Data Fusion in Sensor Networks

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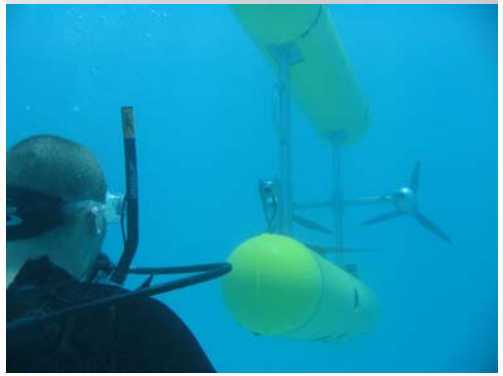
ARC=Australian version of NSF

ARC Centre of Excellence for Autonomous Systems

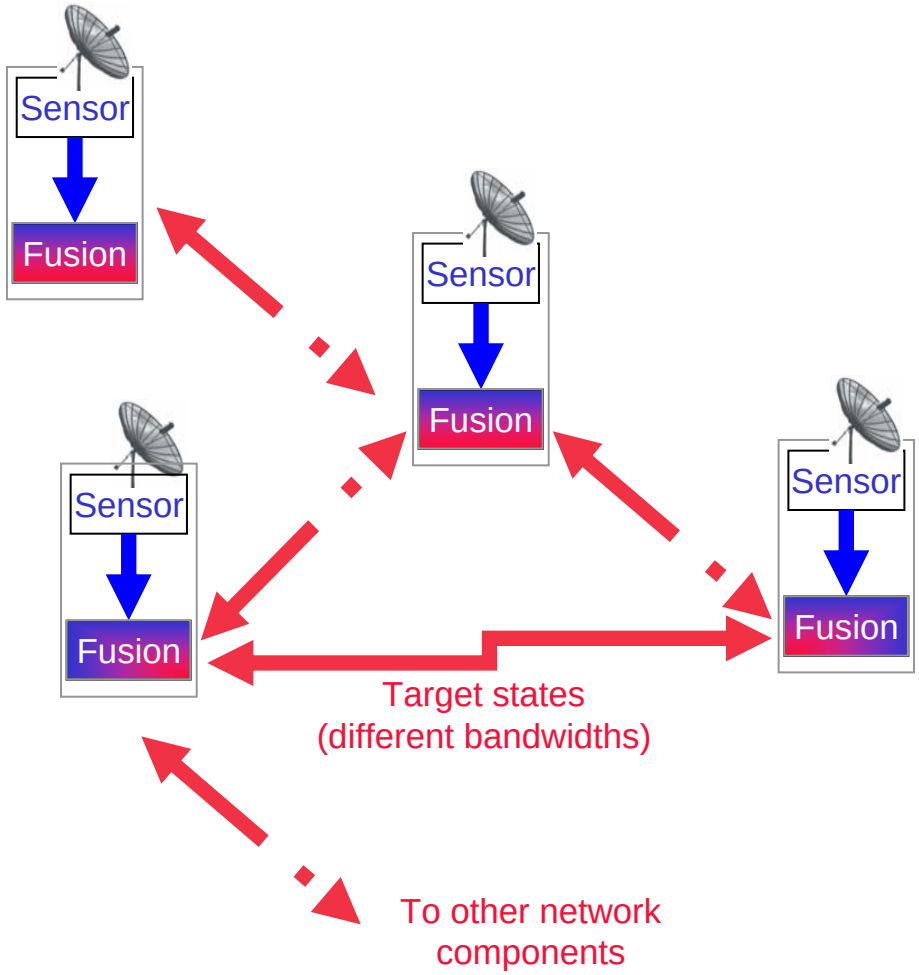
Data Fusion in Autonomous Networks

- **Decentralised Data Fusion (DDF)**
  - The DDF paradigm
  - Decentralised Bayes and information fusion
- **Fusion Challenges (ANSER II)**
  - Learning mixed sensor features
  - Building general density models
- **Control Challenges (RCS-18)**
  - Sensor and communication management
  - Information in system design
- **Future Challenges**



Decentralised Data Fusion (DDF)

- **A set of Network Data Fusion Methods:**
  - Ad Hoc Network
  - Fusion at Sensor/Platform
  - No Central Fusion Site
  - Fully Scalable
- **Decentralised Algorithms Using the Information Filter:**
  - For Target Tracking
  - For Cooperative Control
  - For Cooperative Navigation



Bayes and Information Fusion

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

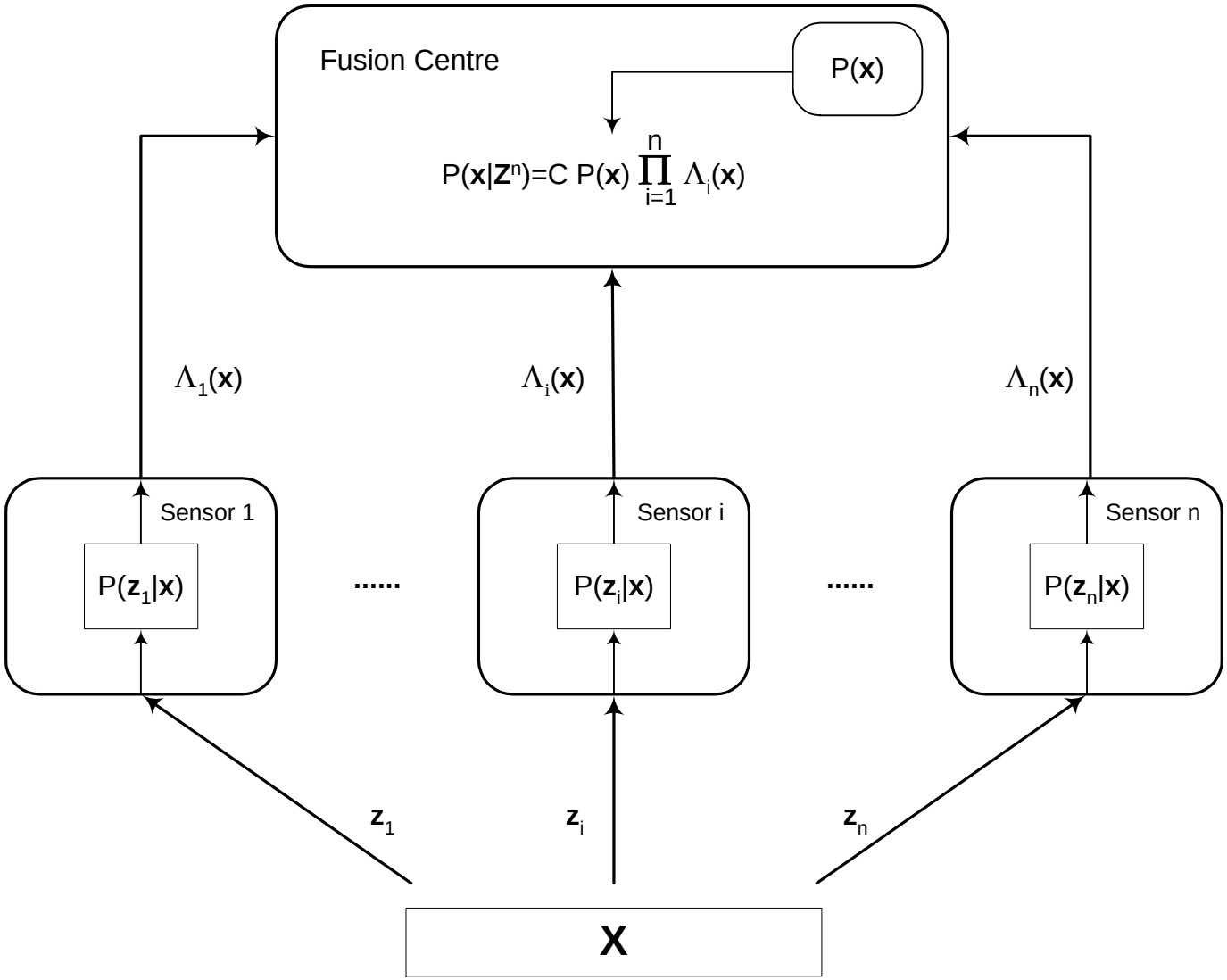
Posterior — Prior — Sensor Likelihoods

- **$\mathbf{x}(k)$ is the state at time k**
- **$z_j(k)$ is the j^{th} sensor observation at time k**
- **$\mathbf{Z}^k$ is the sequence of observations up to k**

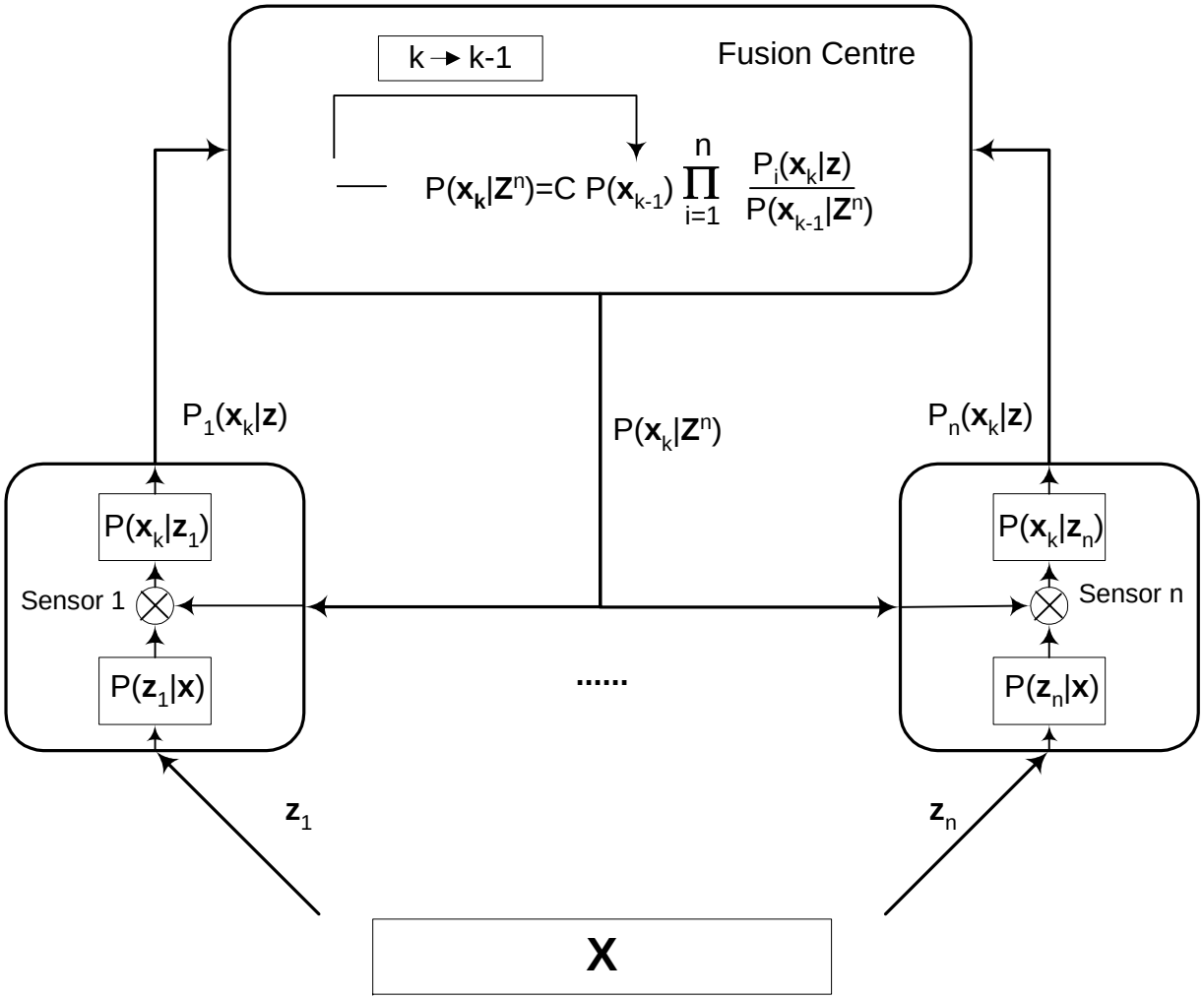
Sensors contribute Likelihoods on $\mathbf{x}(k)$

