Multisensor Data Fusion and Applications

Pramod K. Varshney
Department of Electrical Engineering and Computer Science
Syracuse University
121 Link Hall
Syracuse, New York 13244 USA
E-mail: varshney@syr.edu
Website: www.cis.syr.edu/~varshney

Outline

1. Overview of Multisensor Data Fusion
2. Examples
   - Distributed Detection
   - Multisensor Image Processing
3. Some Ongoing Research Projects

Information Fusion

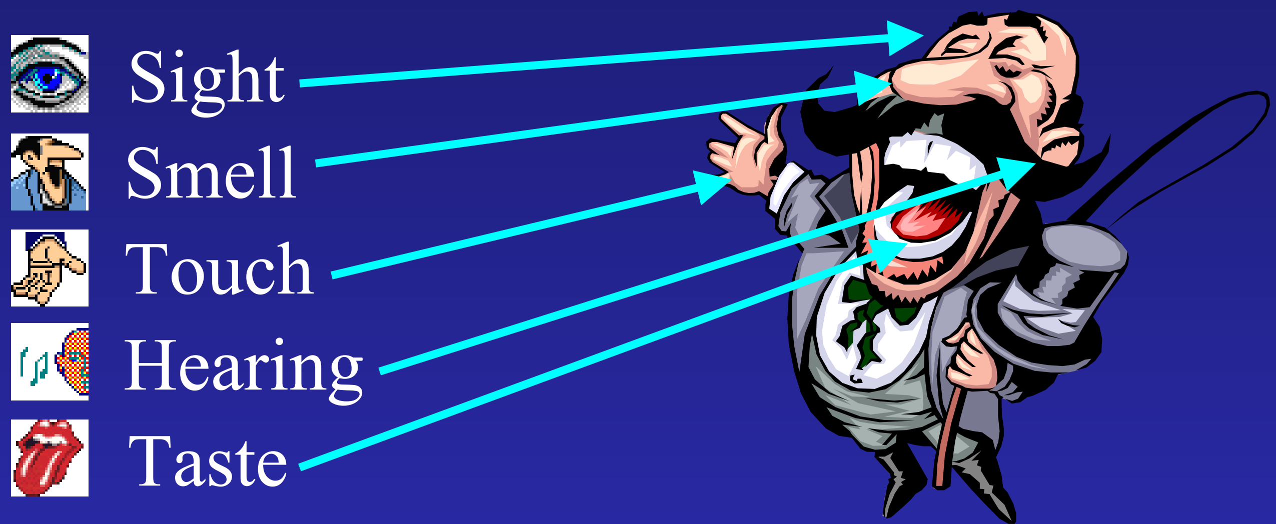
Theory, techniques, and tools for exploiting the synergy in the information acquired from multiple sources: sensors, databases, intelligence sources, humans, etc.

Information Fusion

Goals:

- To obtain a better understanding of some phenomenon
- To introduce or enhance intelligence and system control functions

Human Brain



Integrates sensory information to make inferences regarding the surrounding environment.

Advantages of Multisensor Data Fusion

- Improved system performance
  - Improved detection, tracking, and identification
  - Improved situation assessment and awareness
- Improved robustness
  - Sensor redundancy
  - Graceful degradation
- Extended spatial and temporal coverage
- Shorter response time
- Reduced communication and computing

Applications - Military

- Detection, location , tracking and identification of military entities.
- Sensors: radar, sonar, infrared, synthetic aperture radar (SAR), electro-optic imaging sensors etc.
- Complex problem
  - Large number and types of sensors and targets
  - Size of the surveillance volume
  - Real-time operational requirements
  - Signal propagation difficulties

Applications - Non-military

- Air traffic control
- Law enforcement
- Homeland security
- Medical diagnosis
- Robotics
  - Manufacturing
  - Hazardous workplace
- Remote sensing
  - Crops
  - Weather patterns
  - Environment
  - Mineral resources
  - Buried hazardous waste

