



Multi-Purpose Machine-Intelligence-based Information Fusion (FLASH)

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2007 Chemical Biological Information Systems (CBIS) Conference

10 January 2007

This material is based upon work supported by the National Science Foundation under Grant No. 0329901. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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Overview

Decision Support for diverse CBD applications

FLASH

Decision Support Architecture

Machine-Intelligence Multisource Information Fusion

Uncertain and Disparate Multisource Data (sensors and other sources)

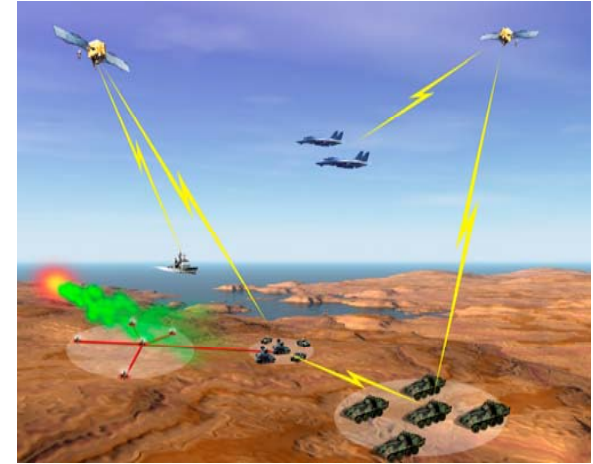
- **Problem**
 - Fusion, recognition and reasoning with uncertain and disparate data (from sensors and other information sources) for demanding decision-support applications, including complex phenomenology and absence of reliable models
- **Relevance**
 - Exploitation of multiple imperfect data sources is key to robust decision support for CBD systems
- **Solution**
 - Advanced algorithmic methods for **decision support**
 - **FLASH: novel cognitive-processing oriented machine-intelligence decision support architecture and methods**
 - **Broad applicability** to CB attack detection and characterization, facility protection, course-of-action guidance and other decision-support tasks



Motivation for FLASH Machine Intelligence Approach

- **CBD domain challenges**

- Complex phenomenology
- Limited reliability of models and processes
- Data inexactness and uncertainty



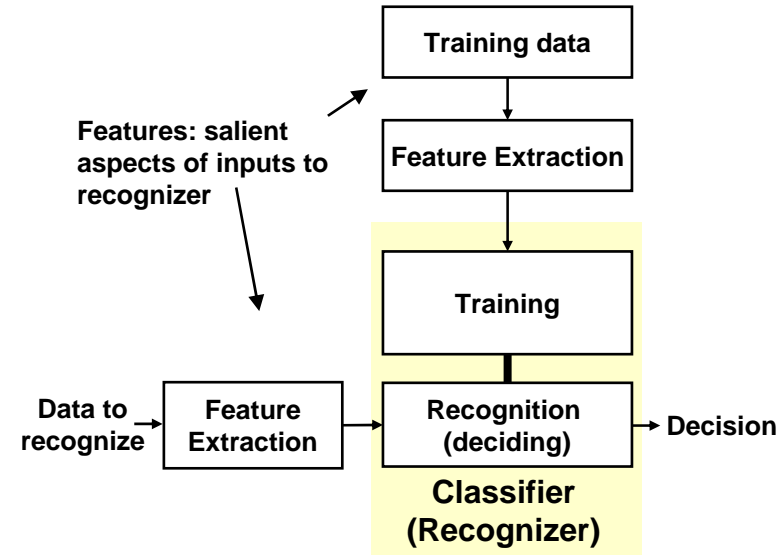
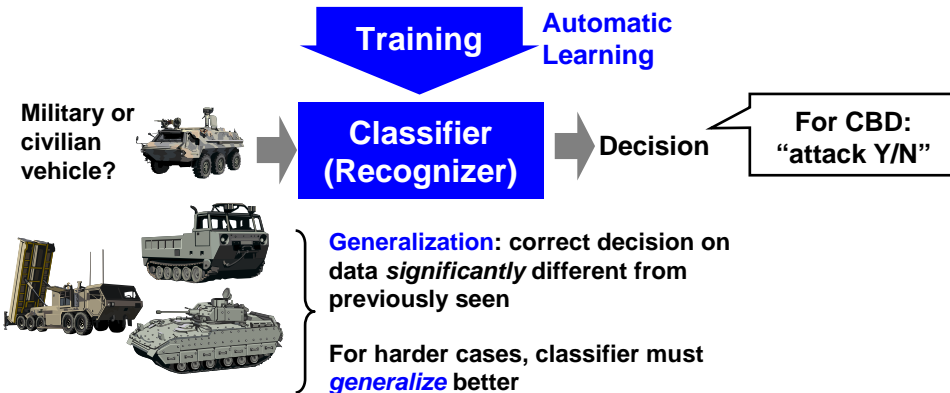
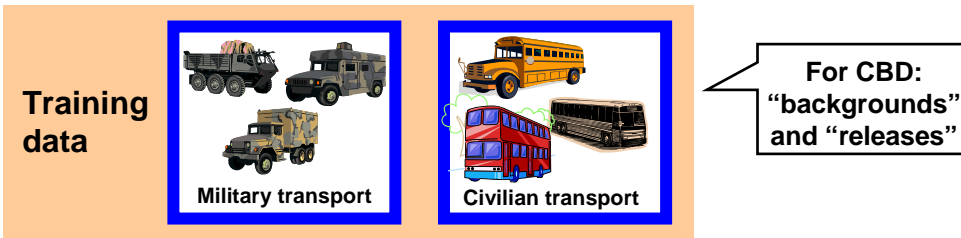
- **Machine-intelligence character of FLASH methods**

- Particularly suitable for demanding decision-support tasks such as CBD
- Generality of algorithmic methods offers potential of multi-purpose functionality
- Alleviate redevelopment problems and costs associated with proliferation of single-purpose approaches lacking scalability and migration capability
- Enable augmented cognition for warfighter, reduce information overload and enhance decision quality



Machine Intelligence and Machine Learning

- Paradigm shift from coding pre-known tasks to coding learning process itself
- Machine intelligence must include learning
 - Automatically *learn* from information embedded in data, to recognize/decide cases not-seen-before
 - Learning implies adaptability
- Cognitive systems – high-end machine-learning systems



Machine intelligence and machine learning alleviate need for precise models, adapt better to unanticipated conditions and different applications



Hybrid Approach

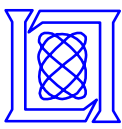
- **Information fusion = inference, recognition, reasoning, and decision-making**
 - Algorithmic process from multiple data sources to **decisions**
 - *Not* about networking, data collection and storage, etc.
- **Existent approaches to information fusion all have limitations**
 - Sample of method areas shown below
 - *Relative* strengths and weaknesses shown do *not* imply method applicability or inapplicability for particular task