$$P(z_j(k) \mid \mathbf{x}(k)) = \Lambda_j(\mathbf{x}(k))$$

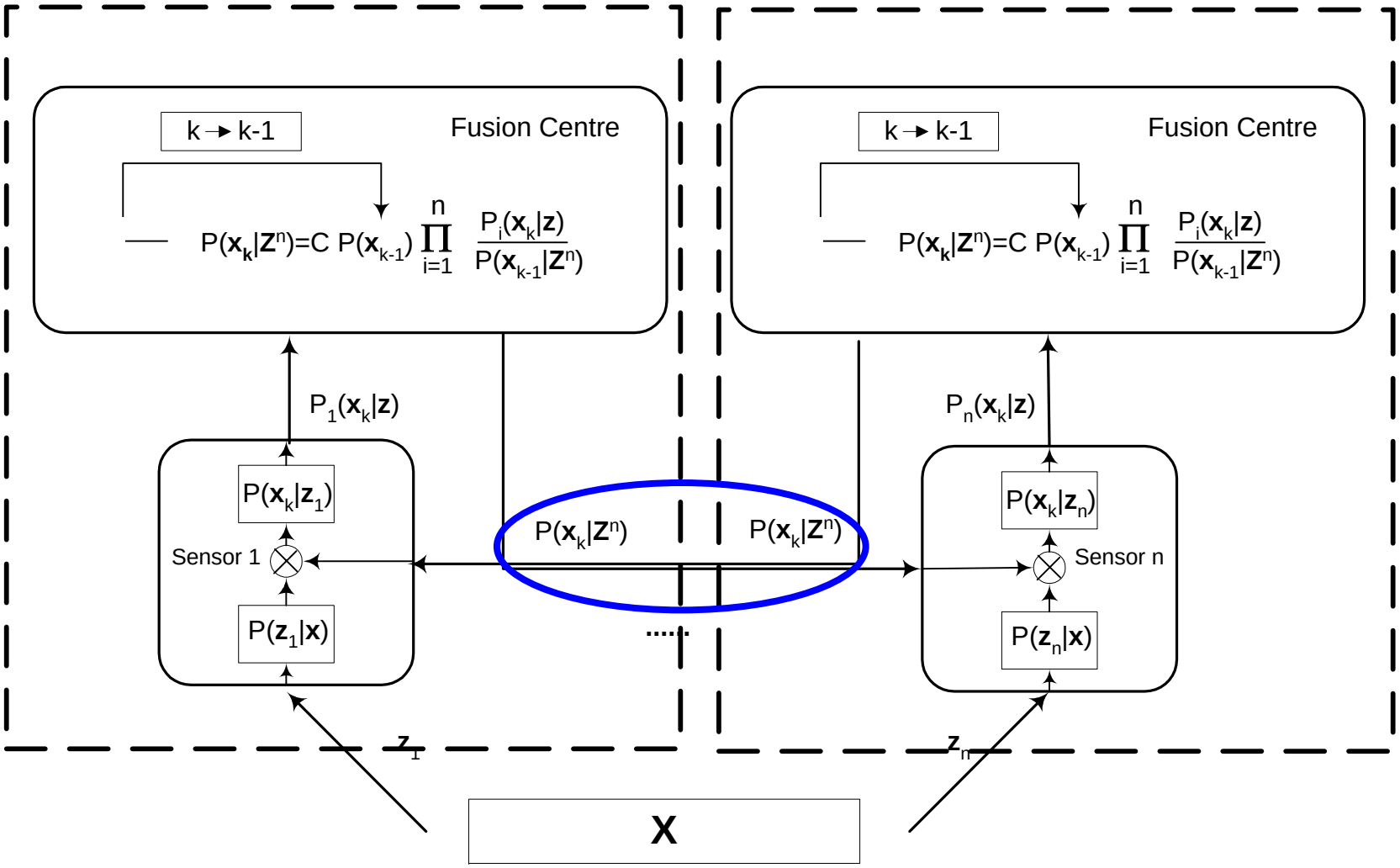
Data Fusion: Distributed Sensing



Data Fusion: Distributed Fusion



Data Fusion: Decentralised Fusion



Bayes and Information Fusion

Bayes: $$P\left(\mathbf{x}(k)\,|\,\mathbf{Z}^{k}\right)=C.P\left(\mathbf{x}(k)\,|\,\mathbf{Z}^{k-1}\right)\prod_{j}P\left(z_{j}(k)\,|\,\mathbf{x}(k)\right)$$

Log-Likelihood: Information, by construction, is additive

$$\ln P\left(\mathbf{x}(k)\,|\,\mathbf{Z}^{k}\right)=\ln P\left(\mathbf{x}(k)\,|\,\mathbf{Z}^{k-1}\right)+\sum_{j}\ln P\left(z_{j}(k)\,|\,\mathbf{x}(k)\right)+K$$

Information: A measure of compactness: $$H(\mathbf{x})=-E\left[\log P(\mathbf{x})\right]$$

Mutual Information: a priori measure of contribution to compaction: $$I(\mathbf{x}:\mathbf{z})=-E\left[\log\frac{P(\mathbf{x}\,|\,\mathbf{z})}{P(\mathbf{x})}\right]$$

Bayes and Information Fusion

Bayes: $$P\left(\mathbf{x}(k)\,|\,\mathbf{Z}^{k}\right)=C.P\left(\mathbf{x}(k)\,|\,\mathbf{Z}^{k-1}\right)\prod_{j}P\left(z_{j}(k)\,|\,\mathbf{x}(k)\right)$$

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Gaussian Case: (Fisher or Canonical) Information Form

$$\hat{\mathbf{y}}(k\,|\,k)=\mathbf{P}^{-1}(k\,|\,k)\hat{\mathbf{x}}(k\,|\,k) \qquad \mathbf{i}_{j}(k)=\mathbf{H}_{j}^{T}\mathbf{R}_{j}^{-1}\mathbf{z}_{j}(k)$$

$$\mathbf{Y}(k\,|\,k)=\mathbf{P}^{-1}(k\,|\,k) \qquad \mathbf{I}_{j}(k)=\mathbf{H}_{j}^{T}\mathbf{R}_{j}^{-1}\mathbf{H}_{j}$$

The Information Filter

Observation updates are simple sums (unlike KF):

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

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

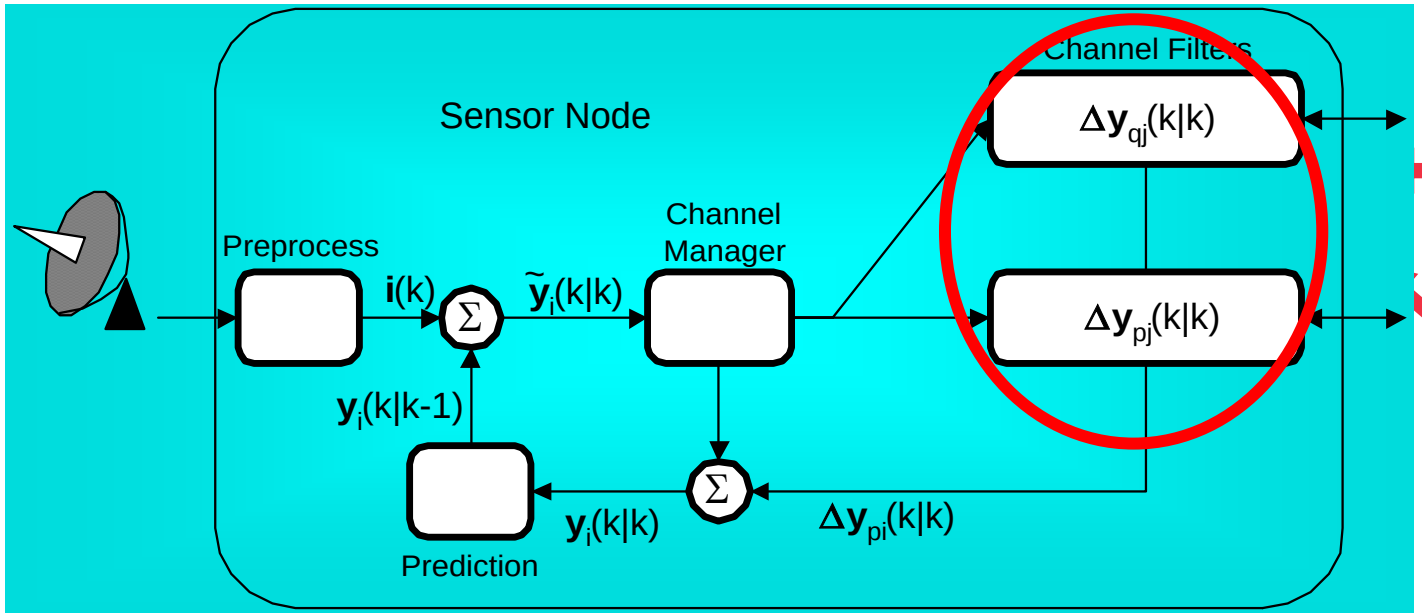
Time/Structure updates are Dual to state (KF) Observation Updates :

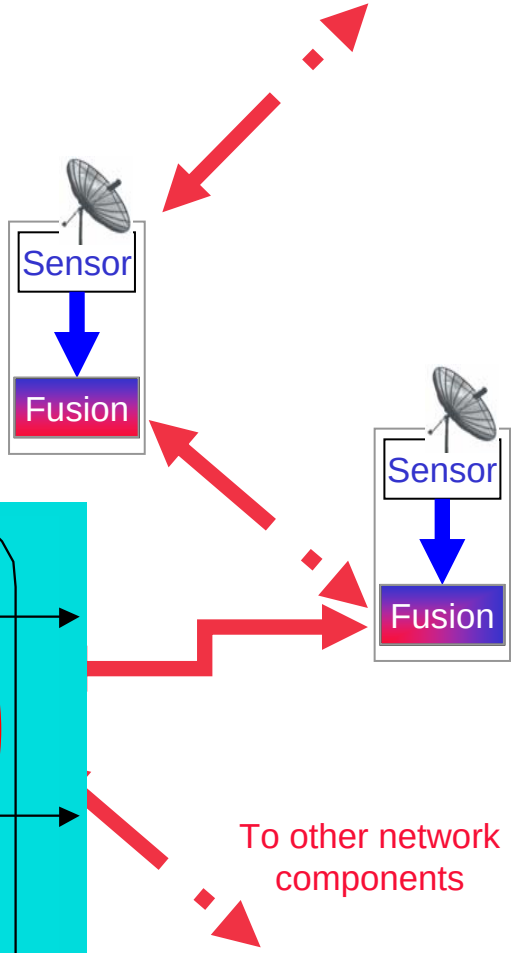
$$\hat{\mathbf{y}}(k+1 \mid k) = \hat{\mathbf{y}}(k \mid k) + \boldsymbol{\Omega}\left[\hat{\mathbf{y}}(k \mid k) + \mathbf{Y}(k \mid k)\mathbf{B}\mathbf{u}(k)\right]$$

