ARC Centre of Excellence for

Autonomous Systems

Data Fusion in Sensor Networks

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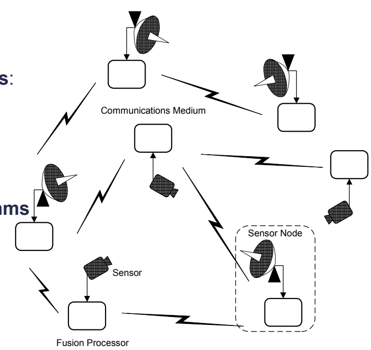
*ARC=Australian Research Council

Overview

- **Decentralised Sensor Networks**
- **Data Fusion in Decentralised Networks**
  - Structure of the problem
  - The essential DDF algorithm: SKIDS
  - Communication and Model Distribution: ISSS, OxNav
  - Timing and UAV demonstration: ANSER
  - The general Bayesian DDF: ANSER II
- **Management and Control in Sensor Networks**
  - Sensor Management
  - Trajectory Control
  - Search and Exploration
- **Future Challenges**

Decentralised Sensor Networks

- **Endogenous Systems**:
  - No central fusion
  - No central comms.
  - No global network knowledge
- **Probabilistic Algorithms**
  - Tracking
  - Navigation
  - Bayes estimation



Decentralised Data Fusion (DDF)

- State and state models
- Observations and likelihood models
- Distributed and decentralised estimation
- The DDF algorithm

Data Fusion: State

$$\mathbf{x}(t), \quad \mathbf{X}^t = \{\mathbf{x}(t_i) \mid 0 \le t_i \le t\}$$

- A track: of position and velocity for example
- A field property: temperature/pressure field for example
- A discrete property: Identity or label for example

A State is a shared across sensor nodes

Data Fusion: Observations

$$\mathbf{z}_j(t), \quad \mathbf{Z}_j^t = \{\mathbf{z}(t_i) \mid 0 \leq t_i \leq t\}$$
$$\mathbf{Z}^t = \{\mathbf{Z}_j^t \mid j \in N\}$$

- A track observation: range, bearing, velocity for example
- A local field observation: temperature/pressure for example
- A discrete observation: presence/absence for example

An Observation is local to a sensor node

Data Fusion: The Sensor Model

$$P(\mathbf{z}_j(t) \mid \mathbf{x}(t))$$

Model Generation

$$P(\mathbf{z}_j(t) \mid \mathbf{x}(t) = x(t))$$

Model Inference

$$P(\mathbf{z}_j(t) = z_j(t) \mid \mathbf{x}(t))$$

$$\mathbf{z}_j(t) \longrightarrow \boxed{P(\mathbf{z}_j \mid \mathbf{x})} \longrightarrow \Lambda_j(\mathbf{x}(t))$$

Sensor Model couples local observations to common global state

Data Fusion: The State Model

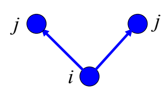
$$P(\mathbf{x}(t_i) \mid \mathbf{x}(t_{i-1}))$$

Temporal Encoding

$$P(\mathbf{x}(t_i) \mid \mathbf{x}(t_{i-1}) = x_{i-1})$$

Structural Encoding

$$P(\mathbf{x}_j \mid \mathbf{x}_i = x_i)$$



State Model couples immediate states to global states

Data Fusion: The Essential Problem

Observation Update

$$P(\mathbf{x}(t_k) \mid \mathbf{Z}^k) = C.P(\mathbf{x}(t_k) \mid \mathbf{Z}^{k-1}) \prod_j P(\mathbf{z}_j = z_j \mid \mathbf{x}(t_k))$$

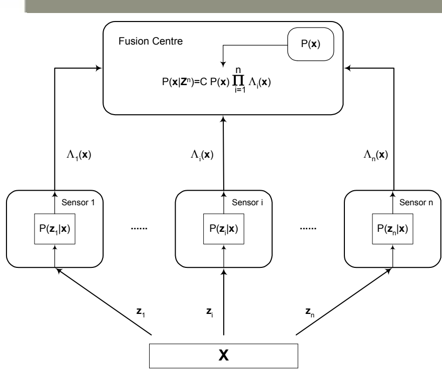
Time/Structure Update

$$P(\mathbf{x}(t_k) \mid \mathbf{Z}^{k-1}) = \int P(\mathbf{x}(t_k) \mid \mathbf{x}(t_{k-1})) P(\mathbf{x}(t_{k-1}) \mid \mathbf{Z}^{k-1}) \, d\mathbf{x}(t_{k-1})$$