Key Issues

- Nature of sensors and information sources
- Location - co-located or geographically distributed
- Computational ability at the sensors
- System architecture - topology, communication structure, computational resources, fusion level
- System goals and optimization

Fusion Levels

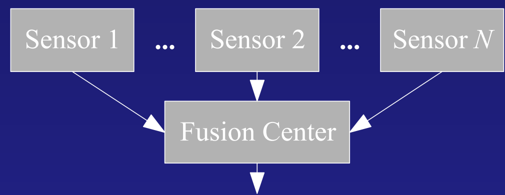
- Data level fusion
  - commensurate sensors, centralized processing
- Feature level fusion
  - feature extraction, reduced communication bandwidth requirement
- Decision level fusion
  - performance loss

Introduction to Multisensor Information Fusion

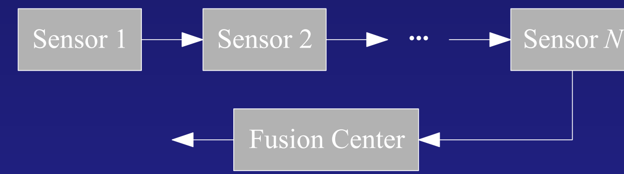
Preliminary information	data	feature	decision
Bandwidth	possibly very large	medium	very small
Information loss	no loss	some	possibly significant
Performance loss	no loss	some	possibly significant
Operational complexity	high	medium	low