	Perform inference	Cope with uncertain data	Cope with disparate data	Suitable for FF - feature fusion	Suitable for DF - decision fusion	Suitable for both FF and DF	Suitable for time-series
Classical signal processing	Relative Weakness	Relative Weakness	Relative Weakness	Relative Strength	Relative Weakness	Relative Weakness	Relative Strength
Bayesian methods	Relative Strength	Relative Strength	Relative Strength	Relative Strength	Relative Strength	Relative Strength	Relative Strength
Non-Bayesian methods	Relative Strength	Relative Strength	Relative Strength	Relative Strength	Relative Strength	Relative Strength	Relative Weakness
Estimation theory	Relative Strength	Relative Strength	Relative Weakness	Relative Strength	Relative Strength	Relative Strength	Relative Strength
Neural networks	Relative Strength	Relative Strength	Relative Strength	Relative Strength	Relative Strength	Relative Strength	Relative Strength

Relative Strength (Green)

Relative Weakness (Red)

We are developing hybrid approach to alleviate limitations of individual methods

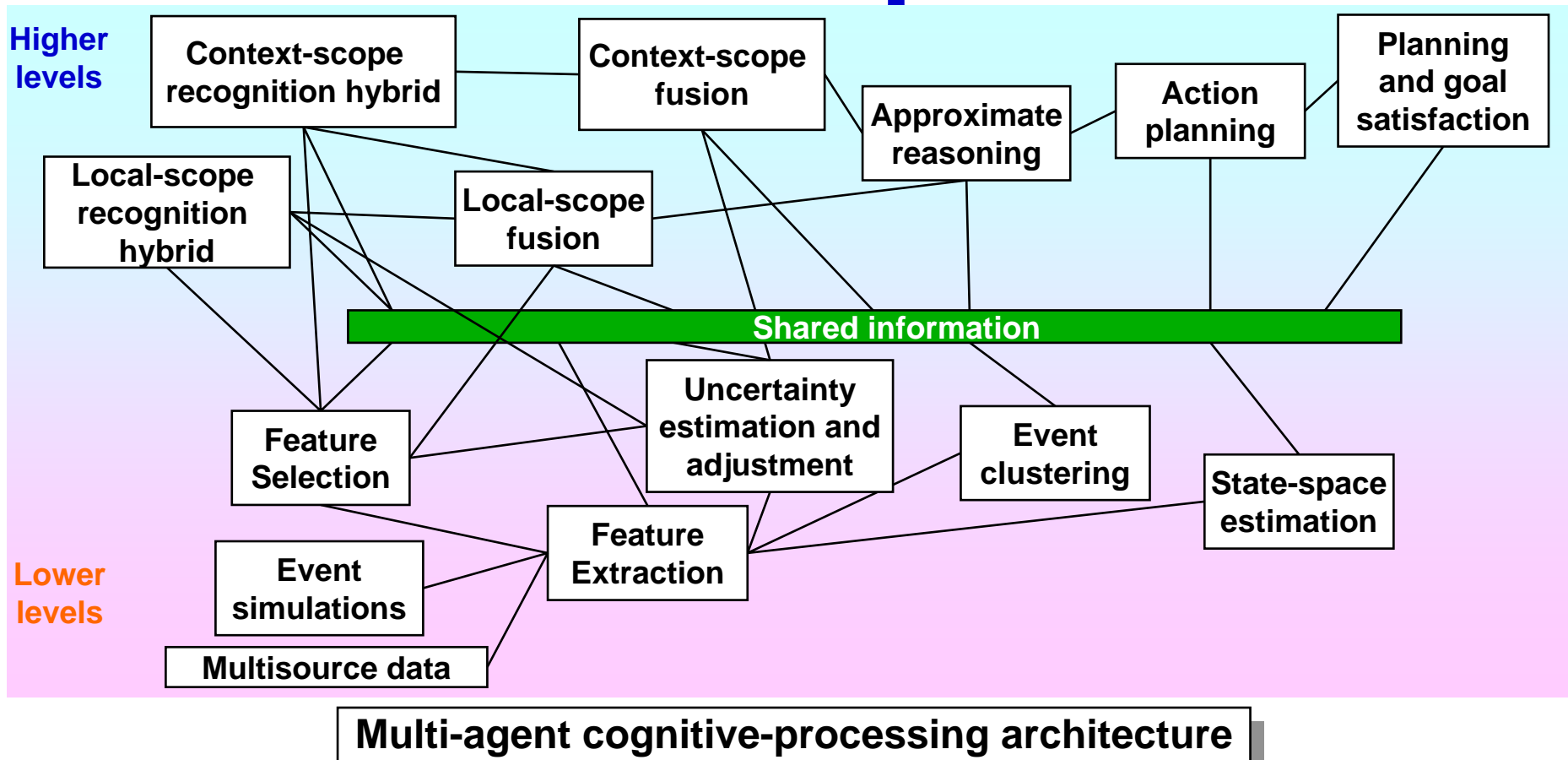


Conceptual View of FLASH

(Fusion, Learning, Adaptive Super-Hybrid)