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

DDF in Operation

- **Network communicates Information**
- **Nodes fuse local observation and communicated Information**
- **Channels communicate local information gain (mutual information)**

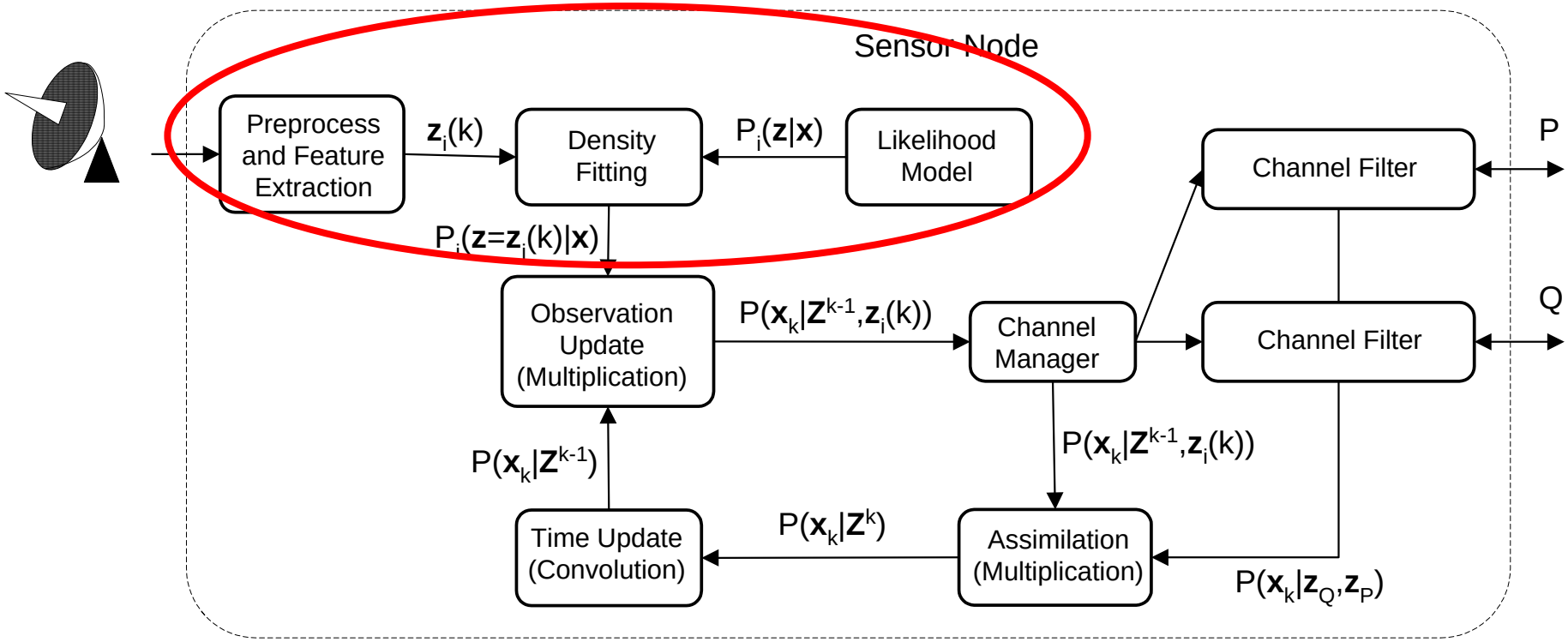




ANSERII: All-Source Bayesian Fusion

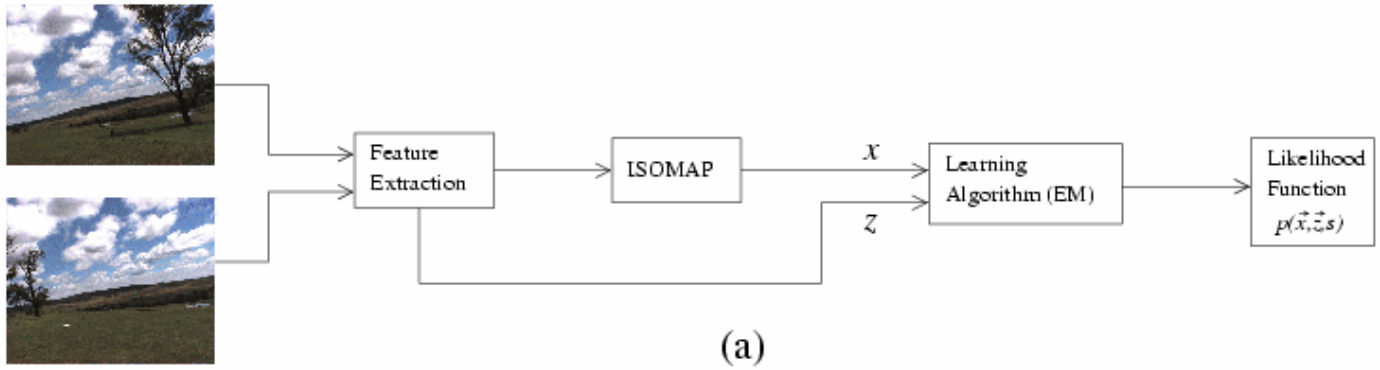
- Full Bayes DDF for fusion of heterogeneous data from UAVs, UGVs, human and data base sources
- Model general feature types; trees, buildings, dams, etc
- Identify and label features, integrate human inferences
- Real-time exploitation of network data by air, ground, human

Bayesian DDF Node Structure



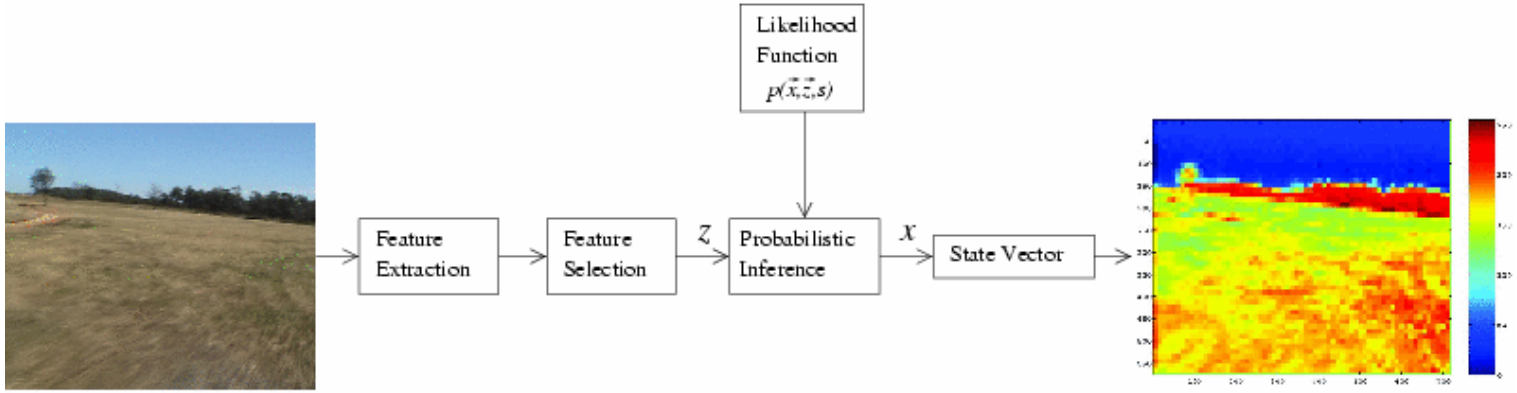
Learning and Inference Process

Learning Diagram



(a)

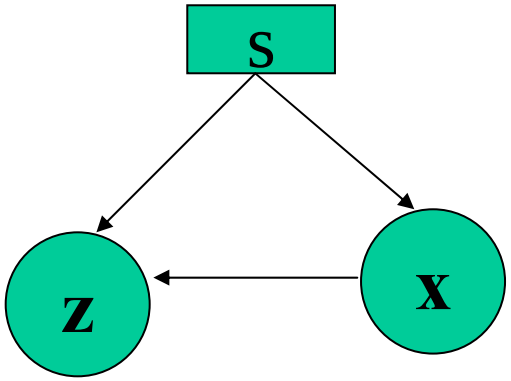
Inference Diagram



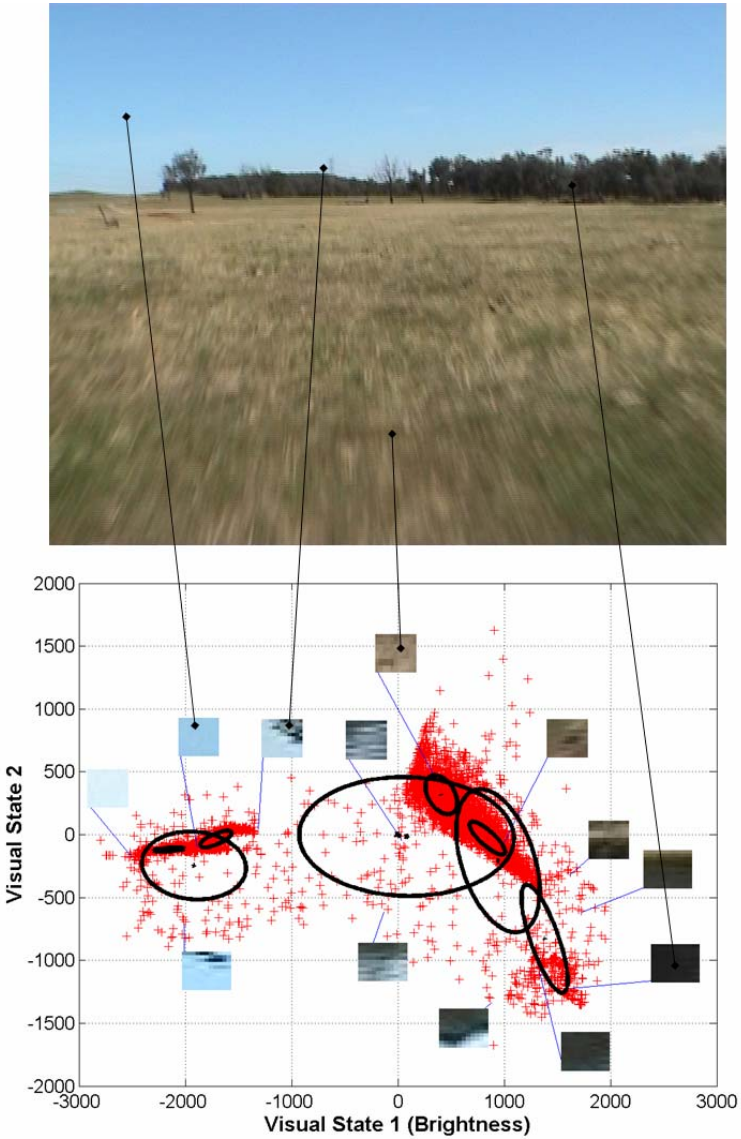
(b)

Step I: Model Generation

- NLDR on image patches
- Find low-D representation for significant patches of interest
- Use VBEM to find number and centre for mixture model

