Collective Perception in Large-Scale Dynamic Systems

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Outline of Presentation

- Perception in Large Scale Dynamic Systems (LSDS)
  - Multi-Sensor Data Fusion
- Challenges in Sensor Fusion
- Bayesian Framework of Data Fusion
- Two specific issues
  - Detection of spurious data
  - Adaptive sensor modeling
- Results

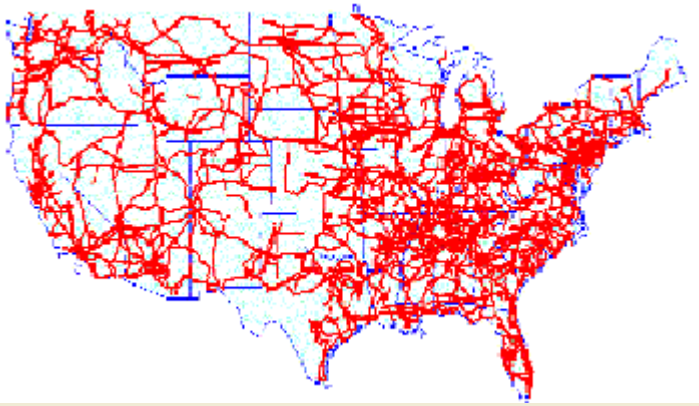
PERCEPTION :
Multiple Sensor Data Fusion

Advantages of Multiple Sensors

- **Sensors Enrich System's Knowledge**
- **Limitations of Single Sensor**
- **Complex, Dynamic, and Uncertain Environments**
- **Multiple Sensors:**

  - Complementary, Redundant,

  Diverse, Timely Information



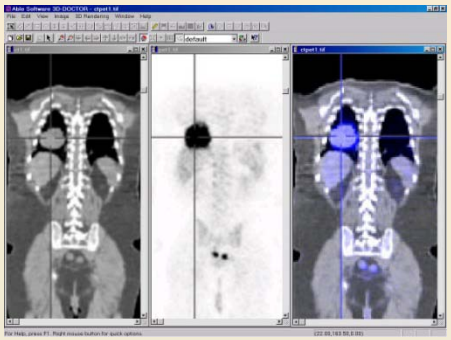
National Electric Power Grid

Source: http://www.anl.gov/Media_Center/logos22-1/electricity.htm

Multi-Sensor Fusion: Commercial Applications

- **Biomedical Applications**

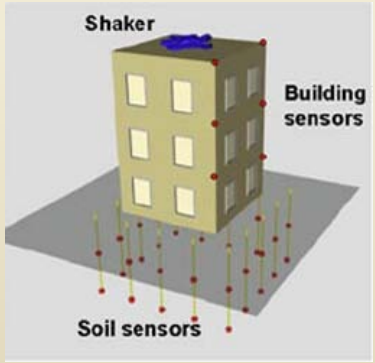
  Diagnostic assistance, fusion of medical images

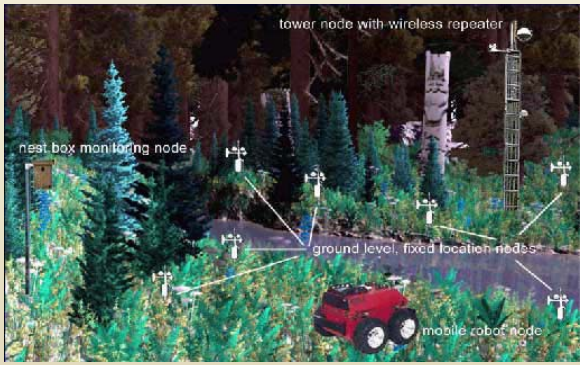


Source: http://www.ablesw.com/3d-doctor/regist.html

- **Health Monitoring**

  Smart Structures, Machines, Diagnosis, Prognosis





Source: www.cs.ucla.edu/~jessicaf/

- **Environment Monitoring**

  Habitat Monitoring, Traffic Monitoring

- **Industrial Applications**

  Robotics, Manufacturing Automation

Source: http://www.wes-tech.com/manuf1.jpg

Multi-Sensor Fusion: Military Applications

- **Battlefield Operations**

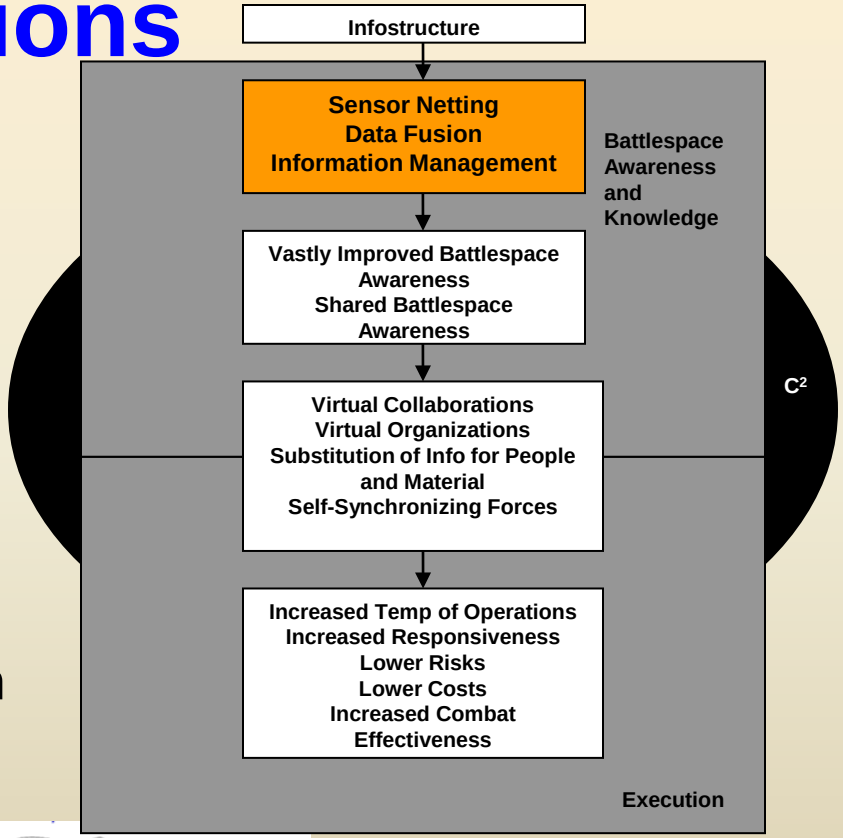
  Detection, Tracking, Identifying and Locating Targets