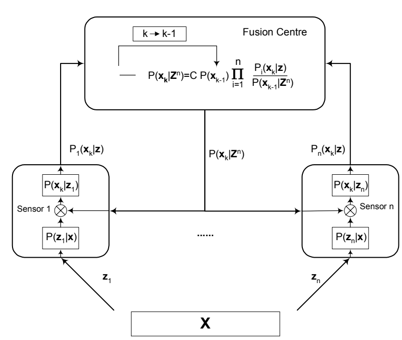
Distributed and Decentralised versions of these equations can be constructed with superficial ease

Conditional Independence of Observations Require Marginal State at current time

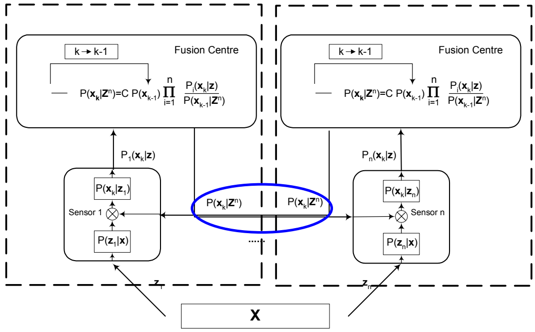
Data Fusion: Distributed Sensing



Data Fusion: Distributed Fusion



Data Fusion: Decentralised Fusion



Decentralised Data Fusion: The Linear Gaussian Case

$P(\mathbf{x}(k)\mid\mathbf{x}(k-1))$:

$$\mathbf{x}(k)=\mathbf{F}\mathbf{x}(k-1)+\mathbf{G}\mathbf{w}(k)\qquad \mathbf{w}(k)\rightarrow N(\mathbf{0},\mathbf{Q})$$

$P(\mathbf{z}_j(k)\mid\mathbf{x}(k))$:

$$\mathbf{z}_j(k)=\mathbf{H}_j\mathbf{x}(k)+\mathbf{v}_j(k)\qquad \mathbf{v}_j(k)\rightarrow N(\mathbf{0},\mathbf{R}_j)$$

$$P(\mathbf{x}(p)\mid\mathbf{Z}^q)\rightarrow N(\mathbf{x}(p);\hat{\mathbf{x}}(p\mid q),\mathbf{P}(p\mid q))$$

The Information Filter

Bayes: $P(\mathbf{x}(k)\mid\mathbf{Z}^k)=C.P(\mathbf{x}(k)\mid\mathbf{Z}^{k-1})\prod_j P(z_j(k)\mid\mathbf{x}(k))$

Log-Likelihood:

$$\ln P(\mathbf{x}(k)\mid\mathbf{Z}^k)=\ln P(\mathbf{x}(k)\mid\mathbf{Z}^{k-1})+\sum_j \ln P(z_j(k)\mid\mathbf{x}(k))+K$$

(Fisher or Canonical) Information Form:

$$\hat{\mathbf{y}}(k\mid k)=\mathbf{P}^{-1}(k\mid k)\hat{\mathbf{x}}(k\mid k)\qquad \mathbf{i}_j(k)=\mathbf{H}_j^T\mathbf{R}_j^{-1}\mathbf{z}_j(k)$$

$$\mathbf{Y}(k\mid k)=\mathbf{P}^{-1}(k\mid k)\qquad \mathbf{I}_j(k)=\mathbf{H}_j^T\mathbf{R}_j^{-1}\mathbf{H}_j$$

The Information Filter

Observation updates are simple sums (unlike KF):

$$\hat{\mathbf{y}}(k\mid k)=\hat{\mathbf{y}}(k\mid k-1)+\sum_j \mathbf{i}_j(k)$$

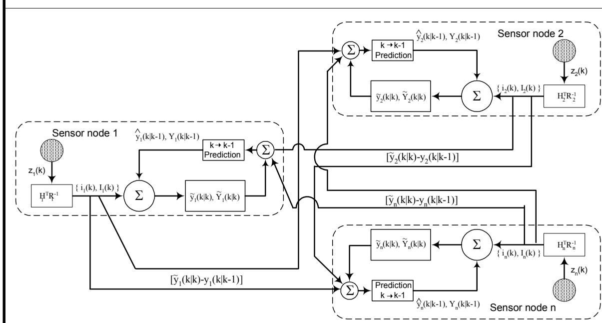
$$\mathbf{Y}(k\mid k)=\mathbf{Y}(k\mid k-1)+\sum_j \mathbf{I}_j(k)$$

Time/Structure updates are Dual to state (KF) Observation Updates :

$$\hat{\mathbf{y}}(k+1\mid k)=\hat{\mathbf{y}}(k\mid k)+\mathbf{\Omega}[\hat{\mathbf{y}}(k\mid k)+\mathbf{Y}(k\mid k)\mathbf{B}\mathbf{u}(k)]$$

$$\mathbf{Y}(k+1\mid k)=\mathbf{Y}(k\mid k)-\mathbf{\Omega}(k)\mathbf{\Sigma}(k)\mathbf{\Omega}^T(k)$$