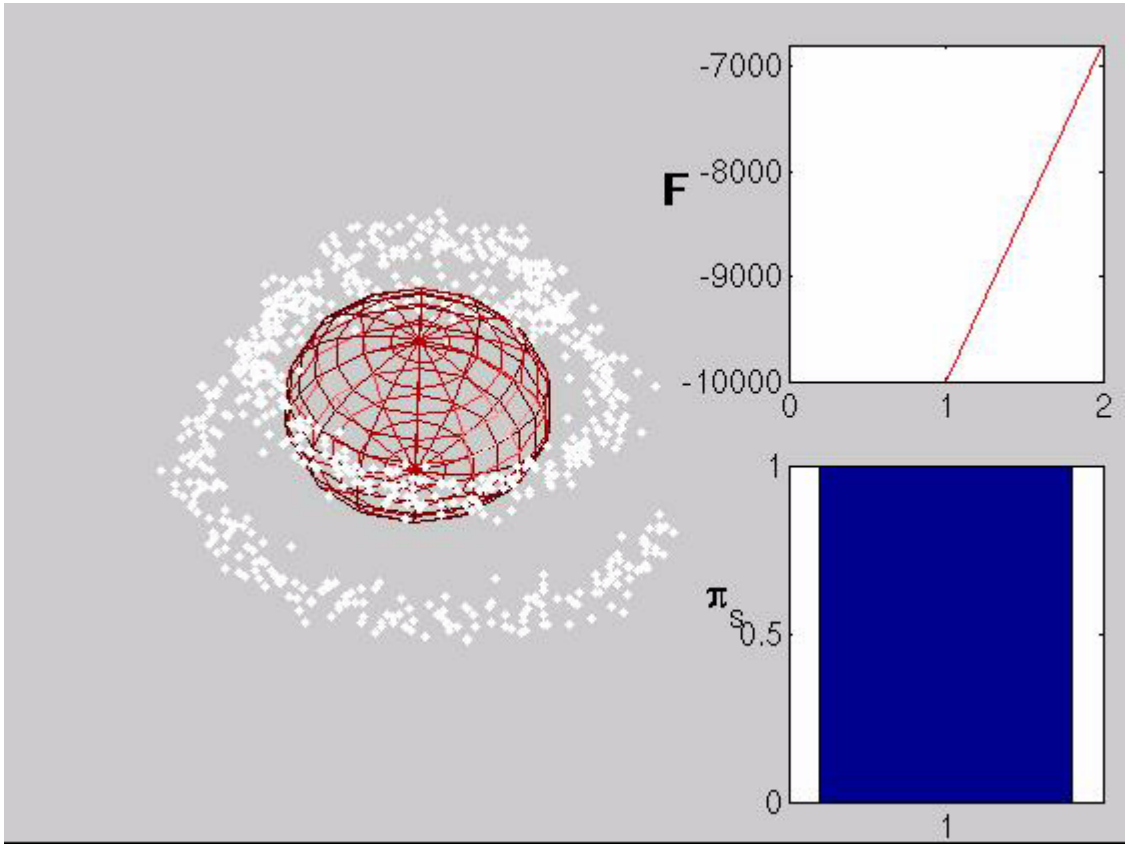


$$P(\mathbf{z},\mathbf{x},\mathbf{s}) = P(\mathbf{z}\mid\mathbf{x},\mathbf{s})P(\mathbf{x}\mid\mathbf{s})P(\mathbf{s})$$

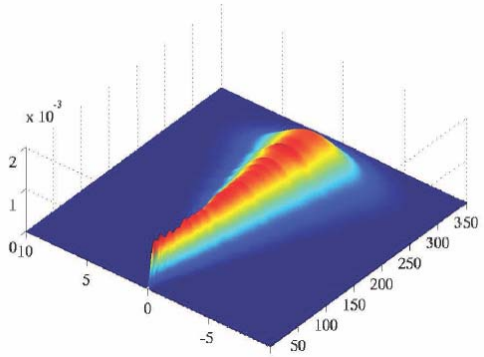


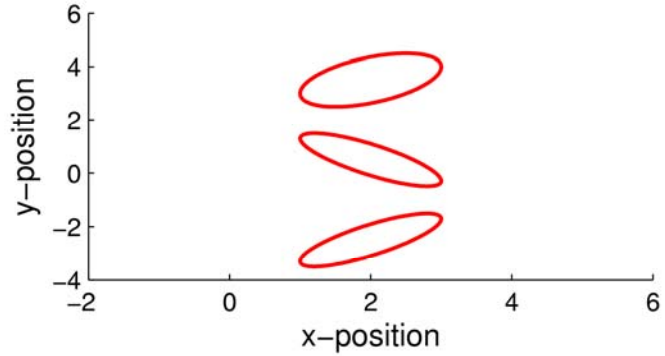
VBEM to Estimate Classifications

- **Need to estimate number and location of classes**
- **Variational Bayes Procedures:**
  - Simultaneous estimation of class number and centre
  - Can deal with order 10^5 state dimensions
- **Unsupervised/semi-supervised classification of sensory data**
- **Automatic generation of Likelihood Function**



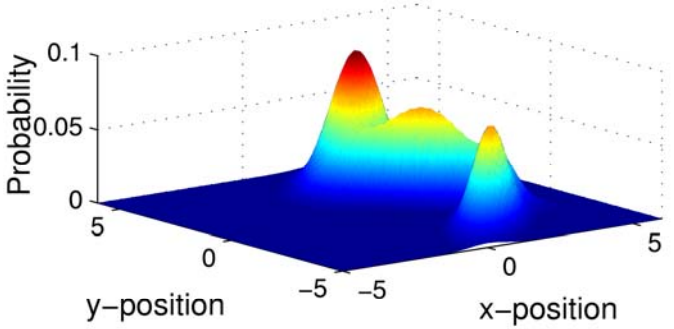
Resulting Location Likelihood Models

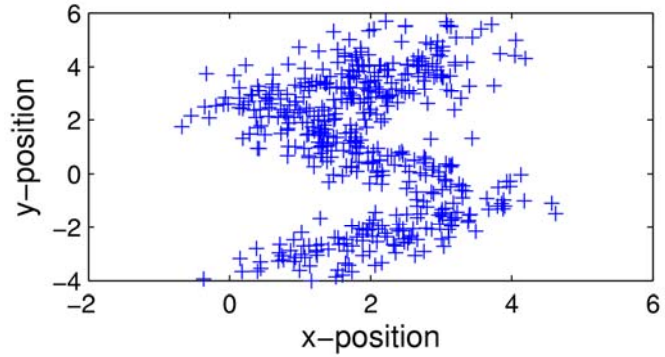




- **Mixture Model for Location Parameters and Likelihoods**

$$P(\mathbf{x}) = \sum_{\mathbf{i}=\mathbf{1}}^{\mathbf{N}} \pi_{\mathbf{i}} \mathcal{N}(\mathbf{x}|\mu_{\mathbf{i}}, \mathbf{\Sigma_i})$$





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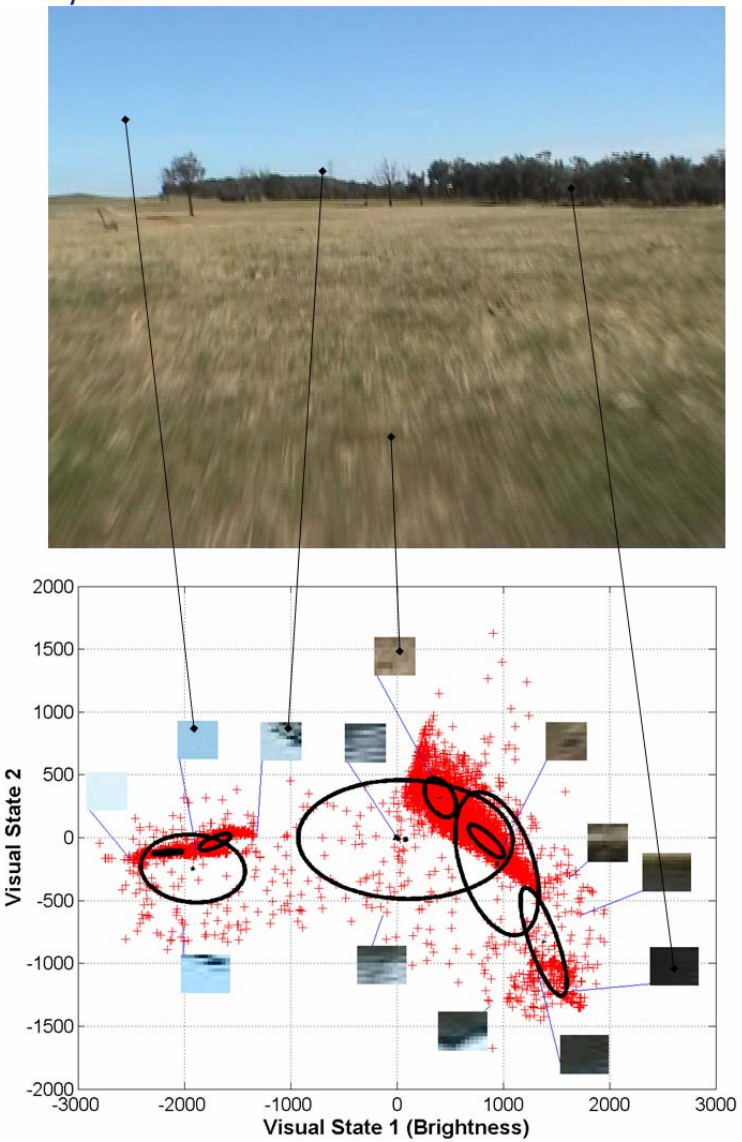
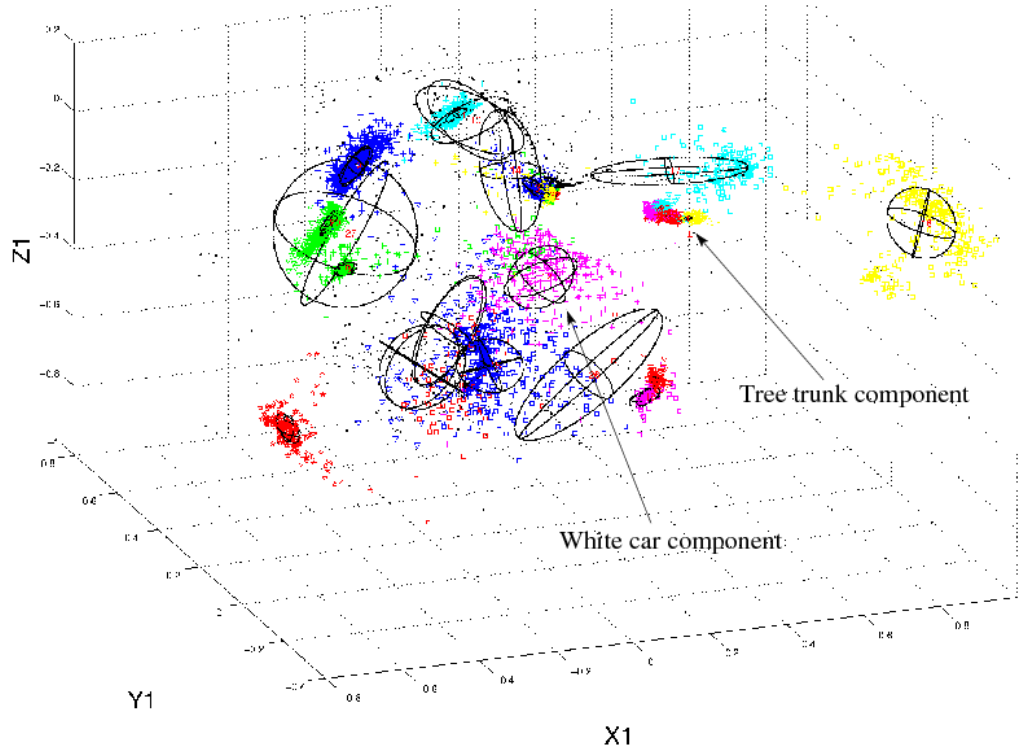
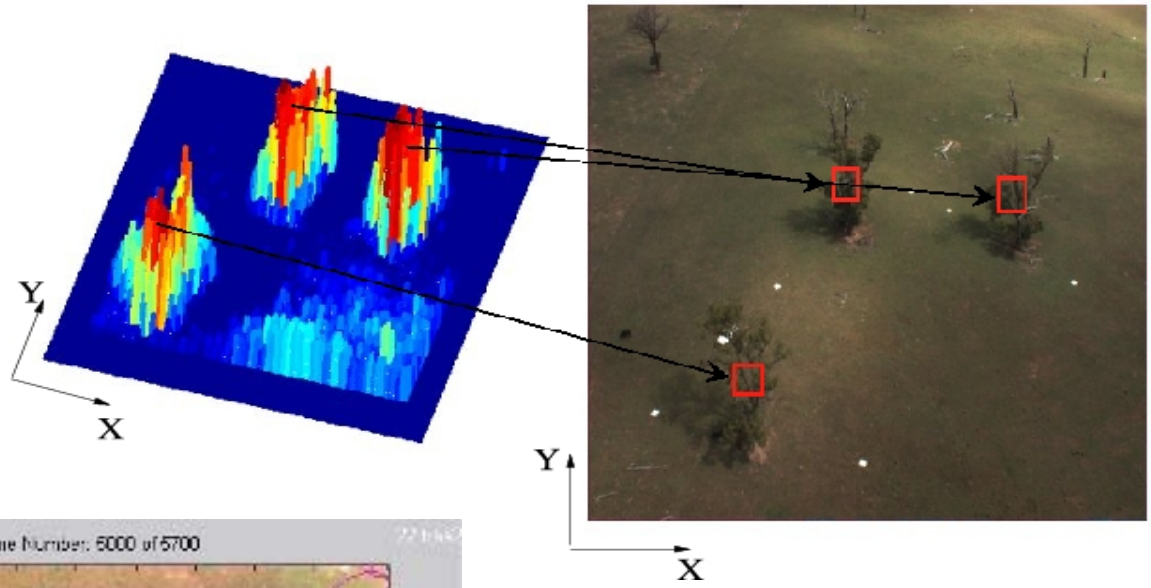
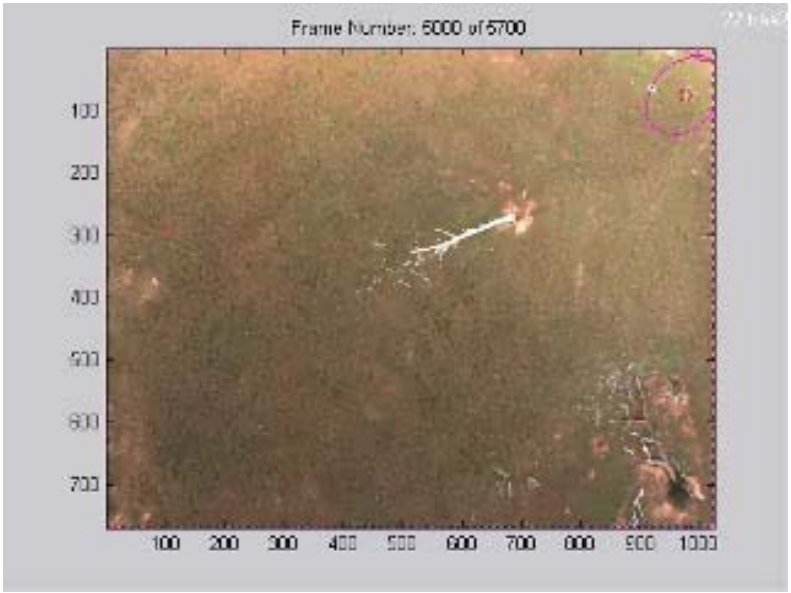