- **Situation Awareness**

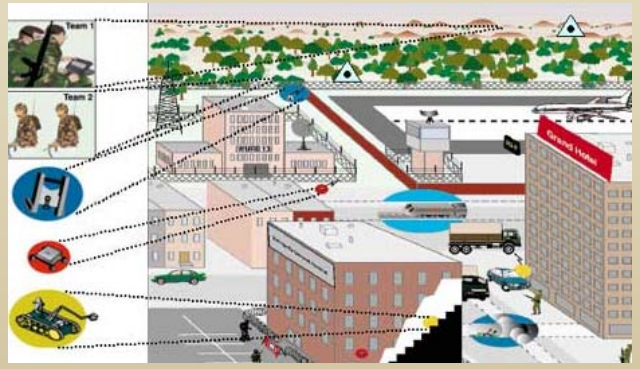
  Web of Human and Non-Human Sources, Information Superiority

- **Network Centric Warfare**

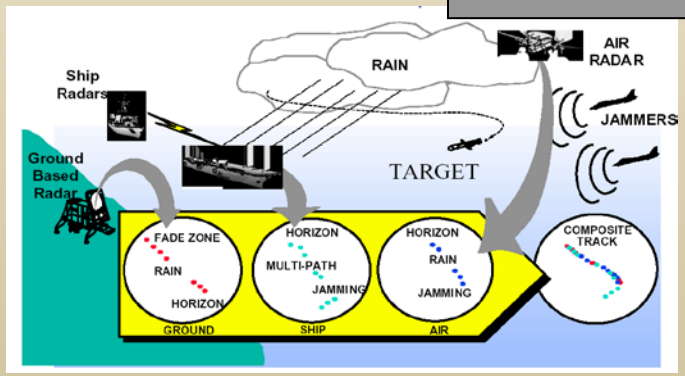
  Linkage between Sensors, Decision Makers and Armaments