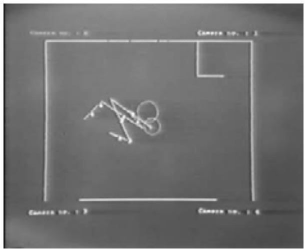
Implementation of the Decentralised Information Filter



SKIDS

- “European First Framework” Project 1986-1991: Distributed/Decentralised Tracking in Civilian Environments
- Sensors
  - Multiple cameras each with embedded processing
  - Optical barriers, acoustic sensing
- Algorithms
  - DDF position/velocity tracking
  - Distributed data association and identification
  - Fully connected

SKIDS (1989 Demo)

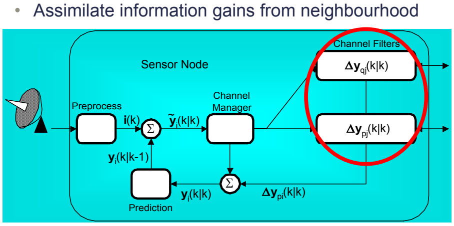


Three Issues Arising From SKIDS

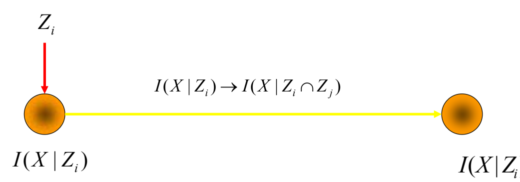
- Communication:
  - Non-fully connected networks
  - Time-varying and ad-hoc networks
  - Communications management
- Modelling States:
  - Partial and distributed models at nodes
  - Estimation of field-like properties
  - Non-Gaussian posteriors
- Control:
  - Sensor Placement
  - Sensor Management

Communication: Operation of Sensor Nodes

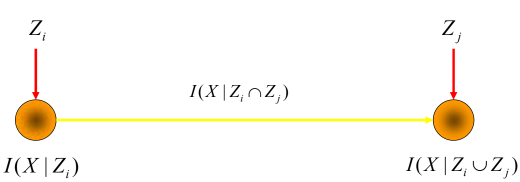
- Nodes fuse information from:
  - Local observations, Local predictions, and
  - Communicated information
- Focus on Channels (the Channel Filter):
  - Communicate local information gain
  - Assimilate information gains from neighbourhood



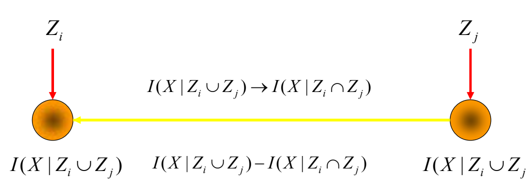
Operation of Channels



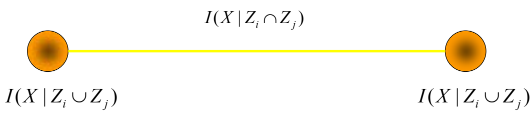
Operation of Channels



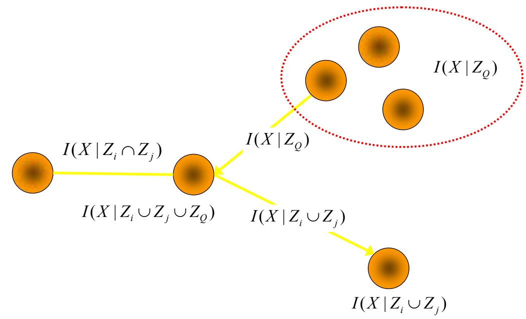
Operation of Channels



Operation of Channels



Scaling The Network



Building Large Networks

- Information propagates through network
  - Without increase in local bandwidth req.
  - Within locality constraints of algorithms
- Broadcast, and tree networks:
  - Optimal (central equivalent) results
  - At the cost of network robustness
- Arbitrary and ad-hoc Networks:
  - Common Information not captured by Channels
  - Either local spanning trees or
  - Conservative update policies (CI, Mutual Info.)

Sub-Model Distribution

Identification of Locally Observable Sub-States:

$$\mathbf{x}_j(k) = \mathbf{T}_j \mathbf{x}(k) \qquad \mathbf{z}_j(k) = \mathbf{C}_j \mathbf{x}_j(k)$$

$$\mathbf{z}_j(k) = \mathbf{H}_j \mathbf{x}(k) \qquad \mathbf{H}_j = \mathbf{C}_j \mathbf{T}_j$$

Construction of Local Transition and Noise Models:

$$\mathbf{F}_i(k) = \mathbf{T}_i \mathbf{F}(k) \mathbf{T}_i^{+} \qquad \mathbf{G}_i(k) = \mathbf{T}_i \mathbf{G}(k) \mathbf{T}_i^{+}$$

