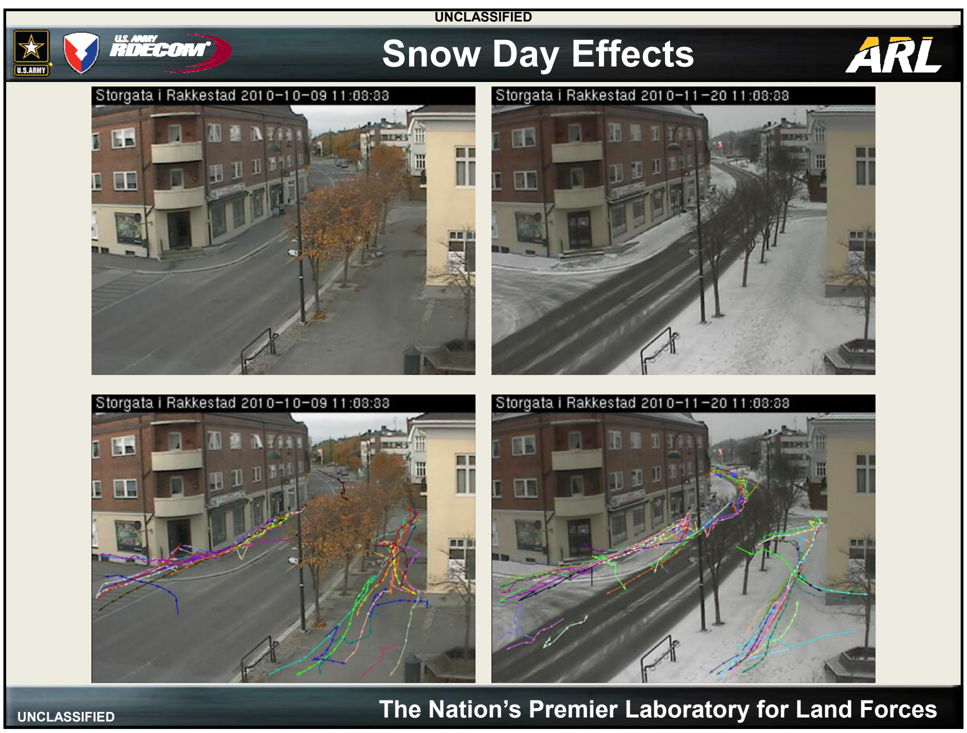
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Snow Day Effects
ARL
Storgata i Rakkestad 2010-10-09 11:08:33
Storgata i Rakkestad 2010-11-20 11:08:33
Storgata i Rakkestad 2010-10-09 11:08:33
Storgata i Rakkestad 2010-11-20 11:08:33
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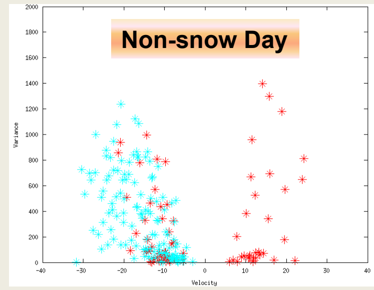
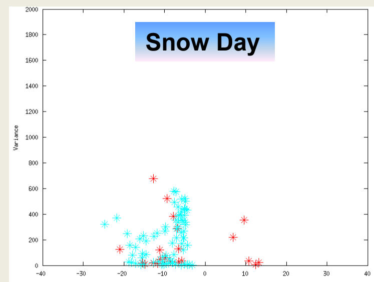
Track Analysis of Snow Day





- Fewer tracks on snow day
- Most people slow down
- Smaller variance in velocity
- Concentrate more on left side of the street

Conclusions

- **Impact of image fusion:** 5 out of the 13 image fusion methods presented here have improved tracking performance at any FAR.
- **Contextual information:** intuitively and empirically shown to be useful to improve the accuracy and efficiency of a tracker or anomaly detector.
- **Challenges:** 1) uncertain availability of meta data; 2) proper usage of meta data in algorithms; 3) diverse and varying nature of meta data; 4) complex coupling effects among meta data.

Impacts of Fusion and Context on Tracking and Anomaly Detection in Videos

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ABSTRACT

The performance of a moving target tracker or an anomaly activity detector can often be improved by fusing multi-modal sensor data and incorporating relevant contextual information. Using suitable image fusion methods, for example, we can demonstrate the improved tracking performance by fusing concurrent video streams from visible and infrared cameras. If suitable contextual information is available and incorporated into the same tracking algorithm, we are confident that an even better performance can be achieved. Similarly, when contextual information is available and exploited, many false alarms in an anomaly activity detector can be explained and avoided. In spite of these advantages in exploiting contextual information, many challenges persist in finding and incorporating the appropriate contextual information in practical applications.

Keywords: Tracking, anomaly detection, video, fusion, contextual information

1. IMPACT OF FUSION ON TRACKING PERFORMANCE

Visible and infrared (IR) cameras are the most common imaging sensors for force protection and video surveillance applications, but each has different advantages and disadvantages in operational scenarios. Due to their complementary strengths and limitations, it is logical to expect that a higher overall tracking performance can be achieved by acquiring concurrent visible and IR imageries and processing them jointly. Some earlier works in fusing visible and IR imageries, however, did not find the expected performance boost. For instance, Cvejic[1] et al. compared the tracking performance of a particle filter and found that the tracking performance was actually worsened by the fusion of images. Mihaylova[2] et al. showed that IR images alone performed just as well or better than most fusion algorithms in tracking, while visible images lagged behind under harsher conditions like occlusions.