Source: http://www.dod.mil/nii/NCW/ncw_0801.pdf

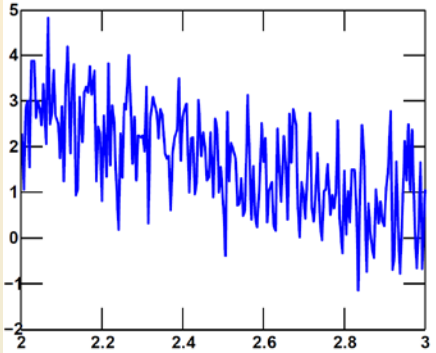


Source: http://www.darpa.mil/ato/programs/tmr.htm

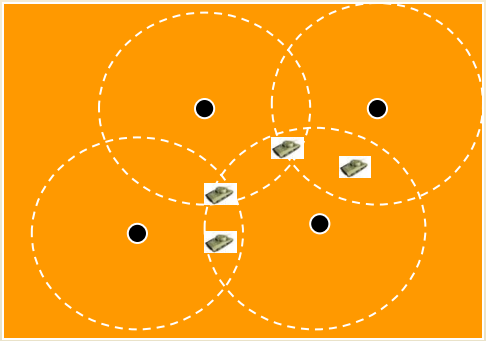


Source: http://www.plansys.com

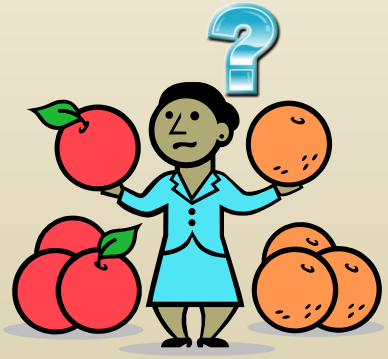
Issues and Challenges



- Sensor Uncertainty: Noise, Ambiguity, Spuriousness



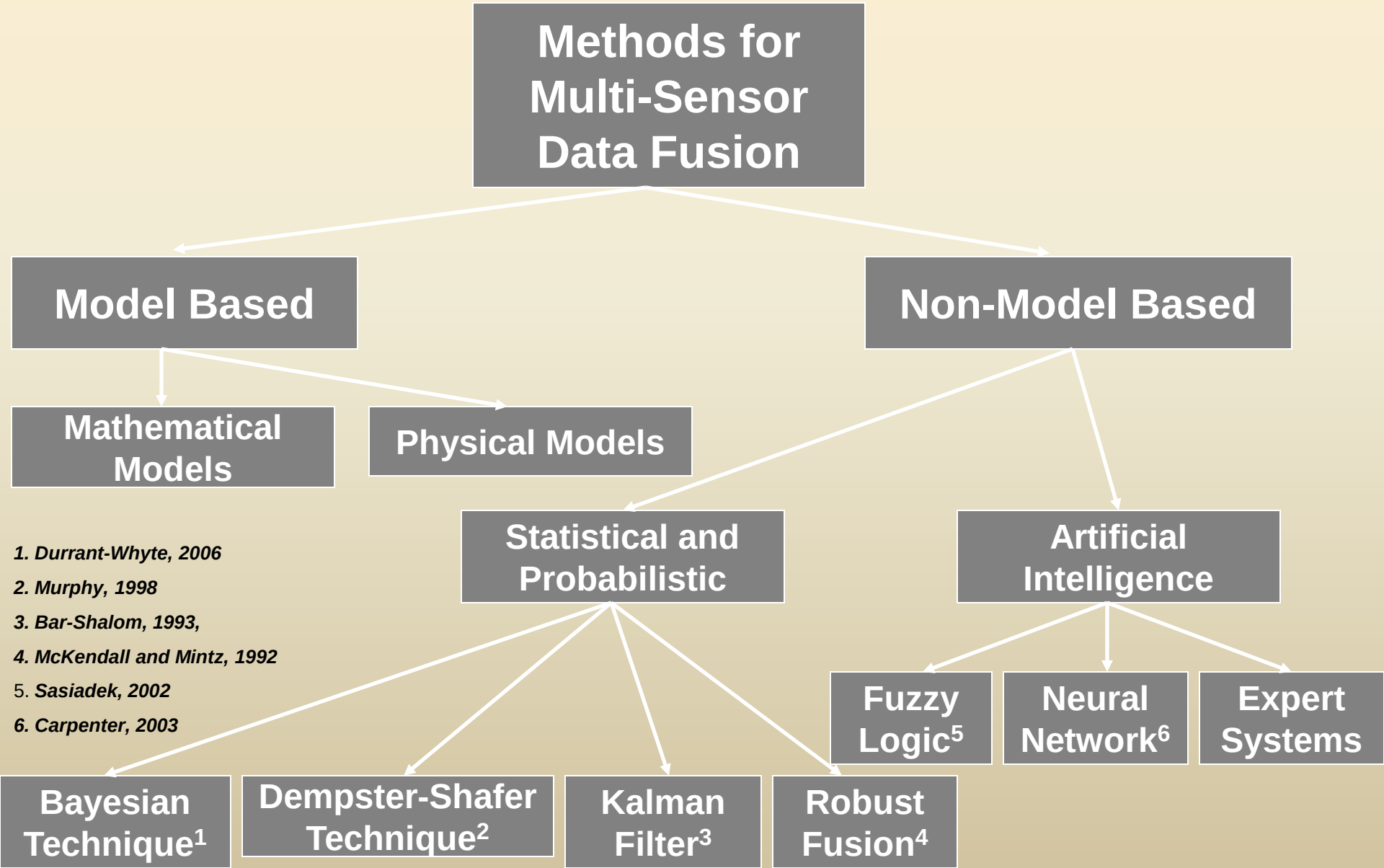
- Data Association



- Sensor Selection: Optimization of Resources

- Complexity and Synergism: Numerous Sources

Sensor Fusion Algorithms



1. *Durrant-Whyte, 2006*
2. *Murphy, 1998*
3. *Bar-Shalom, 1993,*
4. *McKendall and Mintz, 1992*
5. *Sasiadek, 2002*
6. *Carpenter, 2003*

Bayesian Estimation

Probabilistic Data Fusion Algorithm based on Bayes' Theorem

$$p(X = x \mid Z = z) = \frac{p(Z = z \mid X = x)P(X = x)}{\int p(Z = z \mid X = x)P(X = x)dx} = \frac{p(Z = z \mid X = x)P(X = x)}{P(Z = z)}$$

Likelihood Function

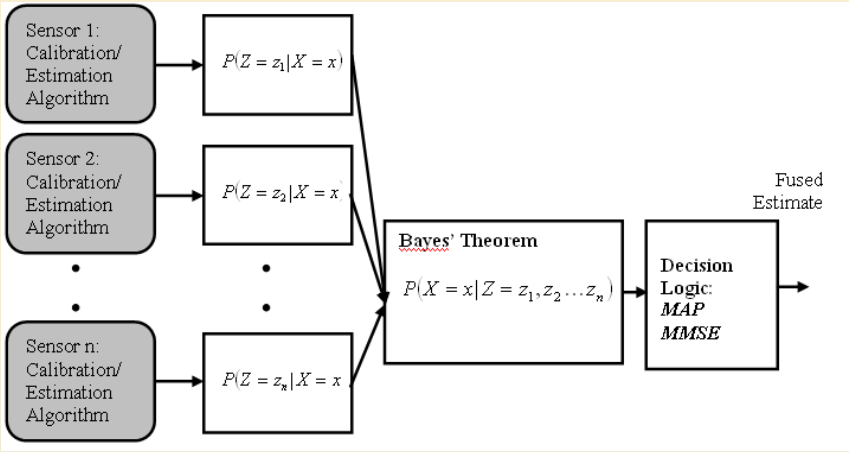
Prior Knowledge

Estimation:

- *MAP* (Maximizing a *Posteriori*)
- Bayes' Estimates such as *MMSE* (Minimum Mean Square Estimation)

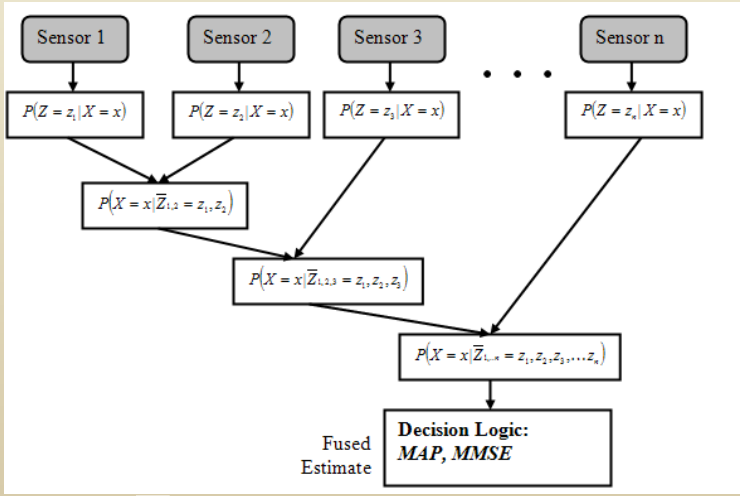
Fusion from Multiple Sources

- **Centralized Fusion**



$$p(X = x \mid Z = z_1, z_2, \ldots z_n) = \frac{p(Z = z_1 \mid X = x)p(Z = z_2 \mid X = x)\ldots p(Z = z_n \mid X = x)P(X = x)}{P(Z = z_1, z_2, \ldots z_n)}$$