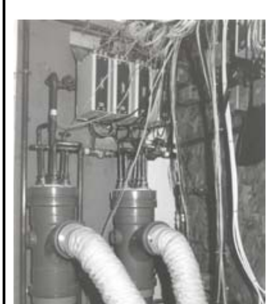
Generation of Inter-Nodal Communication Models:

$${}^{j}\mathbf{x}_i(k) = {}^{i}\mathbf{V}_j\, \mathbf{x}_j(k), \qquad {}^{i}\mathbf{V}_j = \mathbf{T}_i \mathbf{T}_j^{+}$$

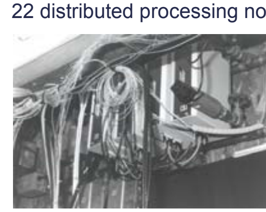
ISSS: 1989-1993

- **Objectives:**
  - Demonstrate scalability of DDF methods to systems ~100s sensors/nodes
  - Explore network connectivity issues and communication policies
  - Implement and validate model decentralisation principles
  - Fault detection and robust recovery
- **Implementation**
  - A mock-up (nuclear) power plant model
  - Primary water coolant, secondary air coolant
  - Boiler, heat exchangers, pumps, by-pass circuits
  - Measurement of pressures, temperatures, flows, etc

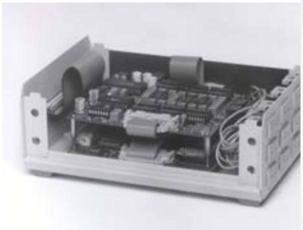
ISSS: Sensor Network

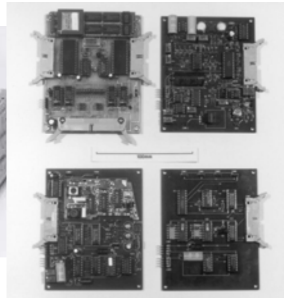


- **Network**
  - 250 sensors (temperature, pressure, flow)
  - 45 control points (valves, power)
  - 22 distributed processing nodes



ISSS: Sensor Nodes





ISSS: Results and Conclusions

- **Communications**
  - Spanning tree algorithms work well in this slowly varying problem
  - Optimal network communication provably not possible in general
- **Model Distribution**
  - Models vary with time and must be re-learnt periodically
  - Mutual Information provides the best method for doing this

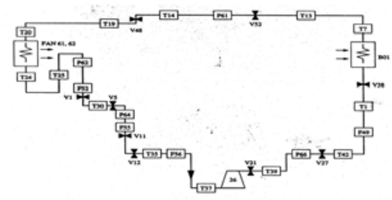
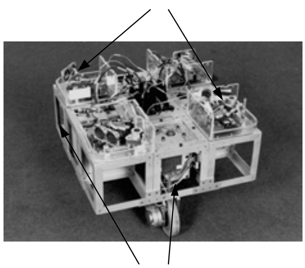


Figure 1: Main low-power circuit

OxNav (1991-1995)

- **Objectives:**
- Modular, Decentralised Mobile Robotics
- Fully Modular Sensors and Actuators
- Fully Decentralised Navigation and Control



Decentralised Navigation

- A Feature-Based Navigator
- Using a tracking sonar to lock-on and track stable features
- Decentralised Information filter for estimating platform and feature locations (origin of the SLAM algorithm)
- Bayes estimator for feature identity/type

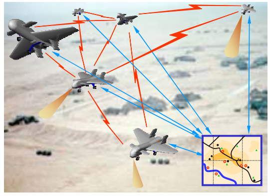
Decentralised and Scalable Control

- Modular, self-contained driven and/or steered wheel units
- A reference with respect to a “virtual” wheel
- No local knowledge of other wheels or platform geometry
- Decentralised information filter closes loop
- A reconfigurable decentralised PID/LQG controller

OxNav: Results and Conclusions

- **Decentralised Estimation**
  - Fundamental Bayes form gives useful insight
  - Structure of hybrid mobile/stationary tracking prob.
- **Decentralised Control**
  - Mutual information is key to sensor management and active data association
  - Bayes, rather than complementary LQG is the right approach to general control problems
- **In 1995, limited interest in sensor networks so I emigrated to Australia to do Field Robotics ☺**

ANSER (1999-2003)
Autonomous Navigation and Sensing Experimental Research



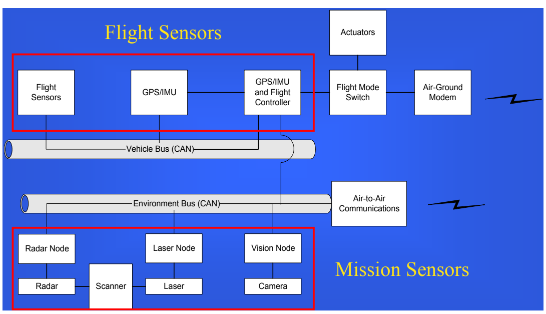
BAE SYSTEMS

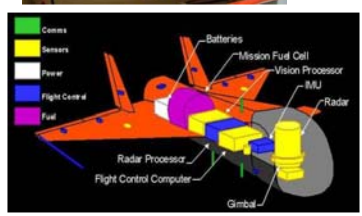
- **Objectives:**
  - To deploy a fully decentralised data fusion system on a group of four or more UAVs
  - To demonstrate functions of target tracking and simultaneous localisation and mapping, decentralised on many sensors in a network of platforms
  - To demonstrate, algorithmically and practically, key network-centric features: Modularity, Scalability, Flexibility and Survivability