$$P(\mathbf{z} \mid \mathbf{x}, \mathbf{s}) P(\mathbf{x} \mid \mathbf{s}) P(\mathbf{s})$$

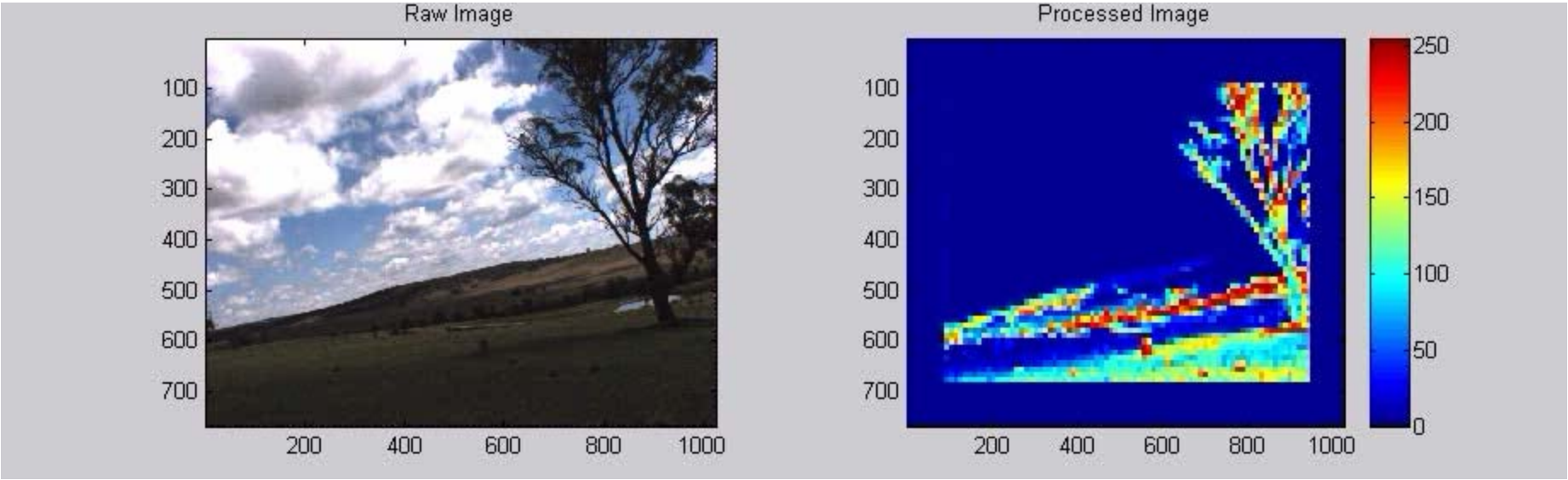
Step II: Model Inference (Air)





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

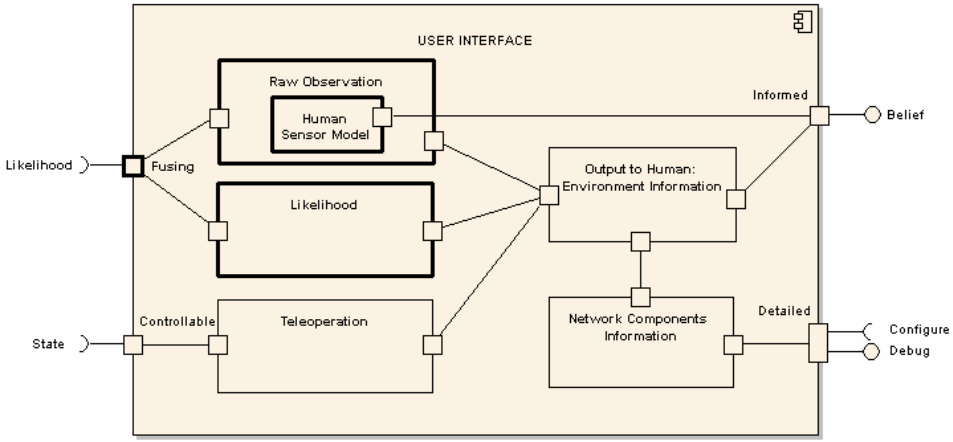
Step II: Model Inference (Ground)

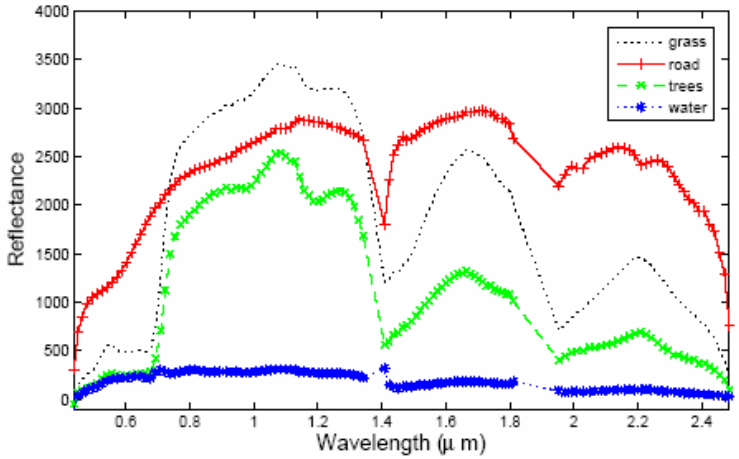


$P(\mathbf{z} \mid \mathbf{x},\mathbf{s})=P(\mathbf{z}|\mathbf{x}=[\mathbf{x},\mathbf{s}])$ is the required likelihood for inference

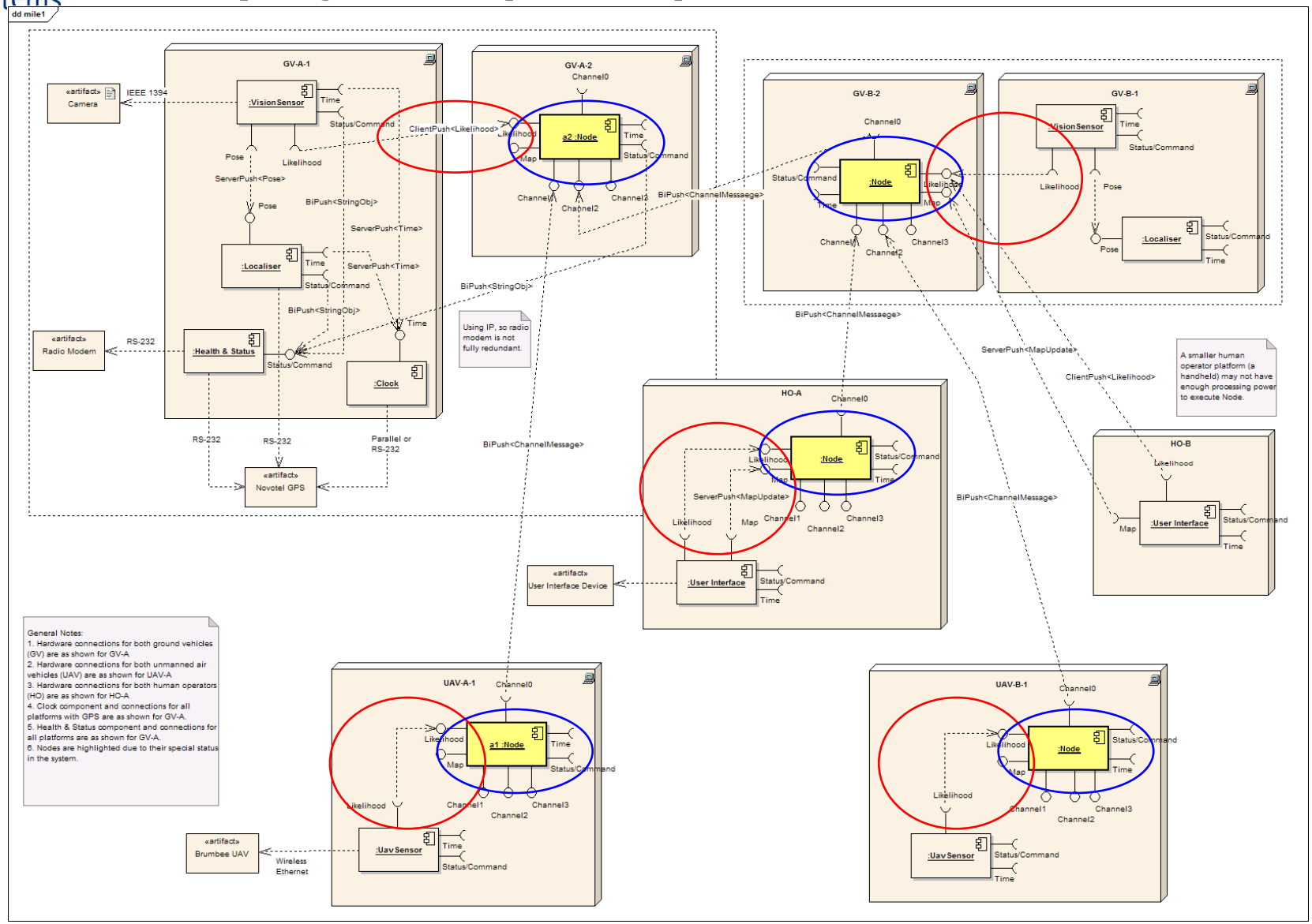
ANSER II Also Uses Data-Base and Human-derived Information