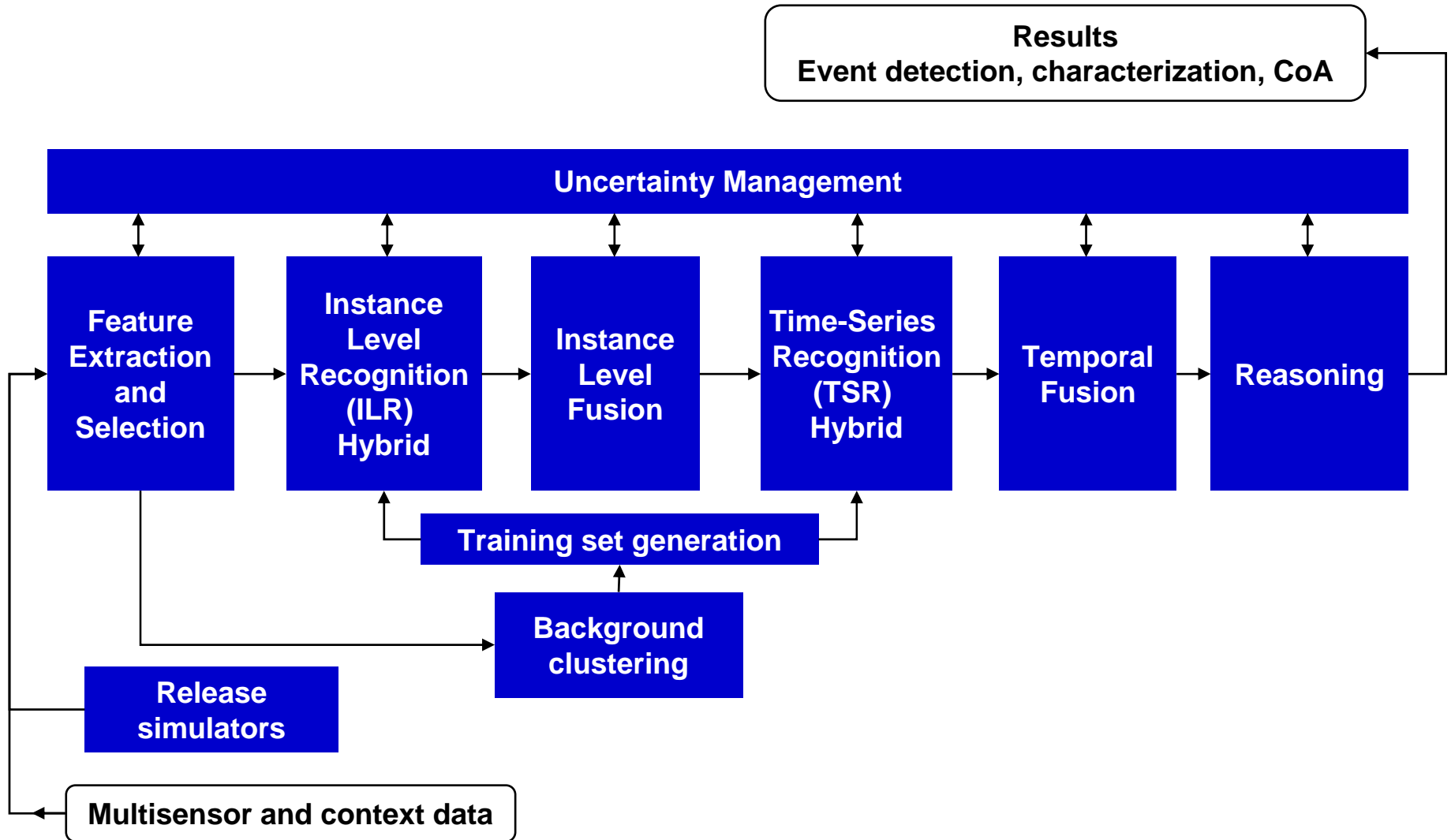
- FLASH integrates diverse machine-intelligence supervised and unsupervised learning and reasoning methods (subsystems, agents) at multiple levels
- Cognitive-processing architecture – inspired by neuroscience, cognitive studies

↪ Detection, characterization, tasking, COA



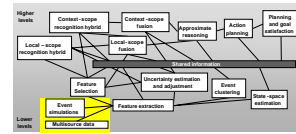


FLASH-1 Simplified Block Diagram





Multisensor Fusion Testbed



- Source of data for CB information fusion and decision support studies
- Portable for deployments in various settings
- Multiple multisensor nodes, easily reconfigurable, seamless addition of sensors
- Foundation for CB “common operating infrastructure”
- Multiple deployments within MIT LL and multi-month data collection campaigns
 - Office building environment
 - Cafeteria with complex background, including cooking facilities operation and proximity to outdoors

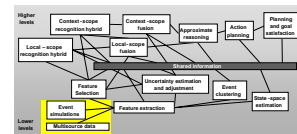


Node contents:

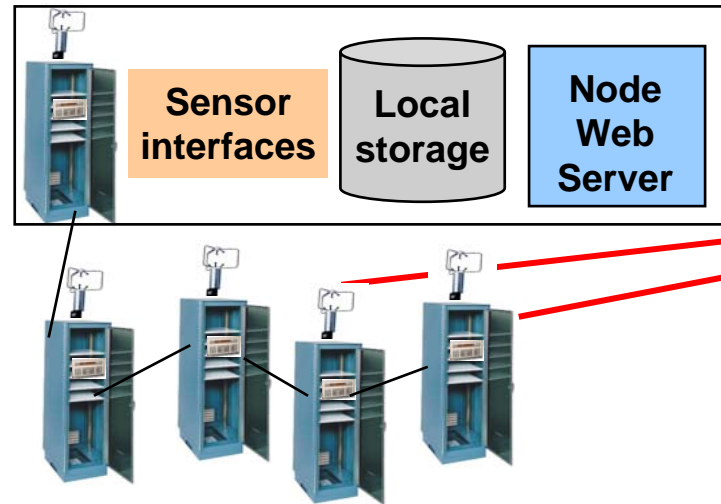
- Multiple optical particle counters
- MIT LL BAWs III
- Airflow sensor
- Space for additional sensors
- Cluster processor
- Power supply



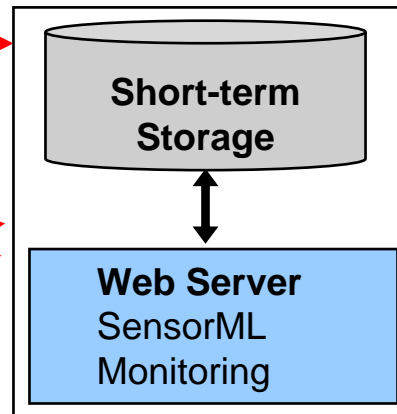
Testbed Data Management System



Multisensor Node Software

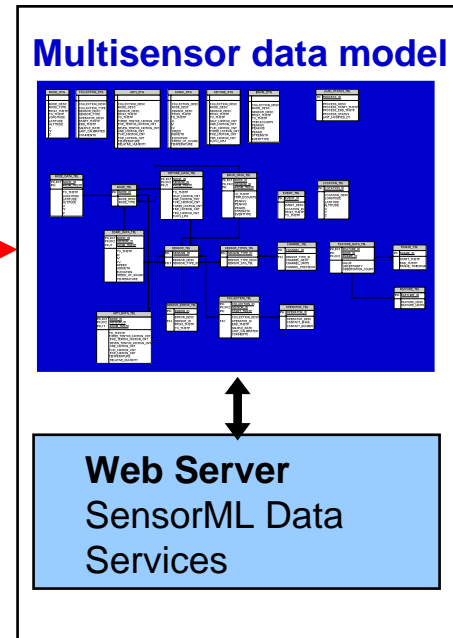


Remote Server

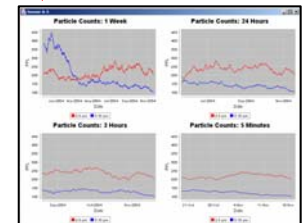


Periodic updates

Central Data Warehouse



Access via Web Services

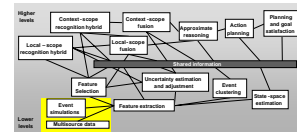


- Extensible and modular
- Encapsulate and insulate sensor specifics
- Data integrity and security
- Data model and warehouse for sensor-independent multisensor data management