Flight Platforms

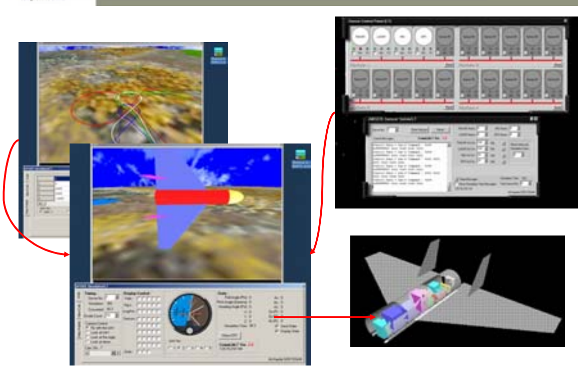
- Four Platforms – Delta Wing Configuration
- Max Speed – 80kts
- Payload Capacity – 20kg
- Wing Span – 3m
- Multiple Sensors per platform
- All modular pay-loads
- All parts interchangeable

On-Board Components

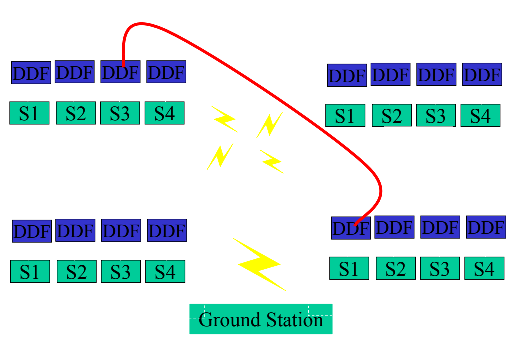




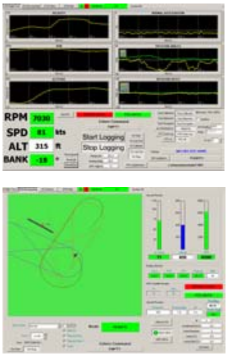
Mission Planning System

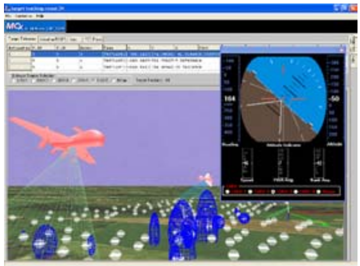


Overall DDF Communications Schematic



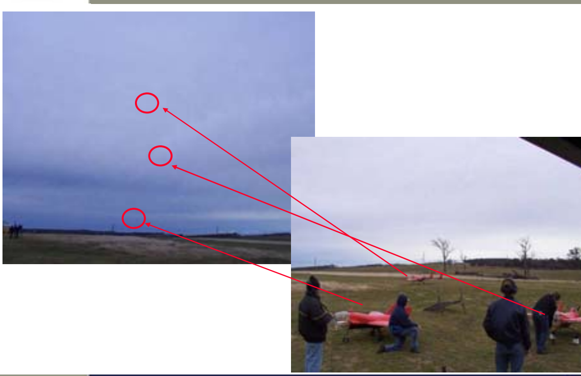
Mission Control



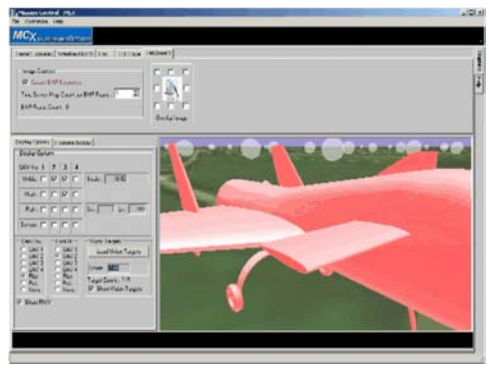


Multi-Vehicle Flights (2000-2001)

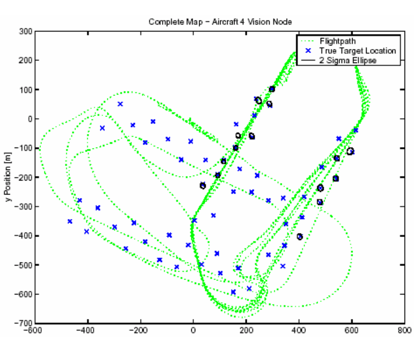
3 Vehicle Flight Test (2002)