- **Decentralized / Sequential Fusion**



$$p(X = x \mid \overline{Z}_{1\ldots n} = z_1, z_2, \ldots z_{n+1}) = \frac{p(Z = z_{n+1} \mid X = x)P(X = x \mid \overline{Z}_{1\ldots n} = z_1, z_2, \ldots z_n)}{P(\overline{Z}_{1\ldots n} = z_1, z_2, \ldots z_n)}$$

Spurious Data Identification and Elimination

Introduce a term representing the probability of event *p(s=0)*

$$\left[p(s=0\,|\,X=x,Z=z_i)\right]_i=\frac{\left[P(s=0)\right]_i\left[p(Z=z_i\,|\,X=x,s=0)\right]}{\sum_s\left[P(s)\right]_i\left[p(Z=z_i\,|\,X=x,s)\right]_i}=\frac{\left[P(s=0)\right]_i\left[p(Z=z_i\,|\,X=x,s=0)\right]}{\left[p(Z=z_i\,|\,X=x)\right]_i}$$

Centralized Fusion Scheme

$$p(X=x\,|\,Z=z_1,z_2,\ldots z_n)=\frac{\left[P(s=0)\right]_1\left[p(Z=z_1\,|\,X=x,s=0)\right]_1}{\left[p(s=0\,|\,X=x,Z=z_1)\right]_1}\times\ldots\frac{\left[P(s=0)\right]_n\left[p(Z=z_n\,|\,X=x,s=0)\right]_2}{\left[p(s=0\,|\,X=x,Z=z_n)\right]_n}\times\frac{P(X=x)}{P(Z=z_1,z_2,\ldots z_n)}$$

Additional Terms Introduced

Decentralized / Sequential Fusion Scheme

$$p(X=x\,|\,\overline{Z}_{1\ldots n}=z_1,z_2,\ldots z_n)=\frac{\left[P(s=0)\right]_n\left[p(Z=z_n\,|\,X=x,s=0)\right]P(X=x\,|\,\overline{Z}_{1\ldots n-1}=z_1,z_2,\ldots z_{n-1})}{P(\overline{Z}_{1\ldots n}=z_1,z_2,\ldots z_n)\left[p(s=0\,|\,X=x,Z=z_n)\right]}$$

Entropy: Information Content

$$H(X)=\int-p(X=x\,|\,Z=z_1,z_2,\ldots z_n)\log\left(p(X=x\,|\,Z=z_1,z_2,\ldots z_n)\right)dx$$

M. Kumar et. al., SPIE 2006 , ACC 2006, IEEE Sensors Journal 2007

Fusion of Three Sensors

Gaussian Sensor Model: $p(Z = z_k \mid X = x) = \frac{1}{\sigma_k \sqrt{2\pi}} e^{\left\{ \frac{-(x - z_k)^2}{2\sigma_k^2} \right\}}$ $k=1,2,3$

Method 1: Simple Bayesian Fusion

Posterior is Gaussian with variance: $(\sigma')^2 = \left[(\sigma_1)^{-2} + (\sigma_2)^{-2} + (\sigma_3)^{-2} \right]^{-1}$

and mean $\hat{x}_{MAP} = (\sigma')^2 \left[\frac{z_1}{(\sigma_1)^2} + \frac{z_2}{(\sigma_2)^2} + \frac{z_3}{(\sigma_3)^2} \right]$

Method 2: Centralized Bayesian Fusion

$$p(X = x \mid Z = z_1, z_2, z_3) = \frac{P(X = x)}{P(Z = z_1, z_2, z_3)} \times \prod_{k=1}^{3} [P(s = 0)]_k \frac{1}{\sigma_k \sqrt{2\pi}} e^{-(x - z_k)^2 \left\{ \frac{1}{2\sigma_k^2} - \frac{\prod_{l \neq k, l=1}^{3} (z_k - z_l)^2}{b_k^2} \right\}}$$

Method 3: Sequential Bayesian Fusion

$$p(X = x \mid Z = z_k, z_{k+1}) = \frac{P(X = x)}{P(Z = z_k, z_{k+1})} \times [P(s = 0)]_k \frac{1}{\sigma_k \sqrt{2\pi}} e^{-(x - z_k)^2 \left\{ \frac{1}{2\sigma_k^2} - \frac{(z_k - z_{k+1})^2}{b_k^2} \right\}} \times [P(s = 0)]_{k+1} \frac{1}{\sigma_{k+1} \sqrt{2\pi}} e^{-(x - z_{k+1})^2 \left\{ \frac{1}{2\sigma_{k+1}^2} - \frac{(z_k - z_{k+1})^2}{b_{k+1}^2} \right\}}$$