Infrastructure suggested as blueprint for CB testbed efforts



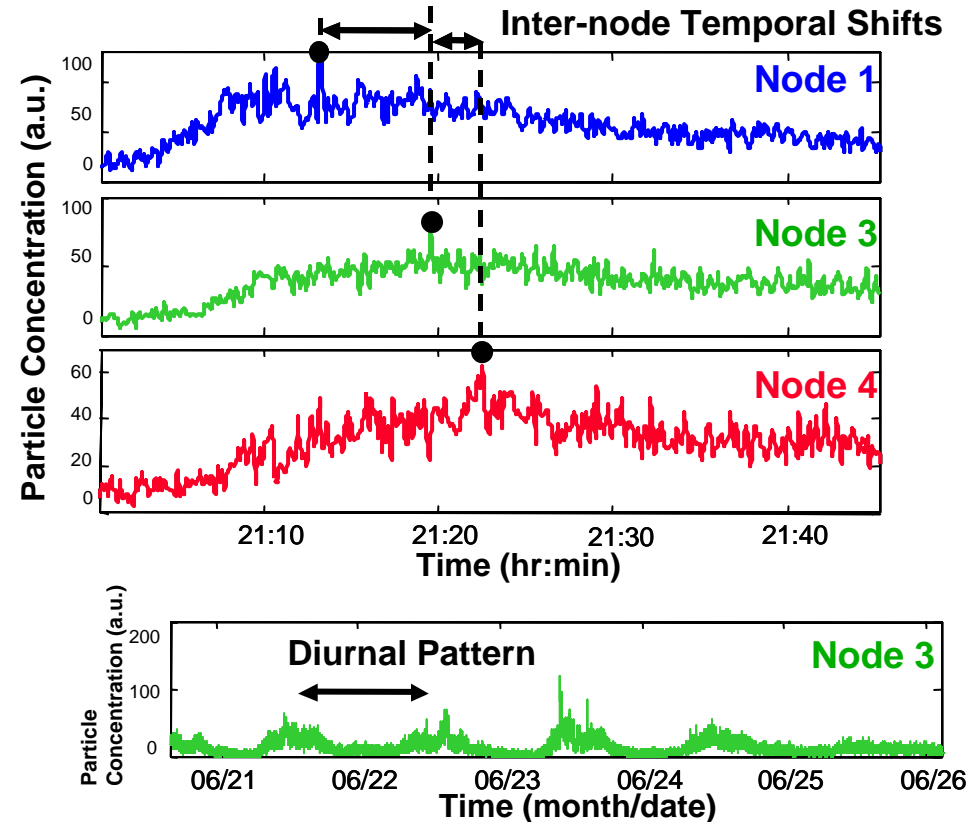
Background Data



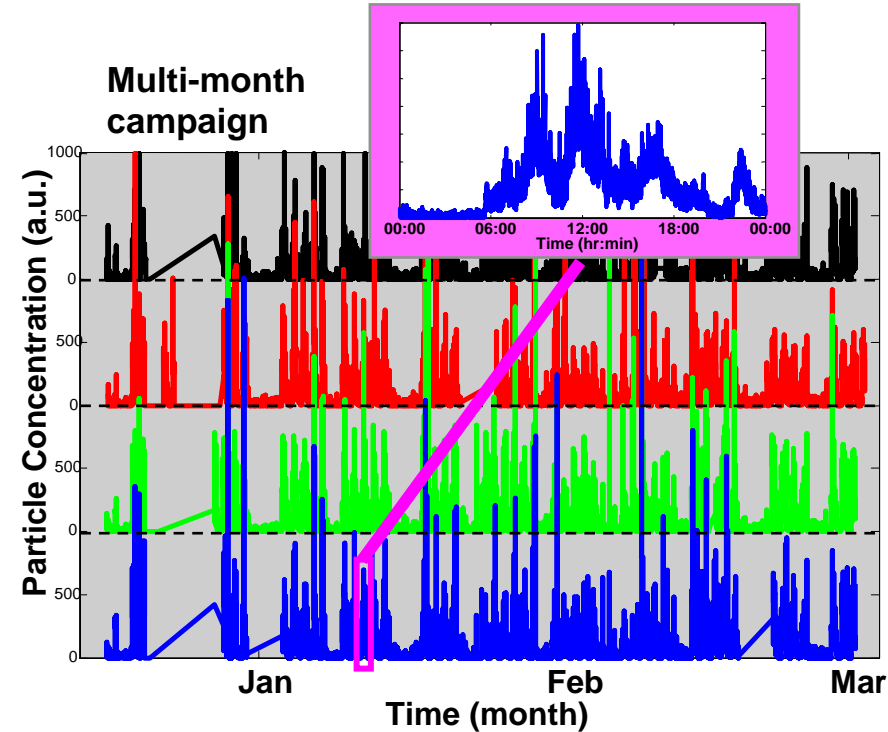
- Extensive indoor-background measurement campaigns conducted
- Collected data used for development of training datasets for machine learning
- Enable background characterization

Background data excerpts

Inter-node Temporal Shifts

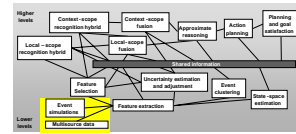


Multi-month campaign



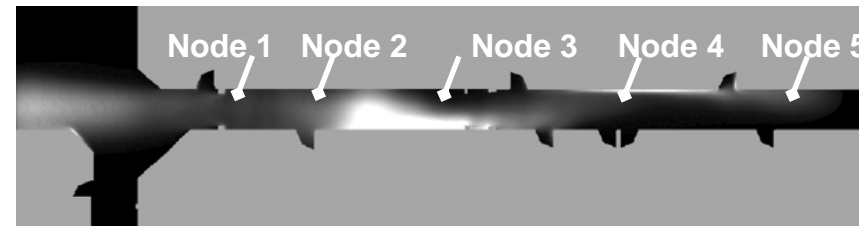
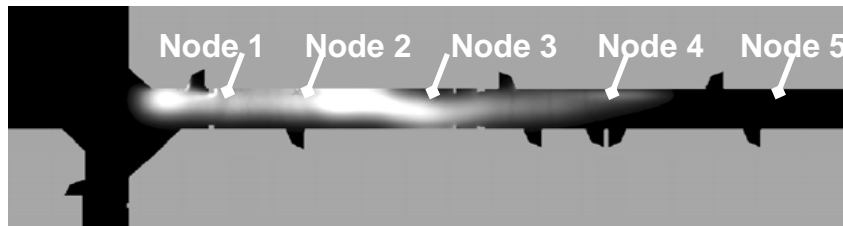


Release Data



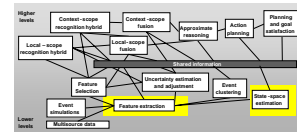
- **Stochastic simulation approach for efficient generation of multiple release-cases to support development of training and testing datasets**
- **Span parameter-space of plausible releases**
- **Computationally efficient, rudimentary T&D (transport and dispersion)**