ANSER Mission Data



3 Vehicle – 4 Nodes Flight Test



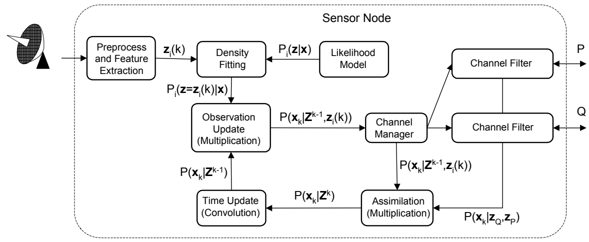
ANSER: Conclusions

- **Information Communications is key**:
  - Timing, delay, asequent and burst communication
  - Maintaining integrity, extensible network operation
  - Channel and information management
- **Data Fusion issues**:
  - Registration and platform bias estimation
  - Cross-platform data association
  - Weak target information not captured well by information filter alone
- **Commercial issues**
  - BAE Systems Chairman's Gold Award
  - Output integrated in to a number of on-going UK, US and Australian Defence programmes
  - (After 15 years of work !)

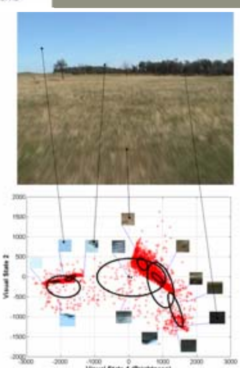
ANSER II: 2004-2006

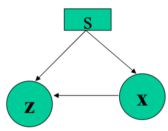
- **Objectives**
  - General Bayesian DDF
  - Heterogeneous Information Sources
  - Inferences from weak sources
  - Rapid exploitation of network data

Bayesian DDF Node Structure



Generation of Likelihood Models



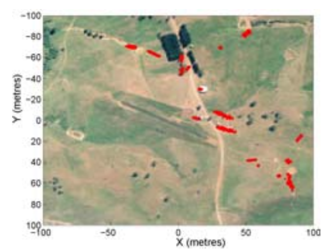


$$P(\mathbf{z},\mathbf{x},\mathbf{s}) = P(\mathbf{z}\,|\,\mathbf{x},\mathbf{s})P(\mathbf{x}\,|\,\mathbf{s})P(\mathbf{s})$$

$P(\mathbf{z}\,|\,\mathbf{x},\mathbf{s})$=$P(\mathbf{z}|\mathbf{x}$=$[\mathbf{x},\mathbf{s}])$ is the required likelihood for inference

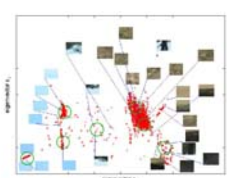
Cross-Platform Fusion

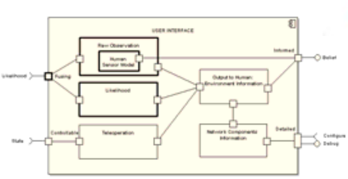
- Bayesian DDF implemented using GMMs
- Variational EM does local estimation of GMM

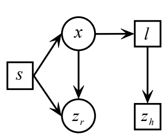


Human DDF Node

- Human operator input:
  - Metric Information
  - Labels
  - Context
- On-line estimation of "operator likelihood"







Decentralised Sensor Management

- How to best acquire target information:
  - Which sensor to point
  - What direction to point the sensor in
  - What trajectory for the aircraft
  - What to communicate between platforms
- Require solutions that:
  - Coordinate decentralised sensor actions
  - Scale to large inhomogeneous networks
- Algorithms which are "information-seeking"

Mutual Information Gain as a Control Metric

- Mutual Information is an *a priori* measure of average Information gain following observation

$$I(\mathbf{x}(t):\mathbf{z}(t)) = \mathrm{E}\left[\log\left(\frac{\mathrm{P}(\mathbf{x}(t)\,|\,\mathbf{z}(t))}{\mathrm{P}(\mathbf{x}(t))}\right)\right]$$

Measures "compression" of posterior density

- Choose the sequence of observations z(*t*) which maximise mutual information gain over a horizon
- Observations depend on platform state x(t)
- State is governed by some control input u(t)
- Choose u(t) to maximise information gain

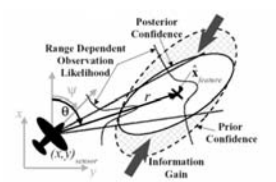
Mutual Information in DDF

- Mutual Information or information gain, is exactly what is communicated in the DDF
- Suggests a Decentralised (Greedy) management and control algorithm:
  - Order strategies according to local information gain
  - Communicate options as information gain
  - Select action which maximises gain for the group
- Appropriate to both sensor management and platform control tasks