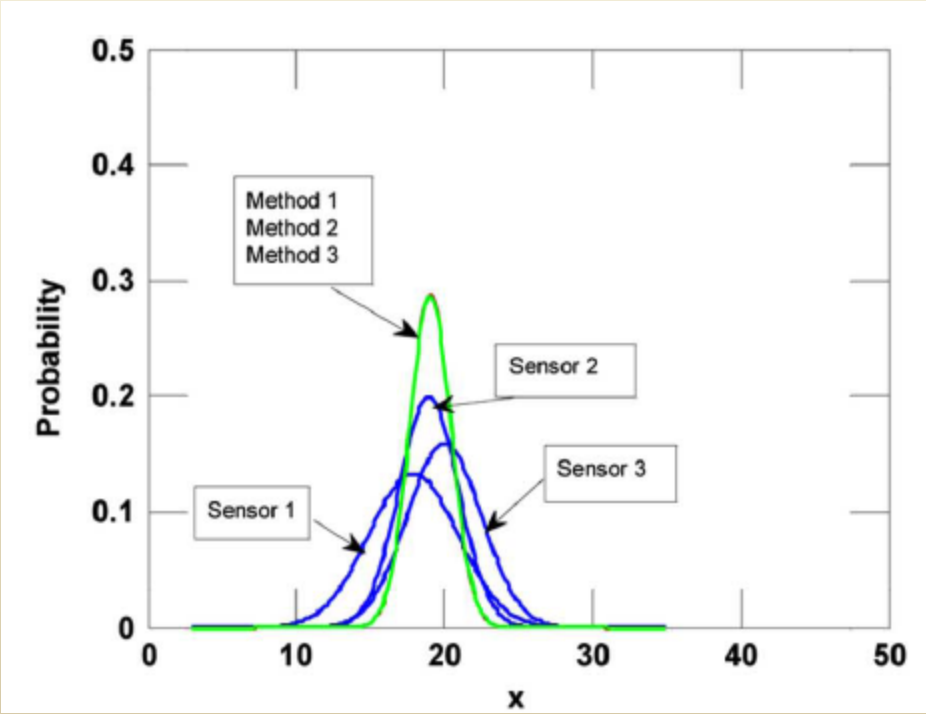
Fusion of Three Sensors (Simulation Results)

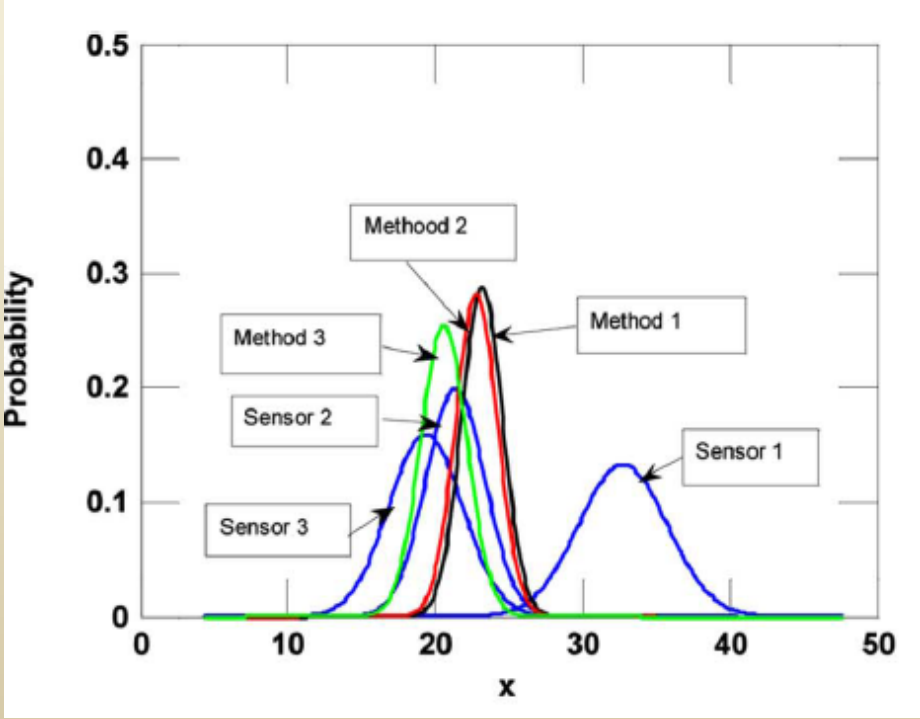
Sensor 1: $[P(s=0)]_1 = 0.90$ and $\sigma_1 = 3$

Sensor 2: $[P(s=0)]_2 = 0.98$ and $\sigma_2 = 2$

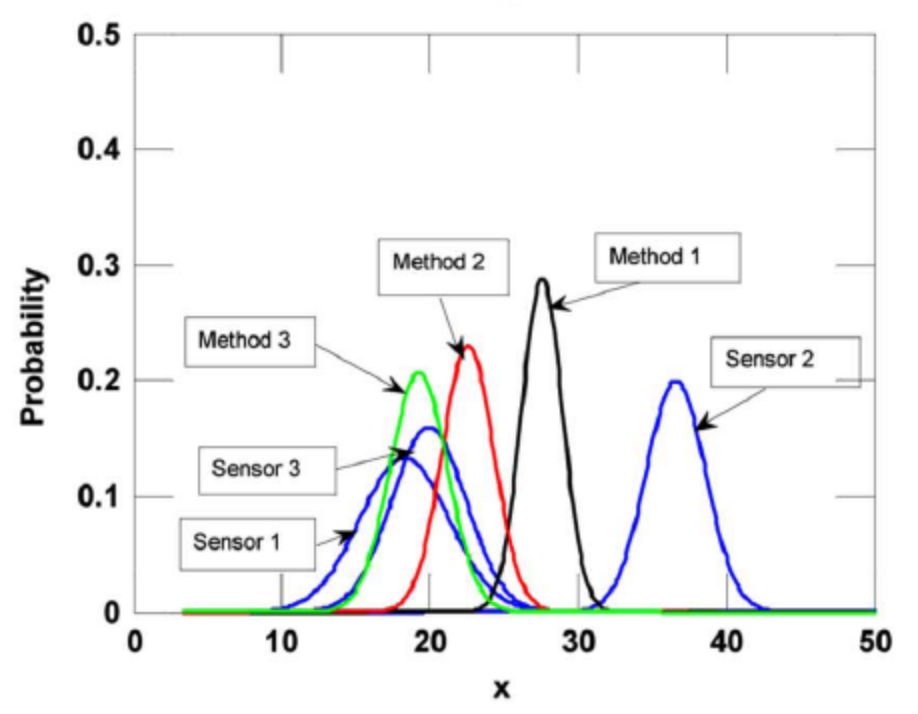
Sensor 3: $[P(s=0)]_3 = 0.94$ and $\sigma_3 = 2.5$