Release simulation example



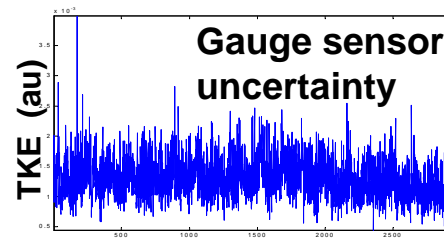
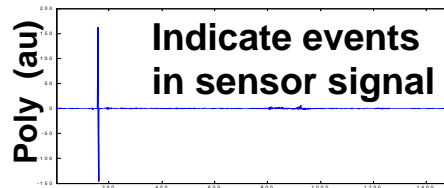
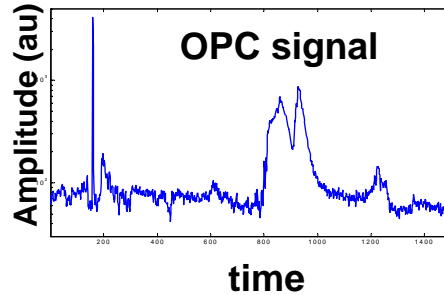


Multisensor Feature Extraction



- Feature design “from first principles” challenging in CB
 - Non-specific sensing modalities, complex T&D
- Diverse set of features, unconventional types and uses

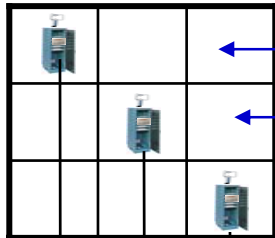
- Signal derivatives
- Entropy
- Histogram differences
- Covariances
- Fourier
- Wavelet
- Polynomial fit
- Turbulent kinetic energy
- Eddy dissipation
- and other...



Temporal localization features

Uncertainty management features

Virtual sensor features

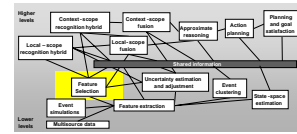


Dynamic modeling

Kalman or Particle filters estimate signal at locations without sensors

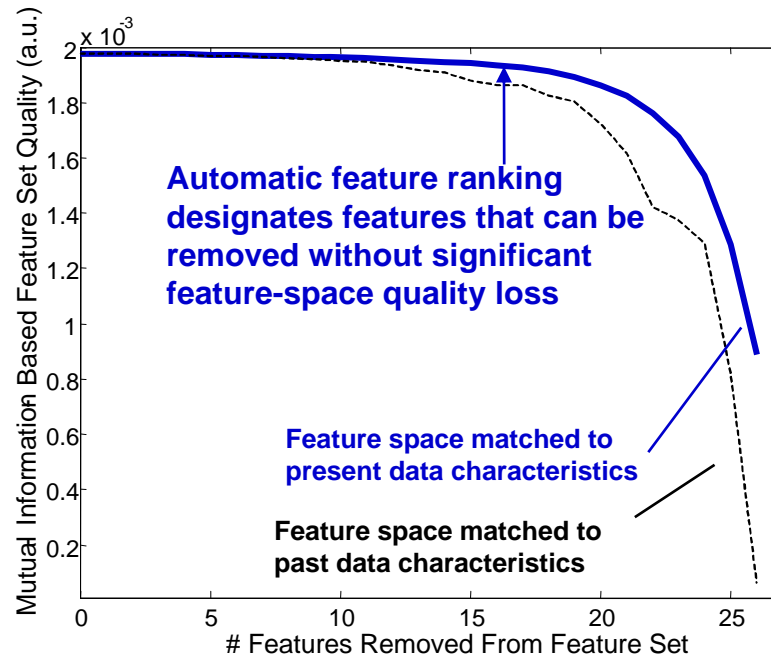


Feature Selection



- Classification task difficulty increases with number of features
- Feature selection automatically decides feature efficacy
- Classifier-independent feature selection methods developed
- Exploitable for dynamic feature space selection

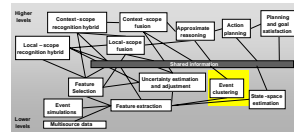
Information-theoretic approach
(mutual information maximization)
ranks features according to how
well they represent the data



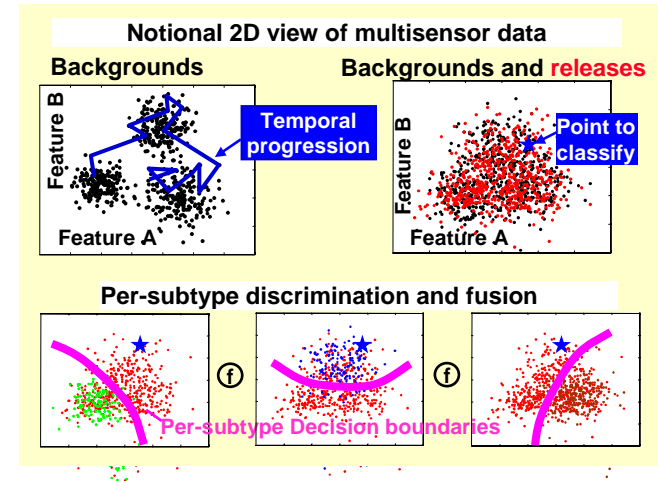
Classifier-independent feature selection approach



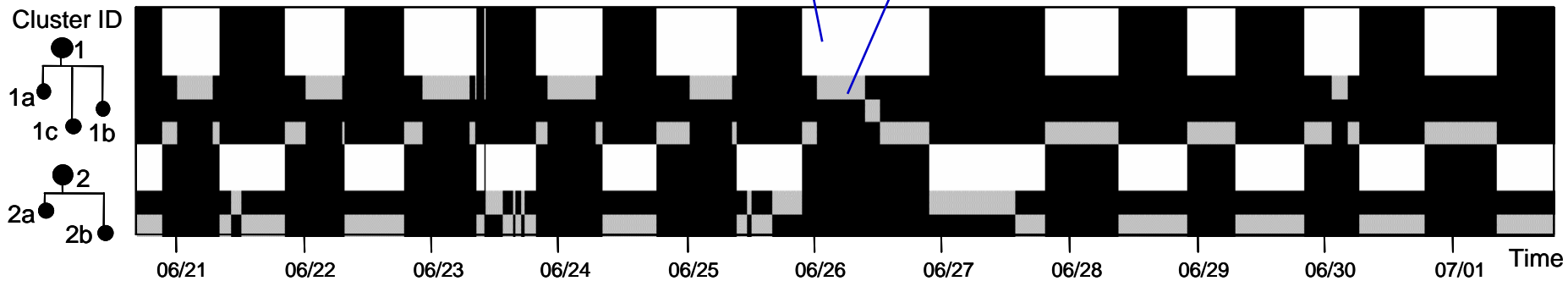
Background Clustering



- **Background vs. release discrimination difficult due to background dynamics**
- **Find background *subtypes* by clustering, and recast problem as set of easier tasks**
 - Subtype vs. release
- **Temporal clustering methods developed**
 - Enhancements over Adaptive Resonance Theory (ART) based clustering