Trajectory Control: A Canonical Example

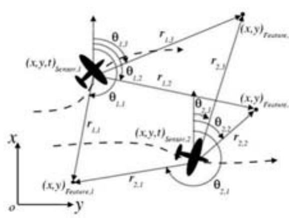
- Bearings-only observation of a point-target from a moving platform

$$\mathbf{I}_{\beta}(t) = \frac{1}{\sigma_{\beta}^{2}\hat{r}^{2}(t)}\begin{bmatrix} \sin^{2}\hat{\theta}(t) & -\sin\hat{\theta}(t)\cos\hat{\theta}(t) \\ -\sin\hat{\theta}(t)\cos\hat{\theta}(t) & \cos^{2}\hat{\theta}(t) \end{bmatrix}$$

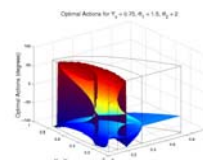


For a single platform solutions are Helical

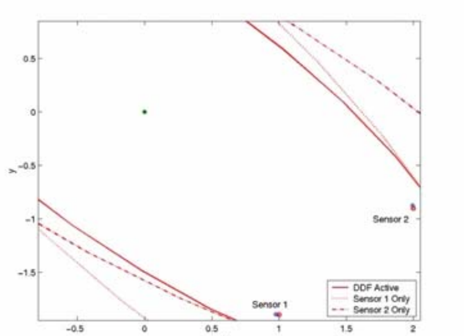
Multiple Platform Management



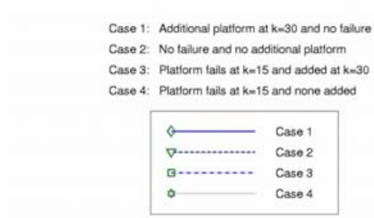
- For a group of platforms:
  - Solutions are parabolas
  - Different initial locations and prior information give different solution sets



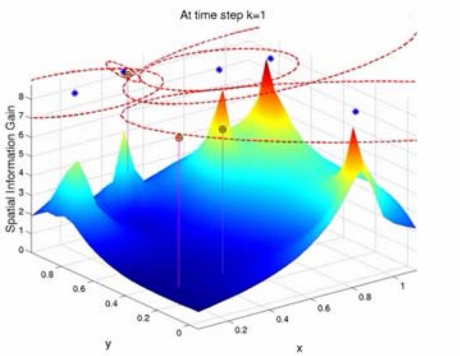
Two Vehicle Cooperative Tracking



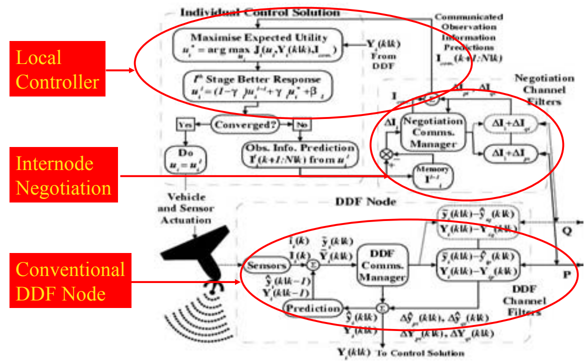
Decentralised Multi-Target Multi- Platform Tracking: Robustness and Scaling



Control as Gradient Ascent in Information Space: The Surfing Analogy

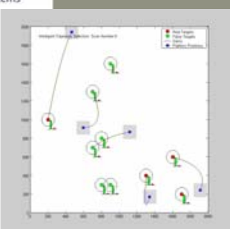


DDF/D-Control Algorithm Implementation



Cooperative Control for Target Detection

BAE Systems & UK MOD

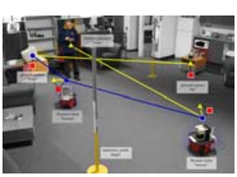


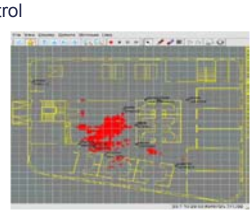
Nature of Information Maximisation Control

- Information gain problems:
  - Are integral pay-off problems
  - And turn out to have simple product/sum structures that are easily distributed
- Information gain problems include:
  - Target tracking/surveillance/reconnaissance
  - Exploration and area covering
- Information gain admits useful solutions and potential insights into the multi-agent coordination problem