Introduction to Multisensor Information Fusion

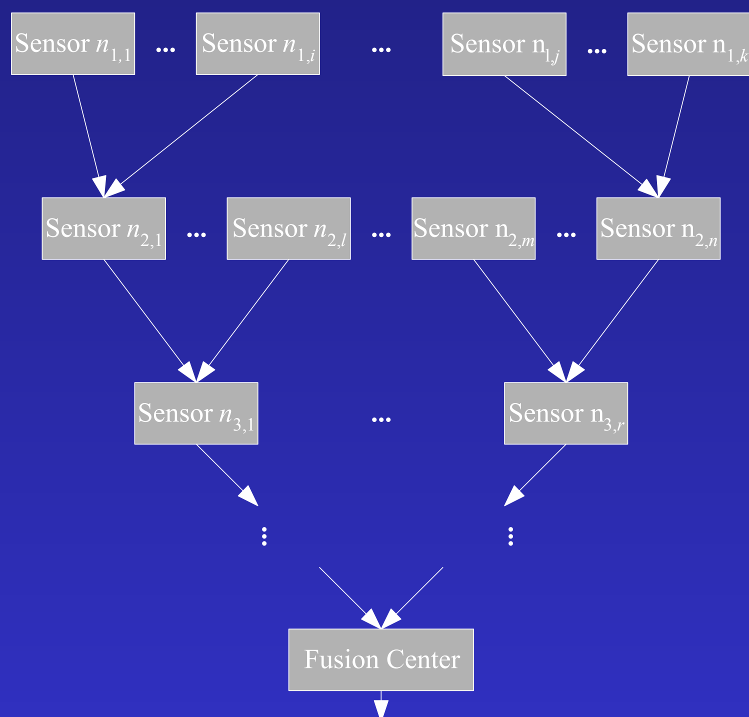
parallel topology



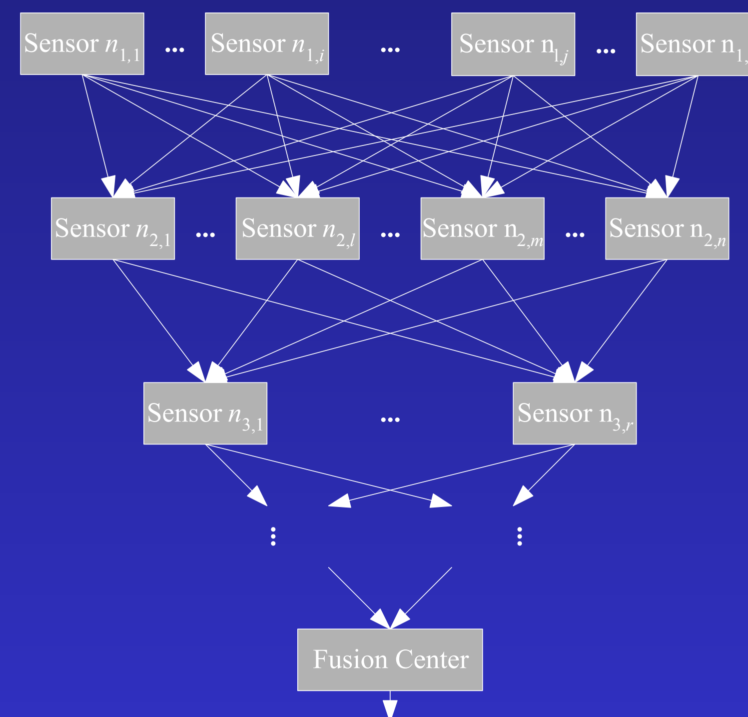
serial topology



tree topology



network topology



Fusion Techniques for Multisensor Inferencing

Tasks

- **Existence of an entity**
- **Identity, attributes and location of an entity**
- **Behavior and relationships of entities**
- **Situation Assessment**
- **Performance evaluation and resource allocation**

Fusion levels

Techniques

- **Signal detection/estimation theory**
- **Estimation and filtering, Kalman filters**
- **Neural networks, Clustering, Fuzzy logic**
- **Knowledge-based systems**
- **Control and optimization algorithms**

Solution of complex fusion problems requires a multi-disciplinary approach involving integration of diverse algorithms and techniques

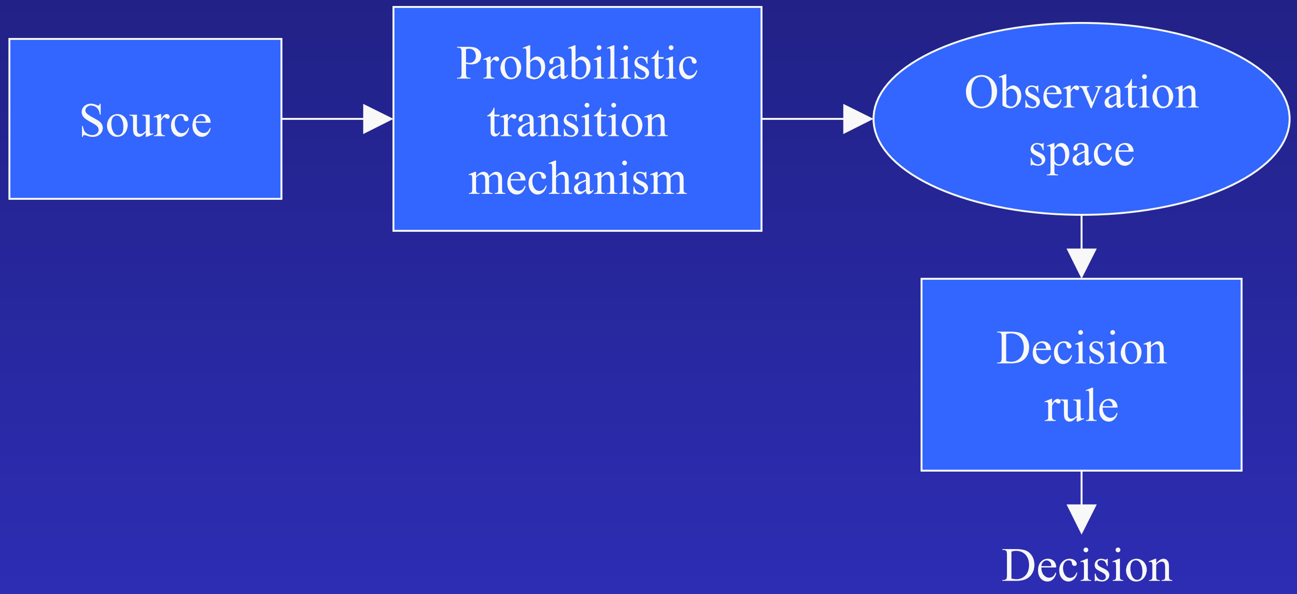
2. Examples

- Distributed Target Detection
- Multisensor Image Processing

The Signal Detection Problem

Binary hypothesis testing:

determination of the presence or absence of a target (H_1 vs. H_0)



