Fusion of Sensor and Model Data

Deb Fish, Oliver Lanning and Paul Thomas
The big picture...

Design / procure

Sensor placement

CB sensor data

Sensor-level fusion

Sensor alarm

Network fusion

Network alarm

Information fusion

Source term

Hazard prediction

Dispersion model

Other sensor data
The big picture...

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Hazard prediction
1) Sensor placement

- 1) Place sensors to maximise probability of any sensor detecting a release
- 2) Place sensors to maximise detection capability of the sensor network
- 3) Place sensors for optimal hazard prediction
- 4) Target UAVs and other mobile sensors...
2) Sensor procurement

• 1) Design individual sensors based on key metrics
  – sensitivity
  – probability of detection
  – false positive rate
  – response time

• 2) Procure heterogeneous network of sensors to optimise key metrics at the system level, for the area to be protected

• 3) Design sensor network to optimise quality of hazard prediction
Optimal biosensor for identification - resonant mirror
Better biosensor for hazard prediction - particle counter?

Impact of single sensor on source term estimation only - conclusions are limited!
3) Fusion of sensor and model data

Seek single, best estimate of current and future hazard by combining sensor data and model predictions. Alternative views: hazard refinement / uncertainty reduction

- Design / procure
- Sensor placement
- Sensor-level fusion
- Network fusion
- Information fusion
- Source term
- Hazard prediction
- Network alarm
- Dispersion model

Seek single, best estimate of current and future hazard by combining sensor data and model predictions.

Alternative views: hazard refinement / uncertainty reduction
3a) Literature Review

• Investigated wide variety of possible methods
  – Bayes theory
  – Kalman Filter
  – Fuzzy Logic
  – Genetic Algorithms
  – Neural Networks
  – Variational Assimilation
  – Optimal Interpolation

• Chosen short list of suitable techniques for implementation into a synthetic environment
Bayesian fusion

\[ p(H \mid D) = \frac{p(D \mid H)p(H)}{p(D)} \]

- Mathematically rigorous
  - Incorporates uncertainty
- Simple in concept
- Incorporates prior knowledge
- Can be extended to incorporate any information
  - Observer range and bearing
- No absolute probabilities
- Difficult to implement (complex integrals)
- Computationally demanding
Kalman filter

\[ x = x^b + K \left( y - H x \right) \]

\[ K = \left( B^{-1} + H^T R^{-1} H \right)^{-1} H^T R^{-1} \]

- Sequential predictor-corrector data fusion method
  - incorporates uncertainty
- Provides prediction of the error covariances
- Incorporates prior knowledge
- KF only for linear models
  - Use extended or ensemble KF for non-linear models
- Can be computationally demanding
Variational Data Assimilation

\[ J(x) = \frac{1}{2} (x - x^b)^T B^{-1} (x - x^b) + \frac{1}{2} \sum_{i=1}^{N} (y_i - Hx_i)^T R^{-1} (y_i - Hx_i) \]

- Variational method
  - Assimilates all sensor data simultaneously
- Determines optimal analysis by solving the cost function
  - Provides gradient of analysis
- Can be very computationally demanding
- Does not determine the analysis directly
Overview of optimal techniques

<table>
<thead>
<tr>
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<th>Use observations at the same time</th>
<th>Use a time sequence of observations</th>
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<tbody>
<tr>
<td>Sequential</td>
<td>Optimal Interpolation</td>
<td>Kalman Filter, Bayes</td>
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<tr>
<td>Variational</td>
<td>3DVAR</td>
<td>4DVAR</td>
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- Most interested in techniques that use a time sequence of observations
  - Assumption that observations occur at the same time introduces additional error

- Comparison of sequential and variational methods
3b) Uncertainty propagation

- Crucial to quantify uncertainty in model predictions, as well as sensor data
  - source magnitude, time and location (x,y,z)
  - number of sources
  - meteorology (in complex environments) and turbulence
  - effects (e.g. casualties)
  - is data representative?
- MOD-funded uncertainty project

Reduce uncertainty, refine hazard
Uncertainty propagation

- Dstl have developed an uncertainty propagation framework:
  - takes probabilistic output from SCIPUFF / UDM
  - propagates uncertainty in casualties due to
    - respirator
    - breathing rate
    - toxicology
    - medical counter measures

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3c) Sensitivity study

- Vary each input parameter in turn
  - source m, x, y, z, t
  - meteorology
  - turbulence
- Use synthetic environment to determine effect on output from range of possible sensors
  - CB sensors
  - meteorological sensors
3c) Sensitivity study

Identify inputs that have
- **little effect on sensor output**
  - neglect ⇒ simplify problem
- **correlations with other inputs**
  - retrieve dominant input
  - use knowledge of correlations to understand / estimate uncertainty in hazard prediction
- **large effect on sensor output**
  - apply short-listed techniques to retrieve these inputs
3d) Implementation in synthetic environment

- It is essential to test the short-listed techniques in a realistic synthetic environment
  - meteorological forecasts subject to significant error
    - 30° error common
  - experimental concentration profiles show strong effects of turbulence
  - no sensor is perfect

Measured effects of turbulence
3d) Implementation in synthetic environment

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Synthetic environment

- Dstl’s synthetic environment includes:
  - model of meandering puffs
  - UDM
  - model of turbulence within puff
  - realistic sensor models
  - biological background model
  - Monte Carlo variation of model parameters

Spray of NADH in water solution (0.642% concentration)

Analysis of data for biological sensor model
Future plans

• Completion of sensitivity study
  – what information do we attempt to retrieve?

• Test short-listed techniques in synthetic environment for chemical, then biological releases
  – Biological data fusion complicated by fluctuating biological background
  – quantitative metrics ($A_{FN}$, $A_{FP}$)
Biological sensor fusion

- Biological sensor model

**Simple particle counter sensor**

- Low fidelity, analogue signal

**Immuno-Assay detector**

- High fidelity, digital (2 state) signal

**Conclusion:** Information requirements differ depending on decision to be made

Try to explain better