Background clustering result

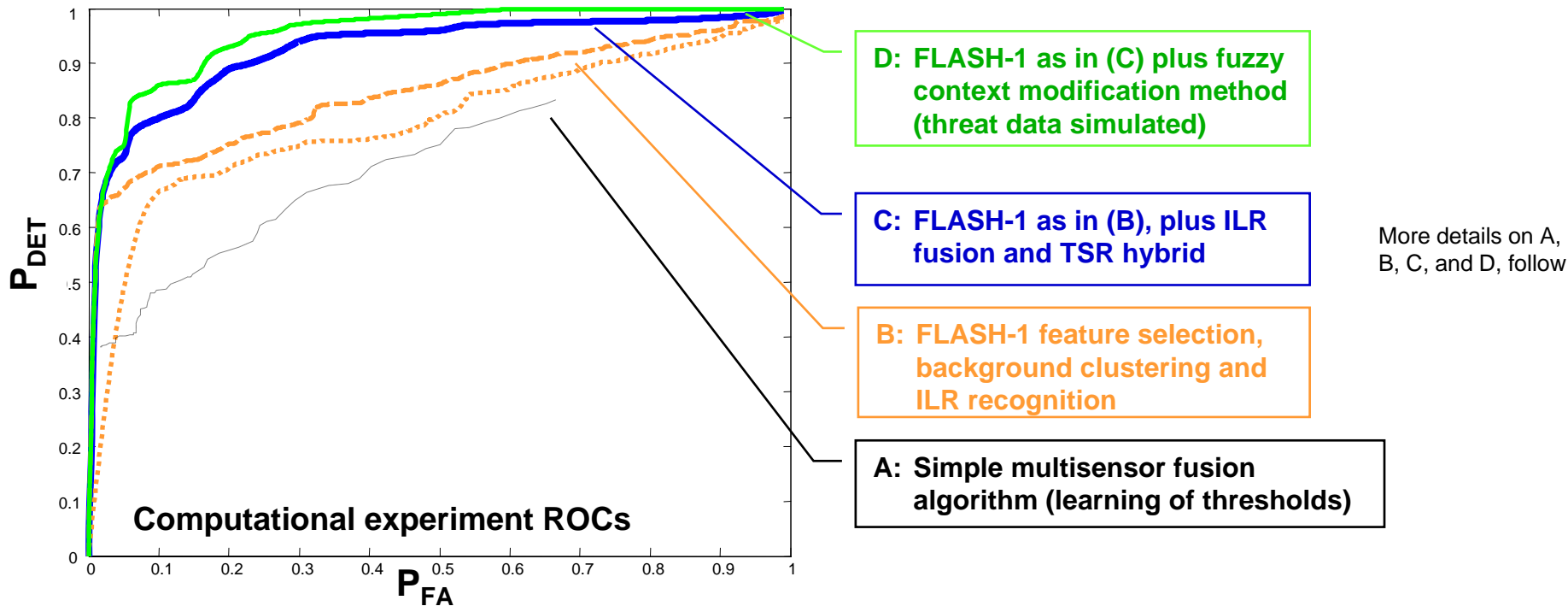


Automatically discover plausible and non-obvious background types



Computational Experiments with FLASH-1

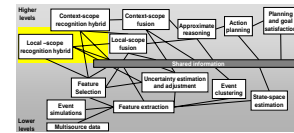
- Preliminary results of relative gains with respective aspects of FLASH
 - Simple non-FLASH fusion scheme provided for reference
- Suggestive of relative benefit of hybrid approach elements, not any specific system performance



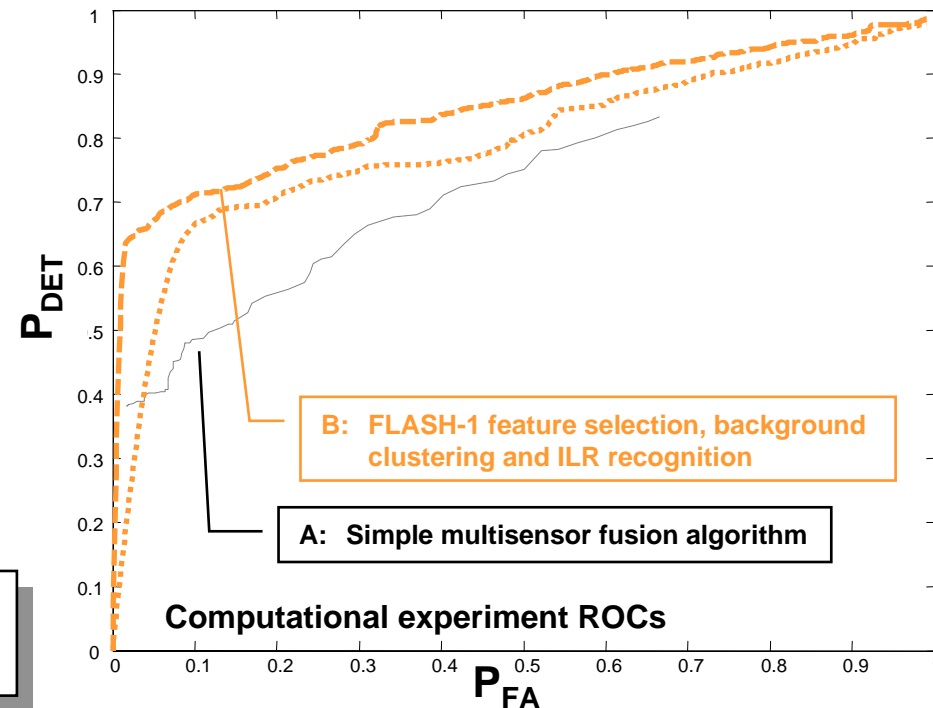
Preliminary results of relative gains illustrate potential of FLASH



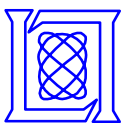
Local-Scope Recognition



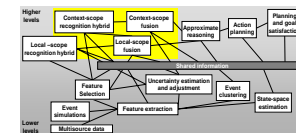
- Instance-Level Recognition (ILR) Hybrid currently based on multiple Support Vector Machines (SVM)
- ILR outputs are functions of distance from decision boundaries of multiple SVMs
- Computational experiments on datasets from deployment 1
- Comparison with “non-FLASH” simple fusion algorithm, based on estimating thresholds