- **Human operator input:**
  - Metric Information
  - Labels, Context
- **On-line estimation of "operator likelihood"**
- **Hyperspectral data "node"**

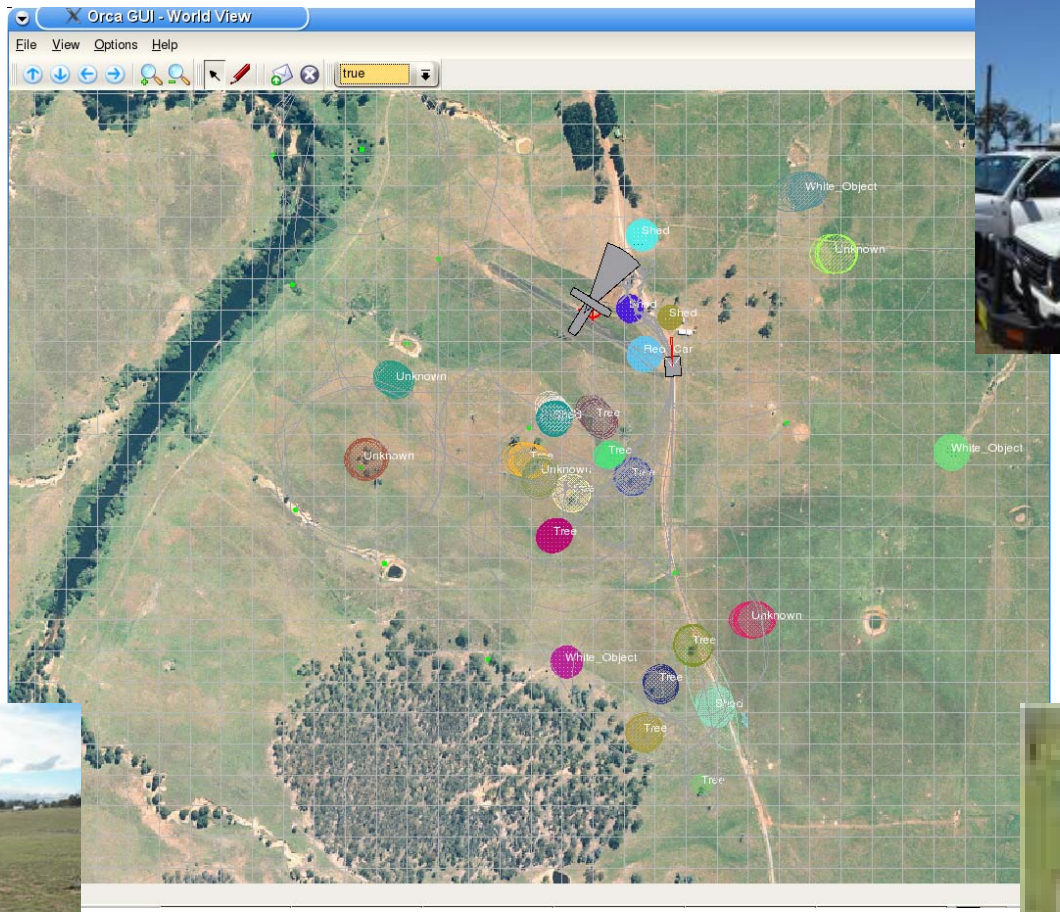




Component-Based Middleware for Deployment (ORCA)