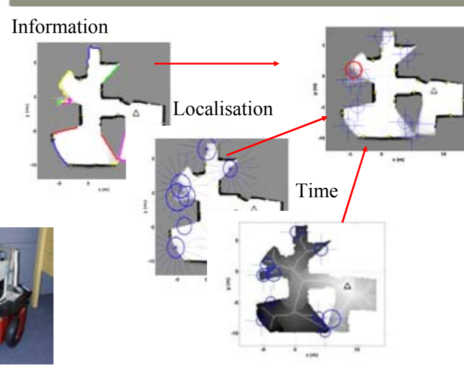
Exploration and Search

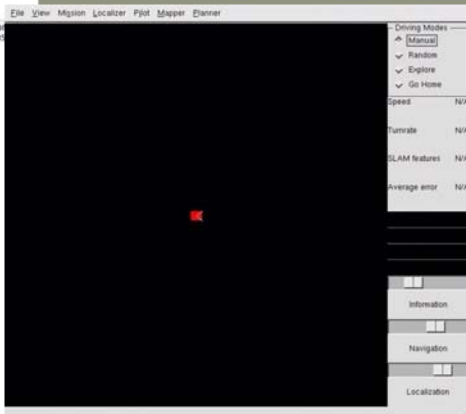
- Exploration/Search are information seeking activities:
  - Find unseen areas
  - Seek "interesting" things
- An integral pay-off problem with a DDF-like solution
  - Heterogenous information sources
  - Heterogeneous control





Exploration: Multiple-Objectives

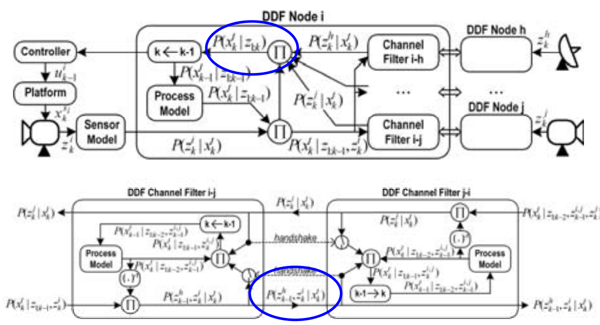




Search: Multiple Sensors, Bayesian Models

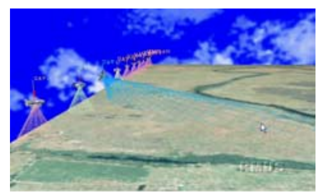
- Objective: Minimise expected time to first detection:
  - Establish a prior for the area to be searched
  - Communicate expected information gain for different headings
  - Select a path which minimises posterior entropy
- Motion models for priors can be used to exploit domain knowledge

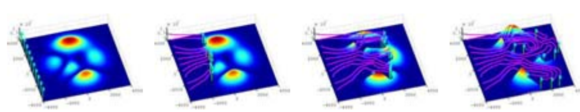
Node-to-Node Negotiation



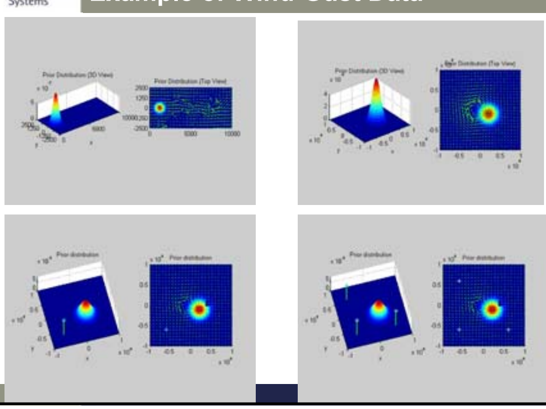
Multi-UAV Search AOARD/AFOSR

- Cooperative Exploration, Search and Tracking
- Scalable solutions
- Use of domain knowledge

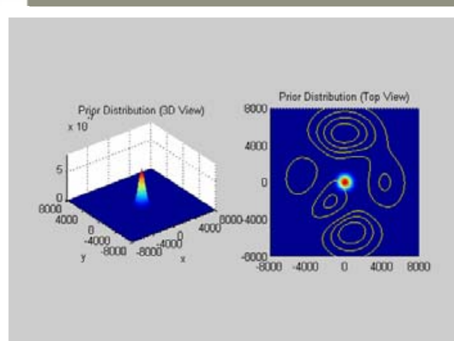




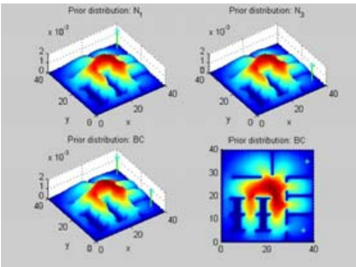
Exploiting Domain Knowledge: Example of Wind-Gust Data



Exploiting Domain Knowledge: Example of Soft Constraints



Exploiting Domain Knowledge: Example of Hard Constraints



Data Fusion in Sensor Networks: Where to Next ?

- There is scope for a general computational model of data fusion in sensor networks:
  - Bayesian/probabilistic
  - Explicit information-theoretic communication
  - Use of mutual-information to learn state coupling
  - Deployable in modular and reusable form
- Future development of higher-level fusion functions:
  - Bayesian network models for situation understanding
  - Information-theoretic management and control
  - Exploitation of human and other weak-source data
- Realistic and challenging application development
  - Identification of key applications
  - Sharing of data sets

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