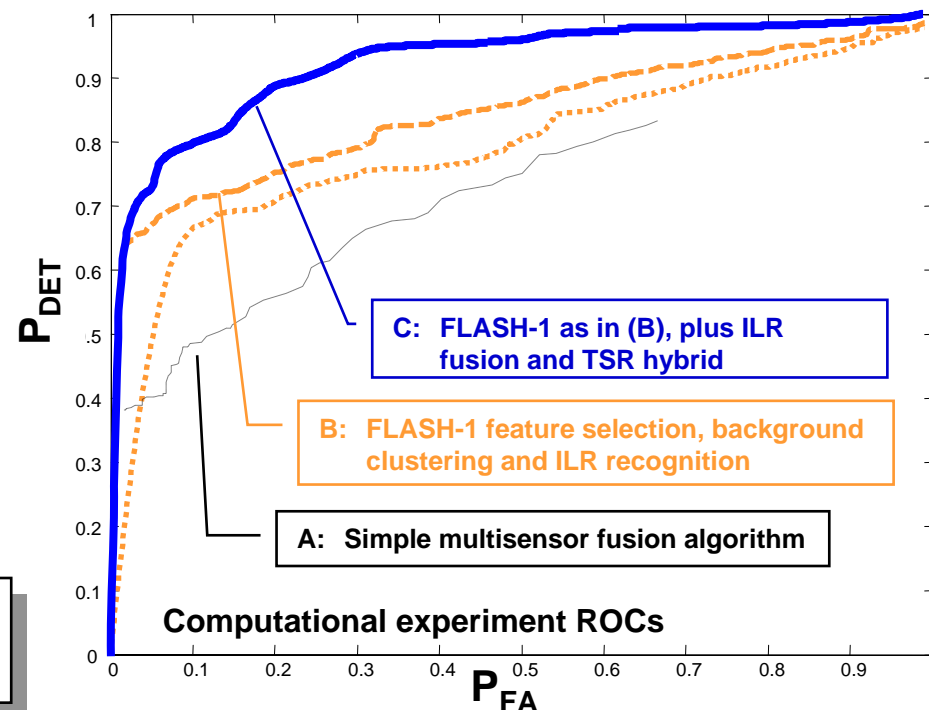
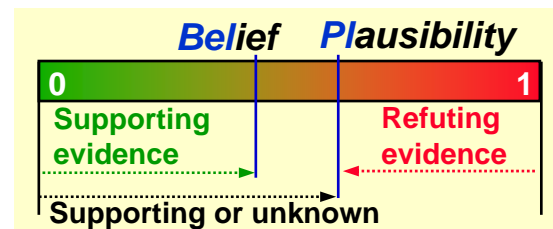
Performance results showing ILR hybrid outperforming simple fusion method



Local-scope Fusion and Context-scope Recognition



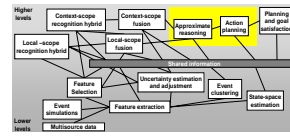
- ILR fusion based on Dempster-Shafer theory of evidence
- Each recognizer in ILR hybrid constitutes separate evidence source
- Time-Series Recognition (TSR) operates on sequences of ILR fusion stage outputs
- TSR based on Hidden Markov Models
 - Continuous Density HMMs (CD-HMMs)



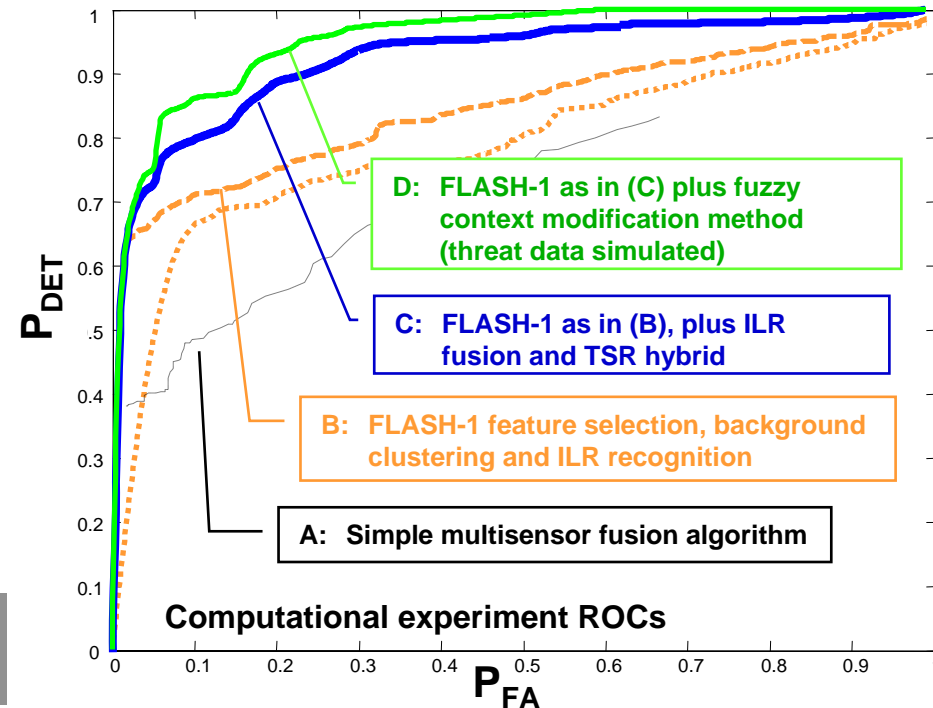
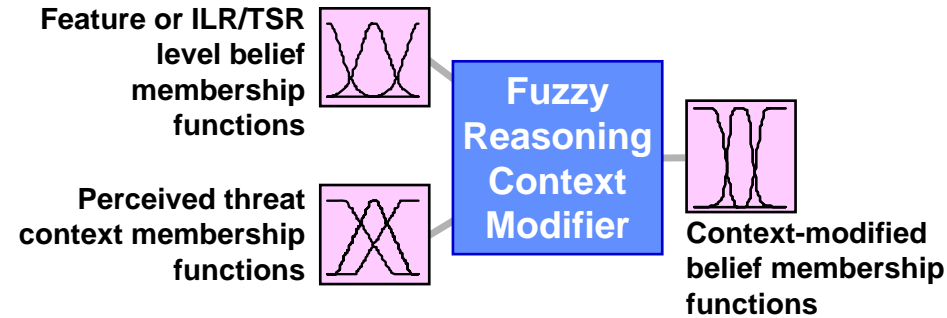
Performance results showing relative gains of FLASH-1 ILR fusion and TSR recognition



Fuzzy Logic Methods in FLASH-1



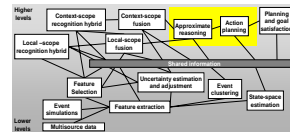
- Fuzzy logic methods convenient for representing descriptive/vague data
- FLASH-1 fuzzy outcome modification exploits certain data as modifiers rather than inputs to classification
- Example: Perceived threat assessment
 - Modulate TSR outcome by perceived threat assessment
 - Context simulated by Gaussian distributions correlated with truth-values
 - Mamdani-type fuzzy inference