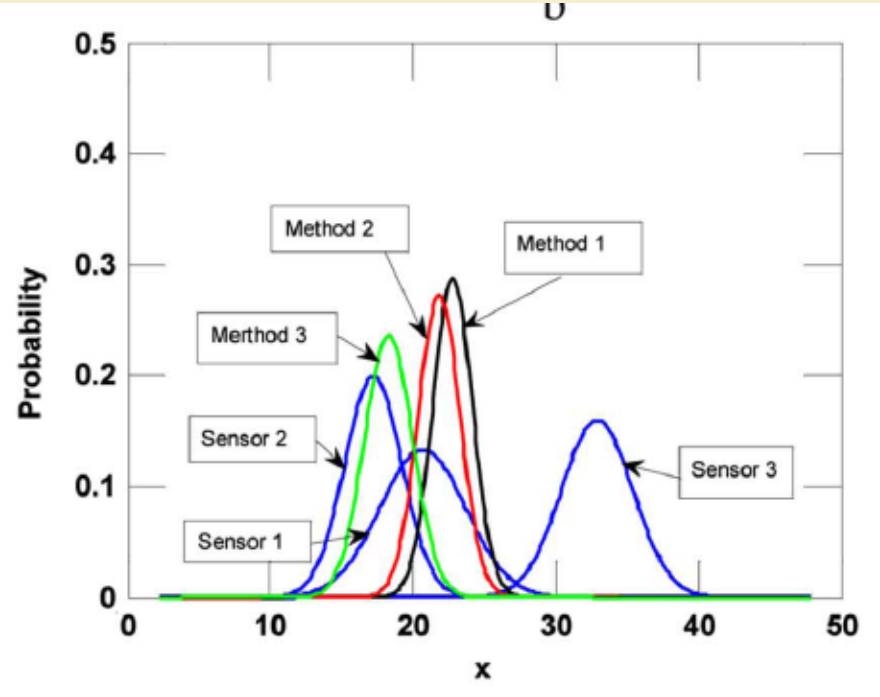
True value of state: $x = 20$





Fusion of Three Sensors
(Simulation Results)





Mean Square Error (10,000 Data Points):

Method 1: 6.94

Method 2: 6.03

Method 3: 5.50

Sensor Modeling

- **Developing an Understanding of Sensor's Limitations / Capabilities**
- **Probabilistic Understanding of Sensor's Uncertainties Expressed as Probability Density Function (p.d.f.):**

$$p(z=z1 \mid x=x1)$$

- **Adaptive Sensor Modeling**
  - **Dynamic Environmental Factors Affect Sensor Performance**
  - **Determining Factors that Affect Sensor Performance and Establishing Function Relationship**

Intelligent Learning

- **Neural Network Learning**
  - **Parameters of sensor models are given by neural network**

$$\theta_i = f\left[\sum_{j=1}^{l}\left\{w_{ji} f\left(\sum_{k=1}^{n} w_{kj} I_k\right) + b_{1j}\right\} + b_{2i}\right]$$

i = 1, 2, ….m

  - **Training Data Not Readily Available**
  - **Innovative Training Algorithms based on Maximum Likelihood**

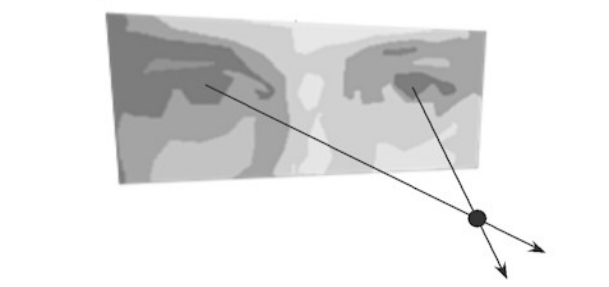
$$L(W,B) = \frac{1}{[NNET(I,W,B)]^n (2\pi)^{n/2}} e^{\left\{\frac{-\sum_{i=1}^{n}(z_i - x_i)^2}{2[NNET(I,W,B)]^2}\right\}}$$