In spite of these pessimistic results in the past, we went ahead in examining the effects of 13 common image fusion methods on the performance of a given moving target tracking algorithm using a large collection of concurrent color visible and long-wave IR (LWIR) video sequences that is referred to as the Second Dataset of the Force Protection Surveillance System (FPSS). The corresponding FPSS tracker[3], which is based on an adaptive background modeling method, was used to examine the tracking performance of all the selected image fusion methods. These 13 pixel-level image fusion methods can be categorized as simple combination methods, pyramid decomposition methods, and wavelet decomposition methods, respectively. Four intuitive pixel-level fusion methods under the simple combination category are simple averaging, intelligent weighting, and selecting maximum or minimum pixel values between the visible and LWIR images. The six pyramid-based fusion methods included in our study are the Laplacian pyramid, filter-subtract-decimate (FSD) pyramid, ratio-of-low-pass (ROLP) pyramid, contrast pyramid, gradient pyramid, and morphological pyramid methods. In the wavelet-based category, we compared the effects of discrete wavelet transform (DWT) using the Daubechies Symmetric Spline wavelet, shift-invariant DWT (SIDWT) using the Harr wavelet, and dual-tree complex wavelet transform (DT-CWT). The computational complexity varied widely between these 13 fusion methods. All nine pyramid or wavelet based methods are much more computationally intensive than the four simple combination methods, especially the SIDWT, gradient, and morphological pyramids.

As expected, all simple combination methods produced tracking performances that lied between those produced by the original color and LWIR images. The FSD, gradient, and DWT achieved slightly worse performance than the original LWIR images at low FARs, whereas the morphological pyramid method clearly lagged behind others under the same conditions. The remaining five fusion methods achieved good results at any false alarm rate (FAR): the Laplacian, ROLP, contrast, SIDWT, and DT-CWT fusion methods. At a low FAR of 0.02 FA per frame, for instance, the hit rates for the original color and LWIR images are 54.29% and 62.99%, respectively, while the corresponding hit rates of the

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images fused by contrast pyramid and ROLP pyramid methods are 76.94% and 75.11%, respectively. With improvements of about 14% over the LWIR images, the performance gains achieved by these two fusion methods are quite remarkable. Contrary to the negative findings in some earlier research, our experiments[4] have shown that certain pixel-level image fusion methods are useful in boosting the tracking performance beyond that achievable with either color or LWIR images alone.

2. EXPLOITATION OF CONTEXTUAL INFORMATION

In addition to fusing pixel-level information in the color and LWIR images, exploiting relevant contextual information associated with these images could conceivably further improve the overall tracking performance. Some contextual information, such as the time, date, weather, or geolocation information, may be more readily extractable from the image metadata, if the associated information were collected and embedded during the image generation process. Some other contextual information, such as holiday, office building, road network, parking lot, or wooded area, may need to be imported from external information sources or inferred from the images through scene understanding algorithms.

Given that the time and season have strong influences on the daylight intensity and ambient temperature in outdoor conditions, while the visible and IR imageries often exhibit complementary characteristics in different ambient lighting and temperature settings, overall tracking performance could be further improved if the visible and IR pixel information are fused more intelligently. For instance, the outputs of visible cameras are often hazy at dawn and dusk, while completely useless in pitch-dark night hours. IR cameras, however, perform the same or better in those hours. On the other hand, a bright summer mid-morning is great to visible cameras, but IR cameras may have a hard time to discern the fading human silhouettes from their surrounding due to the similar body and ambient temperatures in those hours. By weighing heavier on the tracking result from the more reliable sensor according to these time-related considerations, the overall tracking performance should be improved in theory.

Similarly, the weather condition and seasonal characteristics can be used to adjust the usefulness level of visible and IR cameras, as well as the parameters and models of the tracking algorithm, in order to achieve higher overall tracking performance. In a foggy morning or smoky afternoon, visible camera is almost useless, while IR camera can still see pretty well. Since both visible and IR signatures may change drastically when a summer afternoon storm swept through the surveillance area, different models or parameter settings of the image fusion and tracking algorithm may be needed to achieve higher tracking performance.

Recognizing the location and functionality of different infrastructures, such as office building, shopping area, road, parking lot, wooded area, and restricted area, is possible through scene analysis and insertion of external information. By incorporating these contextual information into the existing tracking requirements, higher tracking performance is achievable through the suppression of activities in don't care region, increased sensitivity in critical region, and more accurate modeling/prediction of traffic patterns within the scene. The accuracy of traffic modeling can be further improved by adding the weekday, weekend, and holiday factor into the calculation.

Some common difficulties in effectively using the contextual information in a target tracking application include the unavailability of metadata and relevant external information sources, finding the appropriate actuating point and strength to insert these contextual information, diverse and varying nature of contextual information, and the complex coupling effects among different contextual information types. Despite these challenges, small advances have been made by incorporating certain contextual information when they are available and understandable.

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