Performance results showing further improvements with simulated “context” data

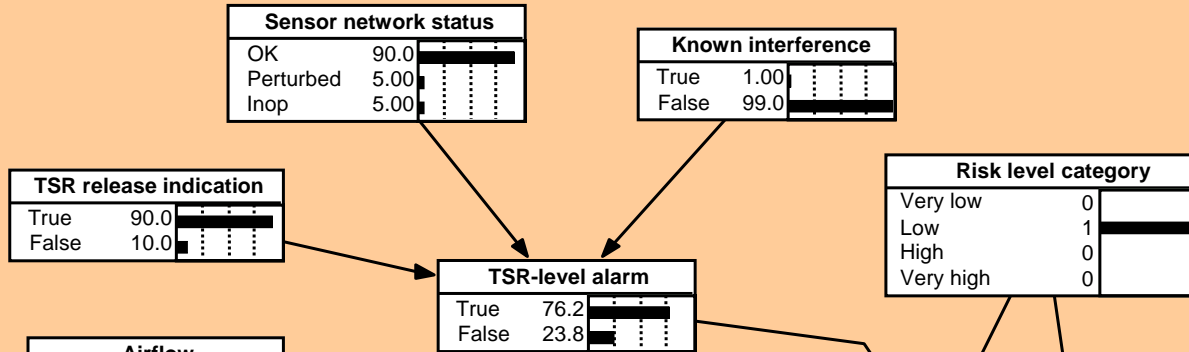


Belief Network Reasoning

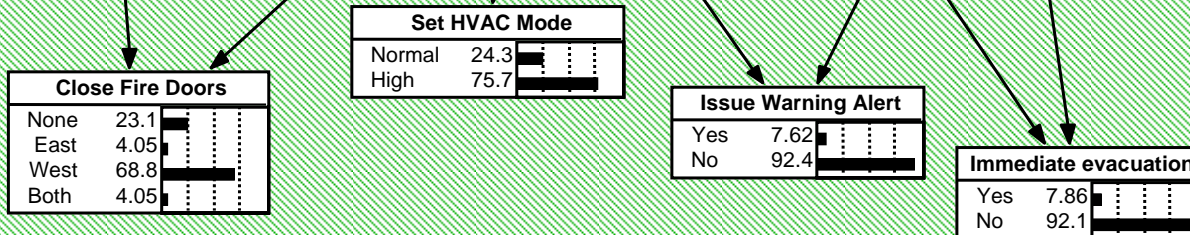


- Knowledge representation with FLASH semantic nets
- Initial results with Bayesian net, indoor protection example

Conditions



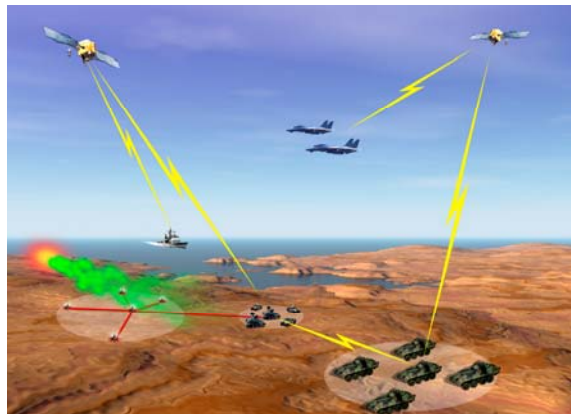
Actions





Course-of-Action Decision Support

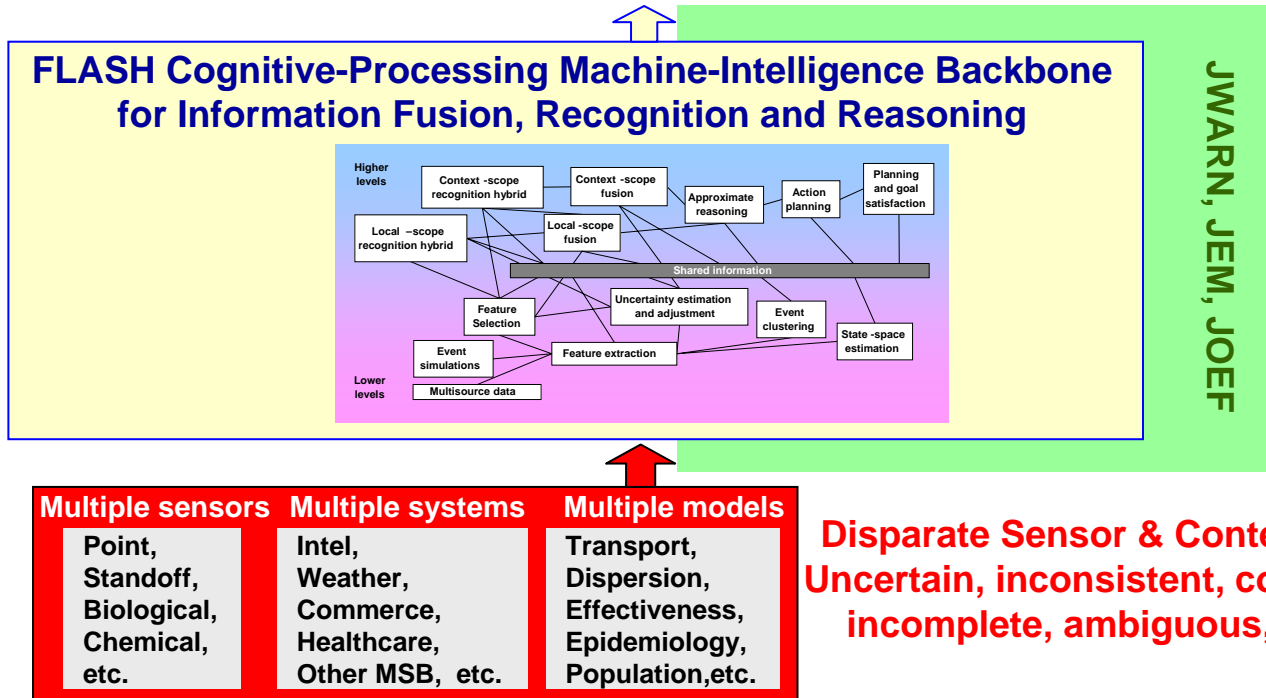
- **Course-of-action (COA) guidance – recognizing relevant battlespace conditions and reasoning to generate available options and tradeoffs**
- **Cognitive processing character makes FLASH approach promising for demanding COA guidance applications**
 - **Machine learning, uncertainty provisions, approximate reasoning**
- **Further options include machine learning from scenarios, past cases, “lessons learned”, desktop exercises, after-action reviews, and information acquired from tacticians and other subject matter experts**





Potential of FLASH for Battlespace Management Systems

Results: Event detection and characterization, effect predictions, course-of-action guidance, tradeoffs, ...



- Potential as information-fusion and machine-intelligence algorithmic backbone for CBRN Battlespace Management systems such as JWARN, JEM, and JOEF
- Intelligent decision-support technology with multi-purpose applicability
 - Attack detection/characterization, prediction, impact assessment, course-of-action, others
- Augmented cognition for warfighters



Summary

- **FLASH: novel cognitive-processing machine-intelligence decision-support architecture and methods**
- **Performance results to date show potential of FLASH**
- **Broad multi-purpose applicability, including CB detection, characterization, Course-of-Action guidance, and other CBR defense decision-support applications**