M. Kumar et. al., IMECE 2006

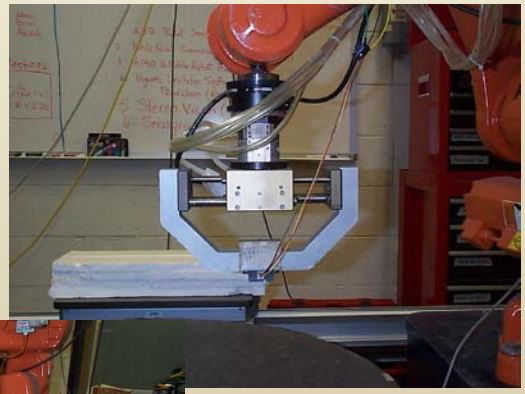
Sensor Fusion Example: Three Sensors

Sensor Modeling

Stereo Vision: Correlation Score of Stereo Match



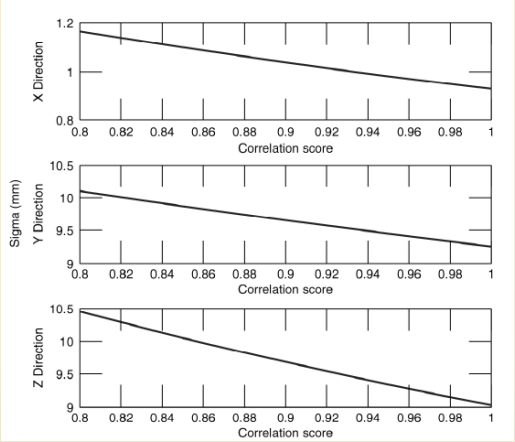
Infra-Red Proximity Sensor: Distance



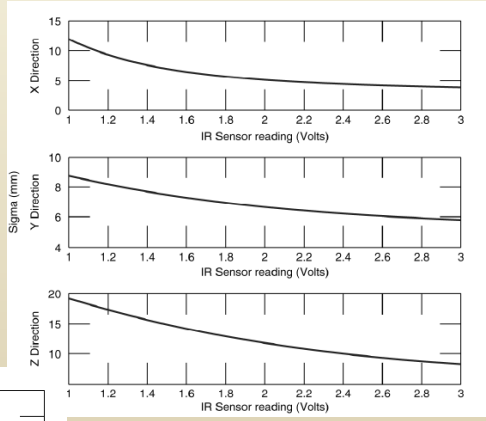
Laser Sensor: Distance

Sensor Fusion Example: Three Sensors

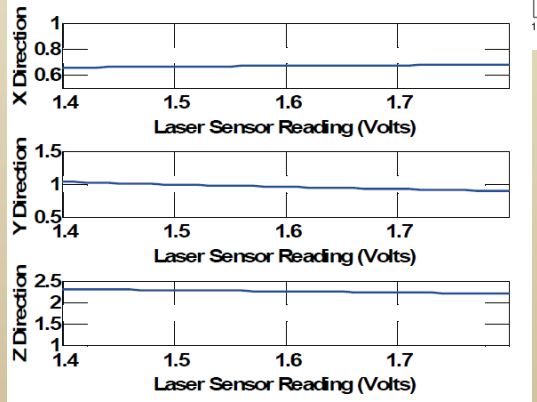
Stereo Vision: Correlation Score of Stereo Match