Components of a hypothesis testing problem

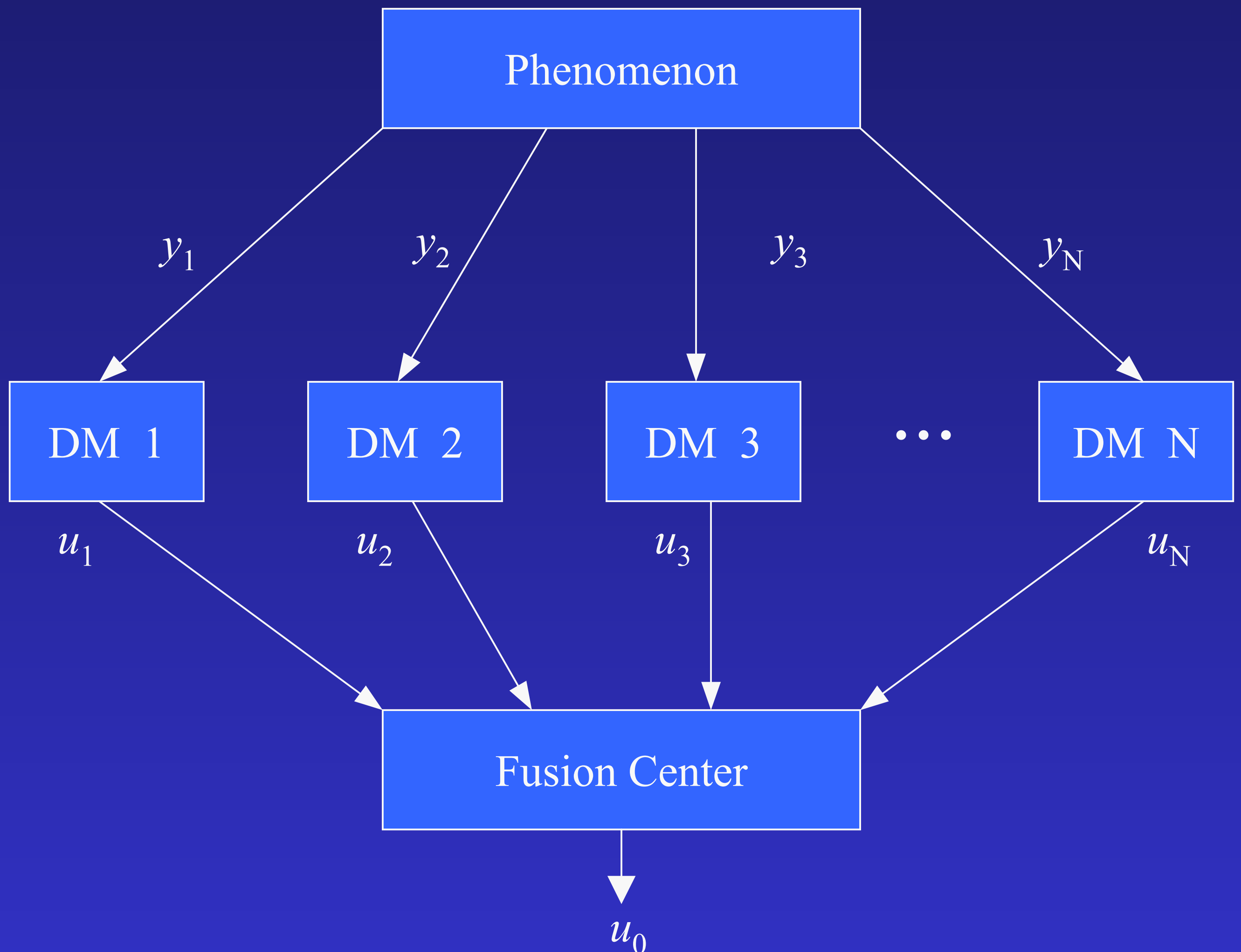
The Distributed Detection Problem

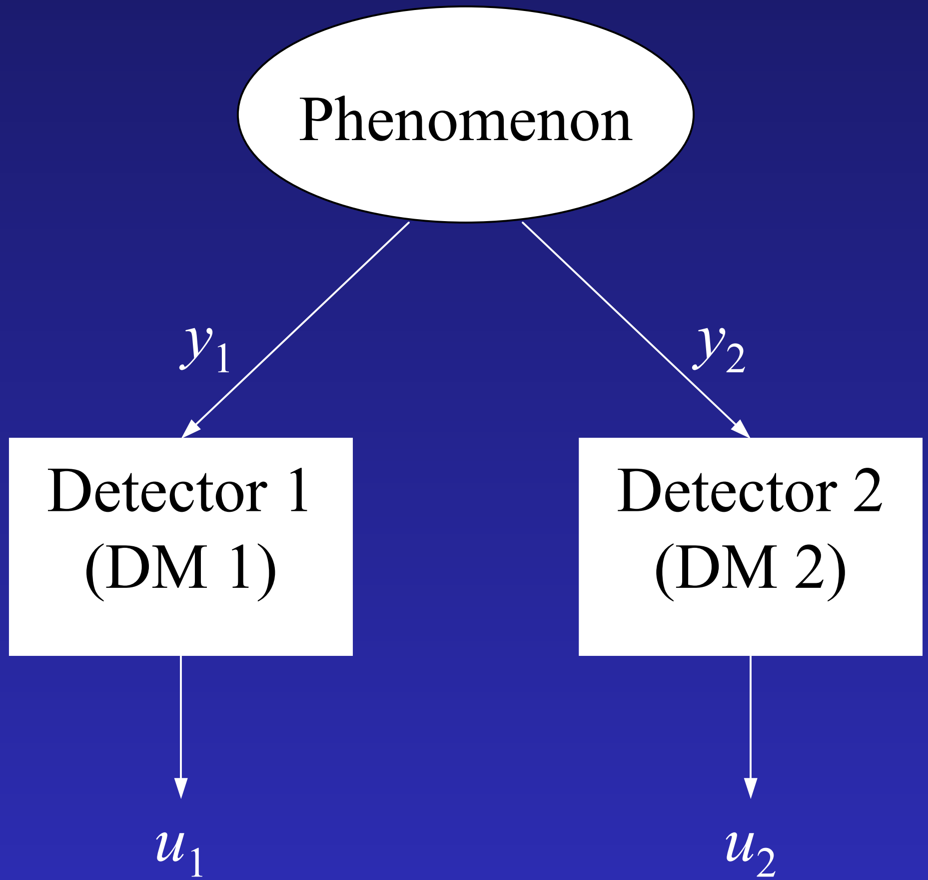
- Solution of a detection problem by a team of interconnected detectors/agents
- Network architecture
  - Sensor placement
  - Fixed vs. mobile sensors
  - Infrastructured vs. ad hoc networks
  - Topology
- Communication and channel bandwidth issues

The Distributed Detection Problem

- Optimization criterion
- Design of optimal signal processing schemes at various detectors and the fusion center
  - NP-Hard problem
- Performance of centralized detection versus distributed detection

Parallel Fusion Network





A two-detector parallel fusion network without fusion

Distributed Detection without Fusion:

Two hypotheses: H_0 and H_1

A priori probabilities: P_0 and P_1

Sensor observations: y_1 and y_2

Joint conditional density: $p(y_1, y_2, |H_i)$

Costs: C_{ijk}, cost of DM 1 deciding H_i, DM 2 deciding H_j when H_k is present

Local or peripheral decisions: u_i

$$u_i = \begin{cases} 0, & H_0 \text{ is declared present,} \\ 1, & H_1 \text{ is declared present.} \end{cases}$$