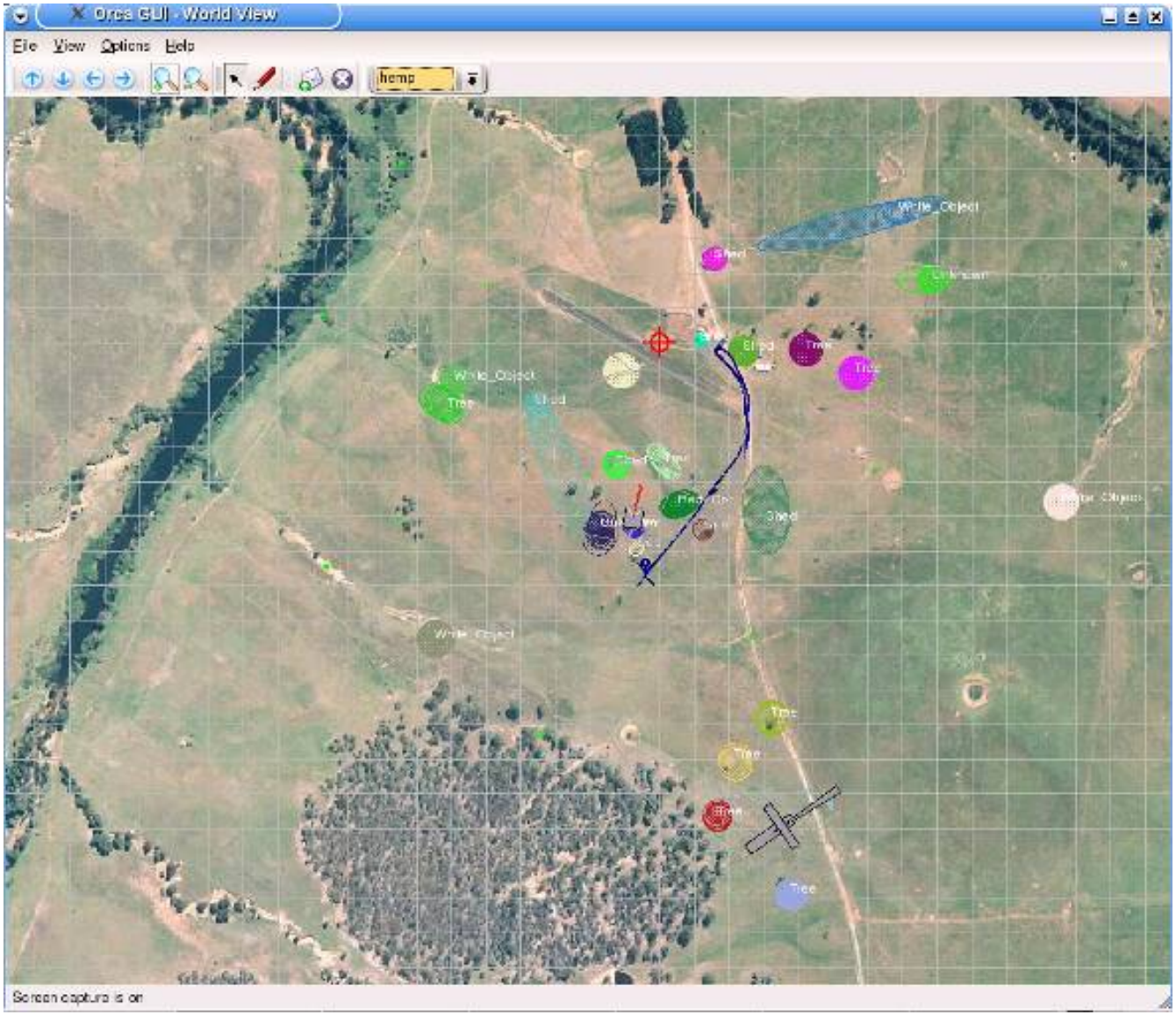


Mission System Implementation



System Video

ANSER II Common Operating Picture

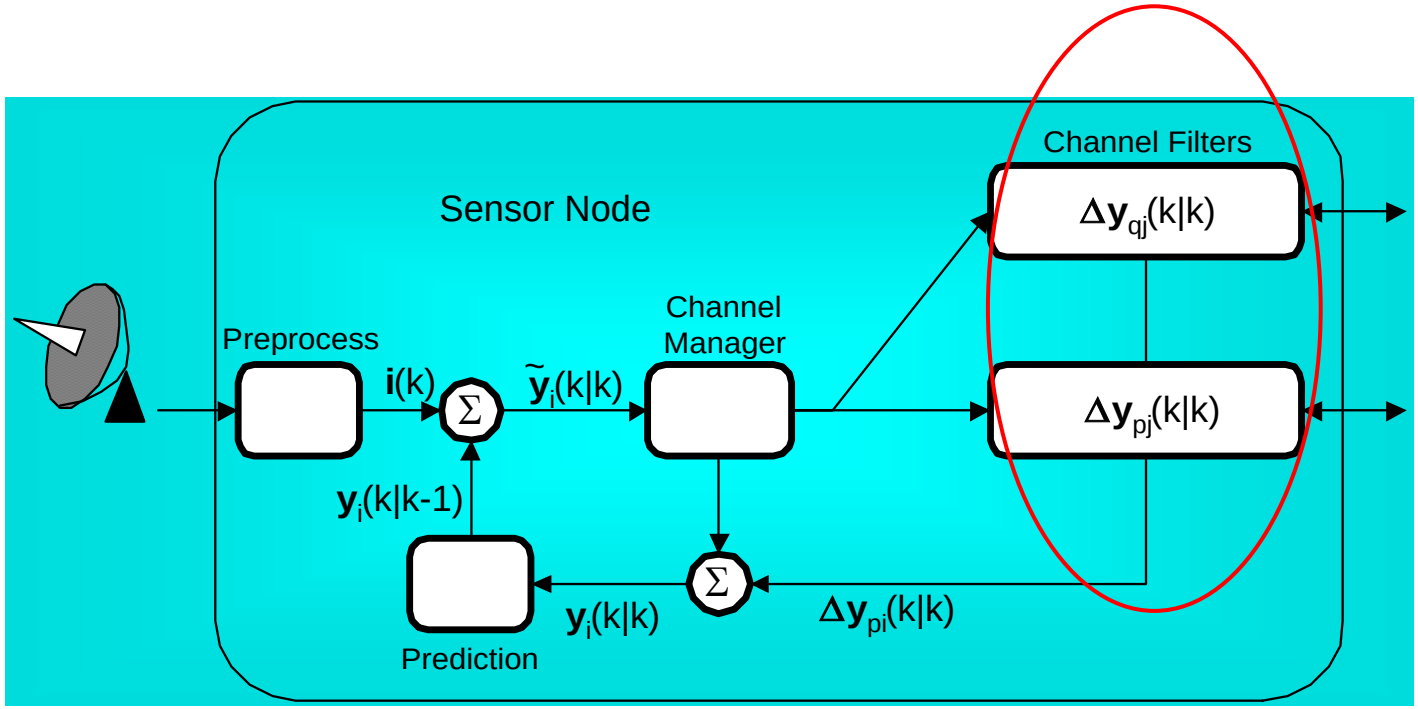


Fusion: Future Challenges

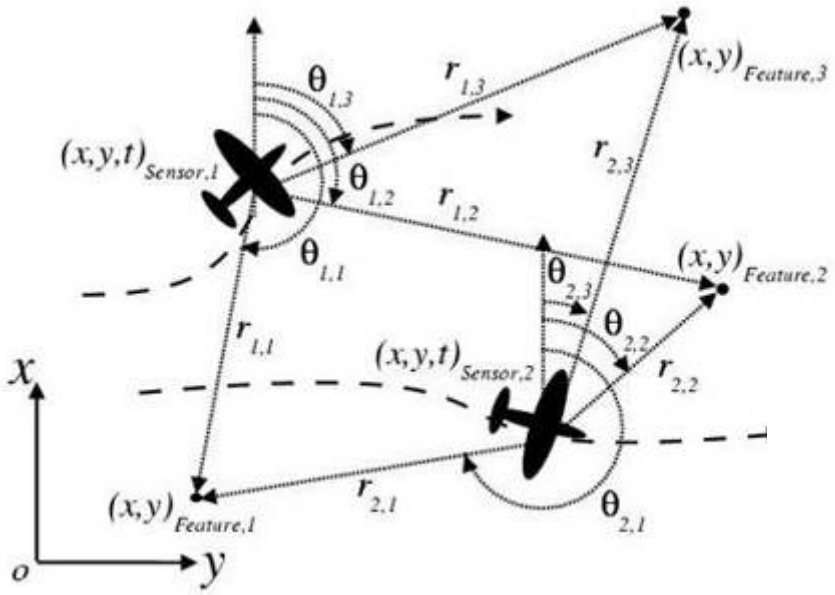
- **Feature Modelling: Finding "x"**
  - Generalising single-sensor feature models
  - Learning mixed-modality feature models
  - Learning and refining abstractions (MI?)
- **Probabilistic Fusion: Finding "P"**
  - High-dimensional density estimation
  - Find a general and efficient density family, closed under fusion operations
  - Data association with general densities
- **Systems design: Finding "z"**
  - Use information to do system design, assembly and reconfiguration

Mutual Information & Control

- **Mutual Information or information gain, is exactly what is communicated in the DDF**
- **Can be exploited in sensor management, communications and platform control**

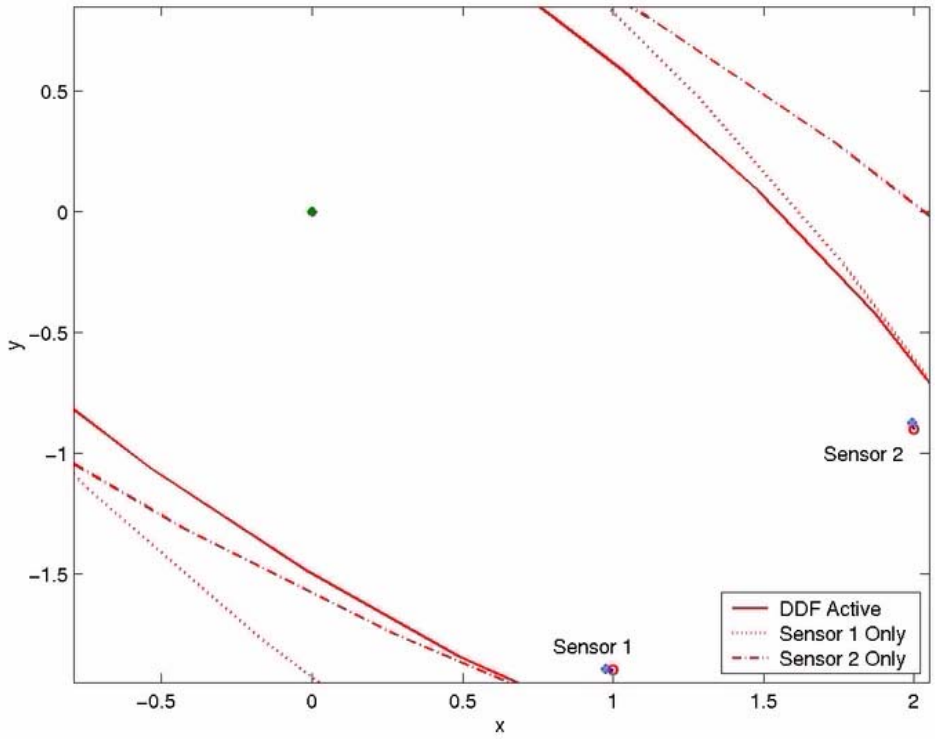


Example Cooperative Control



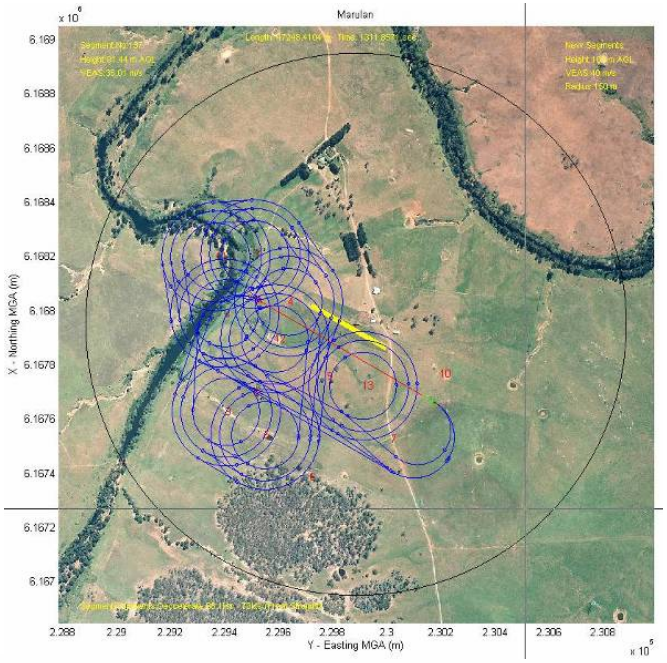
- **The trajectory that maximises information**
- **Information shared (DDF)**

- **Inherits DDF properties:**
  - Scalability
  - Survivability



RCS-18: Future Cooperative UAVs

- **How best to use tactical UAV fleets ?**
- **A list of candidate targets of interest**
- **Coordinate a UAV fleet with mixed sensors to:**
  - Locate,
  - identify and
  - prosecute targets
- **Demonstrate this**

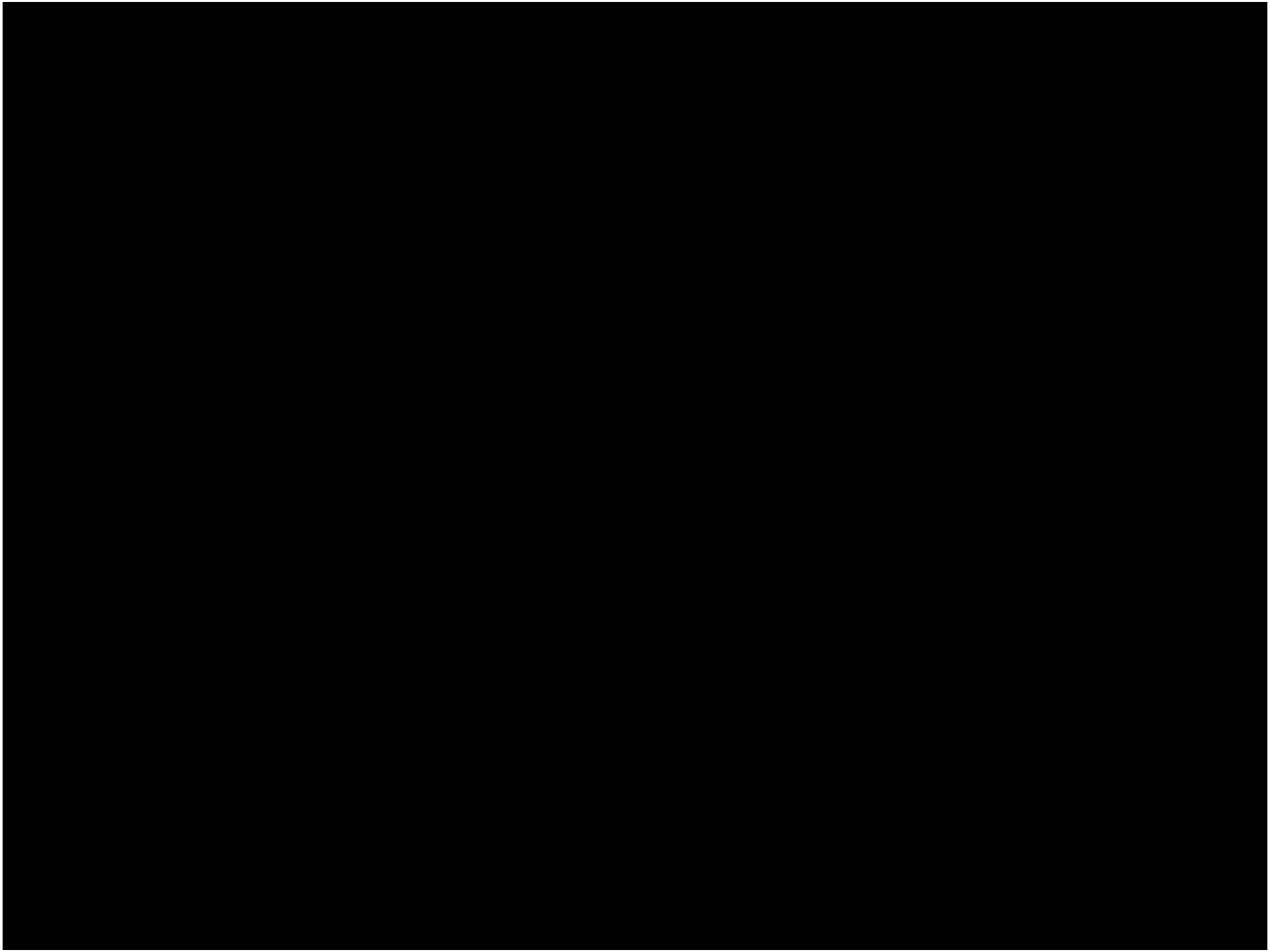


Set-up

- **DDF Enabled on all platforms**
- **Mutual information on target location and IDs**
- **A set of UAV manoeuvres:**
  - Point-to-Point
  - Orbits
- **K-step look-ahead**