Infra-Red Proximity Sensor: Distance

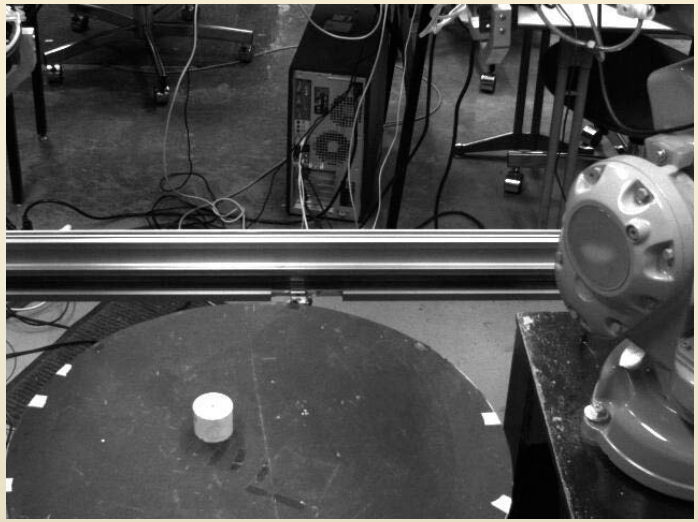


Laser Sensor: Distance

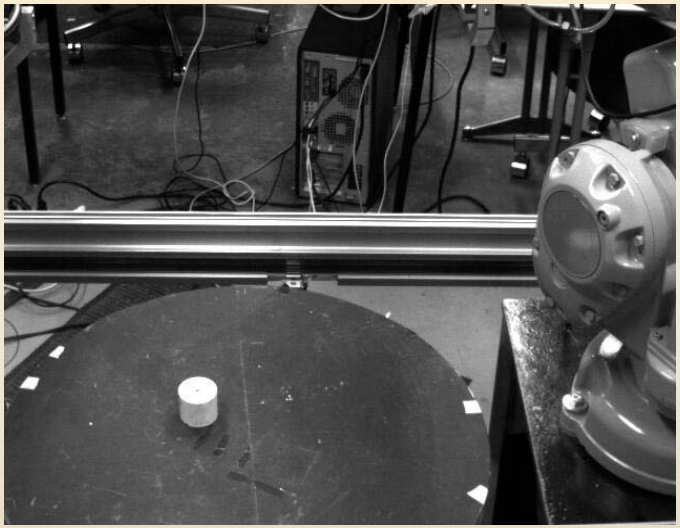


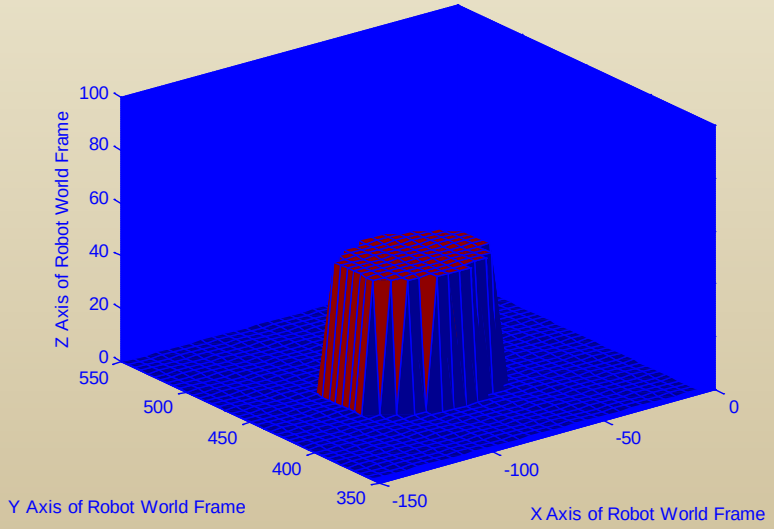
Experimental Results

Left Camera



Right Camera

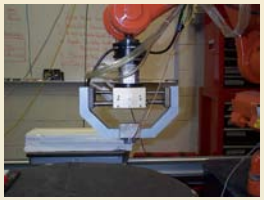




Actual Occupancy Grid

Occupancy Grid

Proximity Sensor



Calculation of Cellular Probability

3-D Occupancy Grid

Laser Sensor

Calculation of Cellular Probability

3-D Occupancy Grid

Stereo Vision

Calculation of Cellular Probability

3-D Occupancy Grid

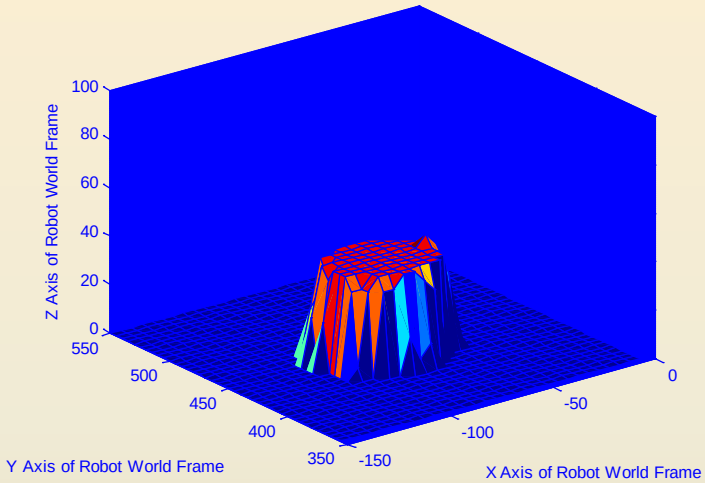
Bayesian Technique

Fused Grid

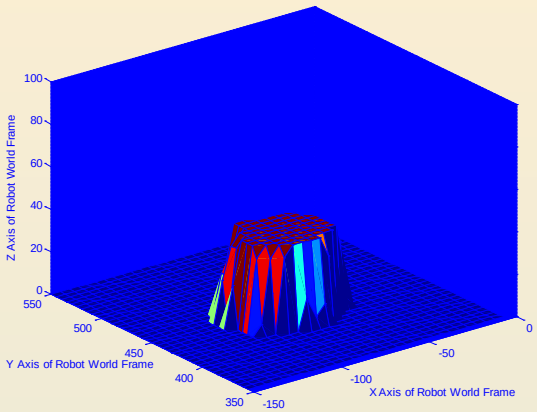
Grid Size: 5mm x 5mm x 5mm

M. Kumar et. al., IECON 2006

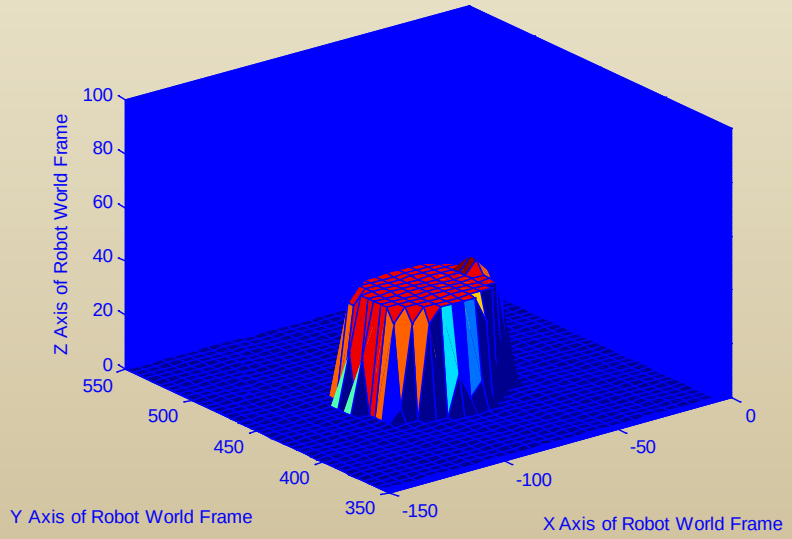
Sensor Fusion - Experiment



Simple Bayesian based on Rigid Sensor Modeling



Simple Bayesian based on Proposed NN Based Modeling



Bayesian with Proposed Inconsistency Detection

Sensor Fusion - Experiment

$$Error = \sum_{C_i} \left[\left| s(C_i) \right|_{actual} - \left| s(C_i) \right|_{sensor} \right]^2$$

Stereo Vision	IR Proximity	Laser Proximity	Simple Bayesian (Rigid Sensor Model)	Simple Bayesian (NN Based Sensor Model)	**Bayesian with Proposed Inconsistency Detection**
1279	1062	399	459	423	**384**

Error: Fused Occupancy Grids

Conclusions

- **Identification and Elimination of Spurious Sensor Measurements**
- **Comprehensive Strategy to Obtain Adaptive Sensor Models**
- **Unified Approach to carry out Fusion of Uncertain Data from Multiple Sensors**
- **Intelligent Learning and Optimization Play Key Role**
- **Overall Objective to Increase the Information Content of the Belief in State**

Acknowledgements

- **Duke University Robotics and Manufacturing Automation (RAMA) Lab**
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Questions?