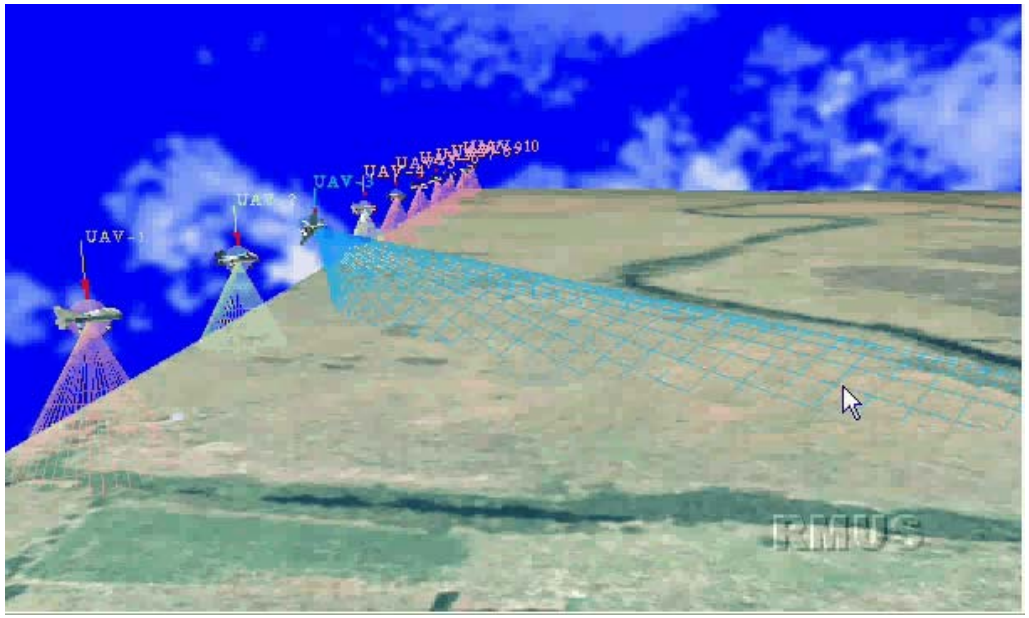
$$\mathbf{I}_{Orbit} = \frac{R\omega}{V}\int_{\varphi s}^{\varphi_e} \mathbf{I} d\varphi$$

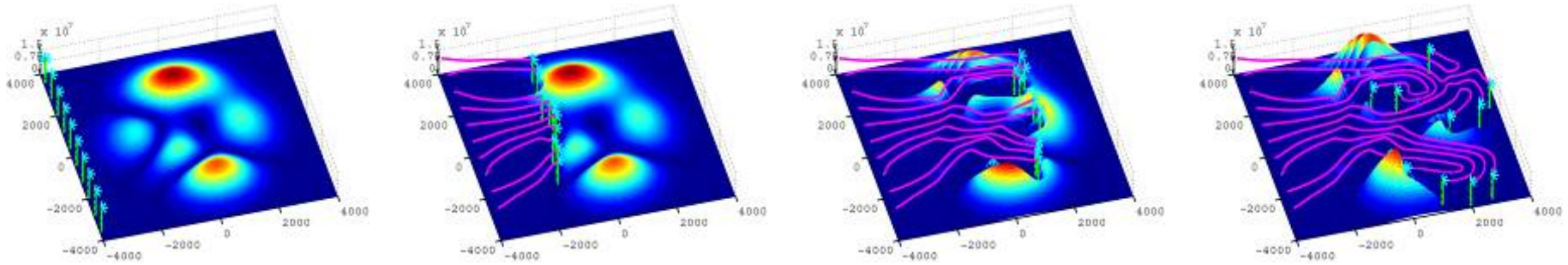
Targets



Extending the Paradigm

- **Other information-maximising controllers**
  - Resource use (platform, communications)
  - Target cuing, hand-off, etc
  - Search, Exploration





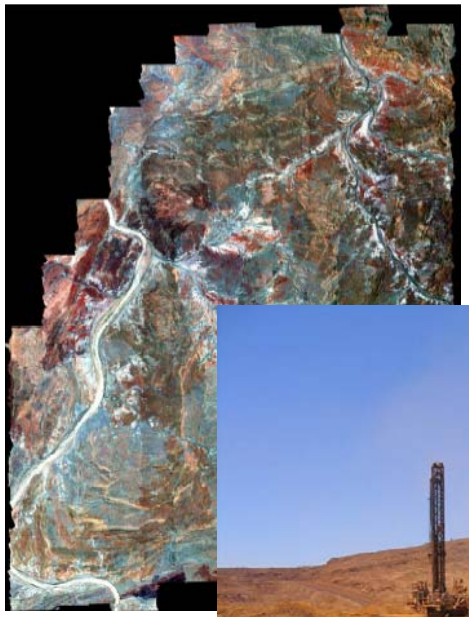
Control: Future Challenges

- **Dealing with Constraints**
  - Process constraints
  - Time constraints (rendezvous)
- **Cooperative Planning**
  - Heterogeneous platforms: Who does what and when
  - Re-tasking

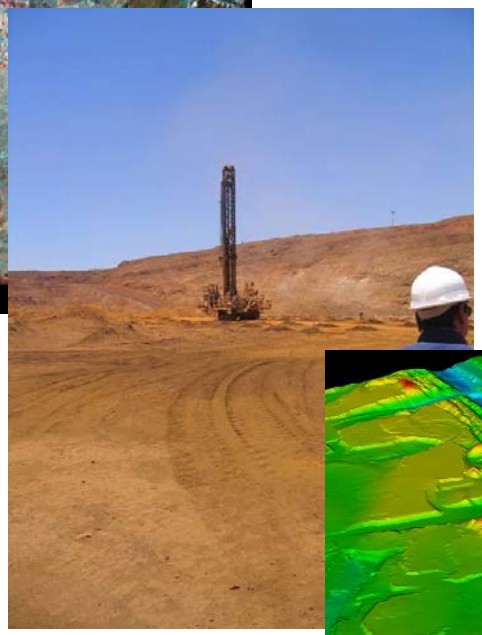
Future Challenges

- **Theory**
  - Spatial Scales
  - Temporal Scales
  - The autonomous sensor
- **The application**
  - Mine picture compilation
  - Large-scale sub-sea surveys

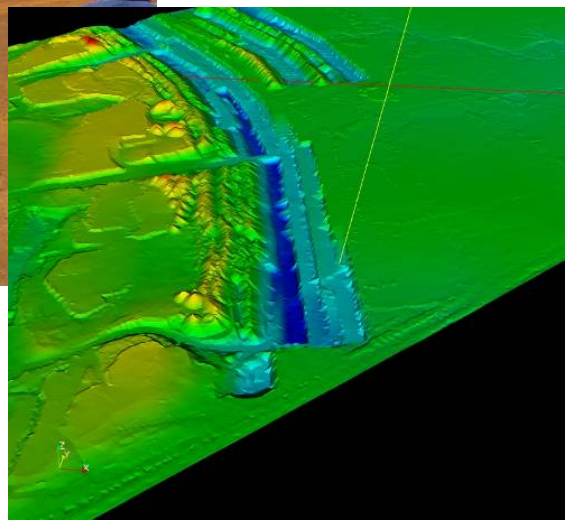
Mine Picture Compilation



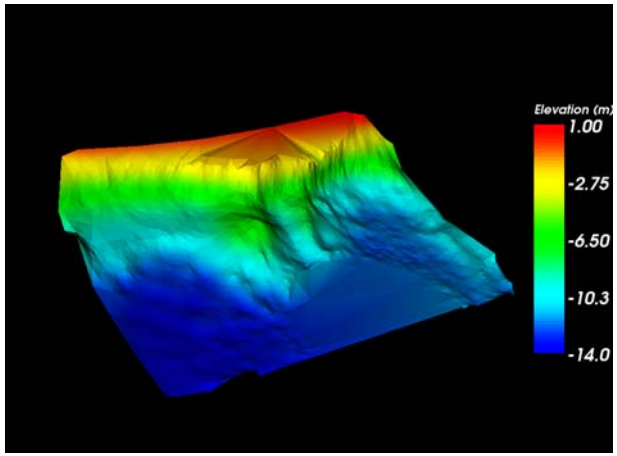
Multi-Spectral



Geophysical



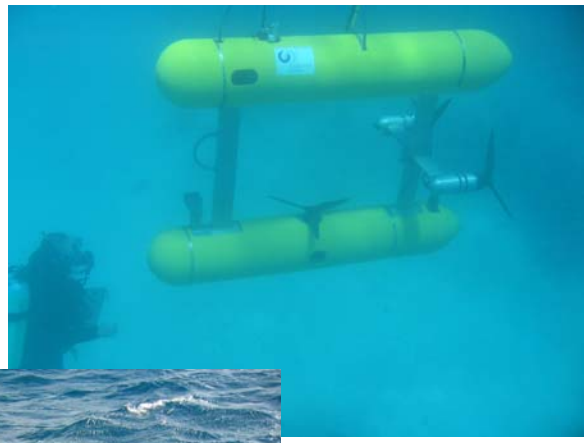
Airborne Laser



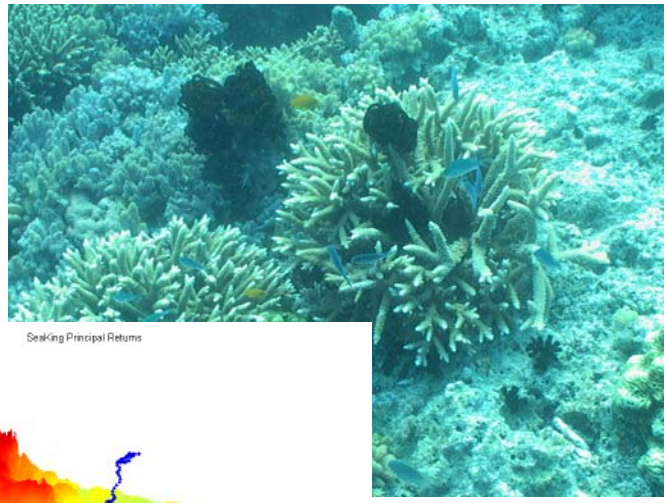
Face Radar

Large-Scale Sub-Sea Surveys

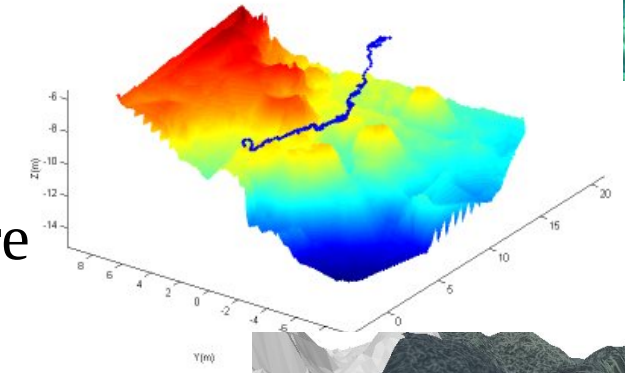
Acoustic



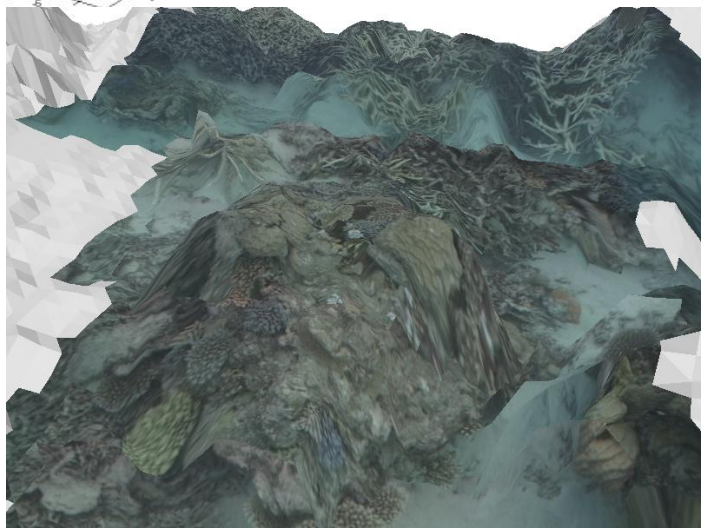
Visual



Temperature



Chemical



Laser