Objective: Minimization of the Bayes risk $\Re$

Under conditional independence assumption, the decision rule at each detector is an LRT. Threshold at detector 1 is

$$t_1 = \frac{P_0 \int_{y_2} p(y_2 | H_0)\{[C_{110} - C_{010}] + p(u_2 = 0 | y_2)[C_{100} - C_{000} + C_{010} - C_{110}]\}}{P_1 \int_{y_2} p(y_2 | H_1)\{[C_{001} - C_{111}] + p(u_2 = 0 | y_2)[C_{001} - C_{001} + C_{111} - C_{001}]\}}.$$

The two thresholds are functions of each other.

$$t_1 = f_1(t_2)$$

$$t_2 = f_2(t_1)$$

Observations:

- The above solution provides locally optimum solutions. When multiple local minima exist, we need to search for the globally optimum solution.
- Two thresholds are coupled.

Consider the cost assignment

$$C_{000} = C_{111} = 0,$$
$$C_{010} = C_{100} = C_{011} = C_{101} = 1,$$
$$C_{110} = C_{001} = k.$$

Assume that the two local observations are conditionally independent, identical and are Gaussian distributed.

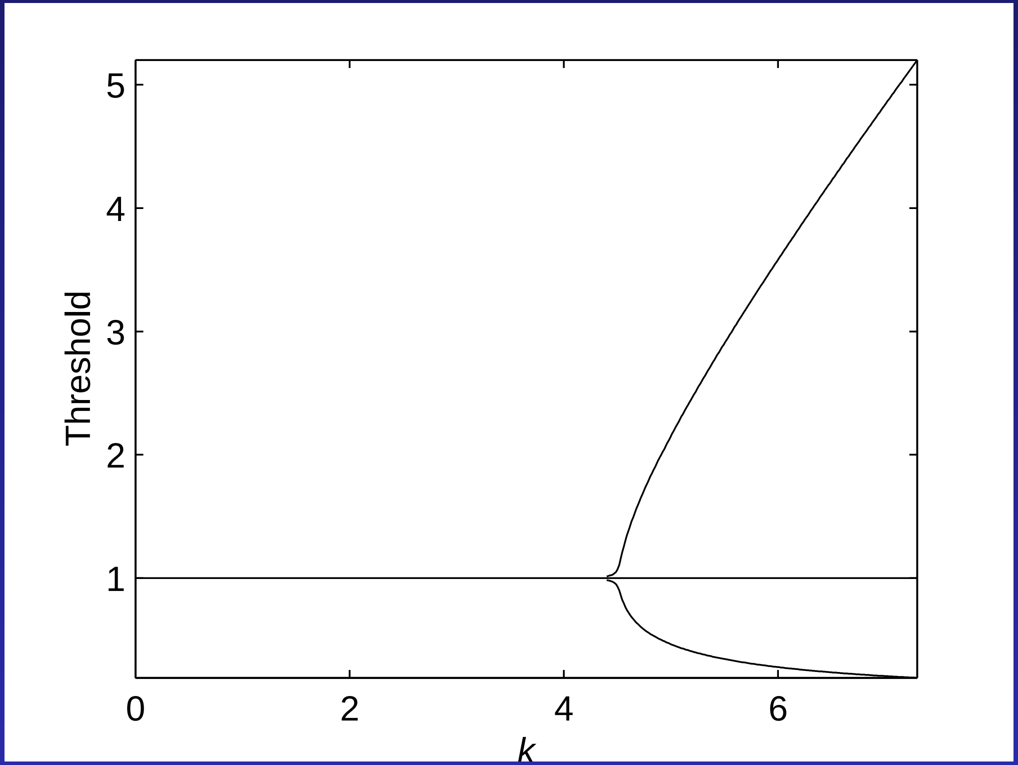
Resulting thresholds are

$$t_1 = \frac{(k-1) + (2-k)\ \operatorname{erf}\left(\dfrac{\sigma \log t_2}{m_1 - m_0} + \dfrac{m_1 - m_0}{2\sigma}\right)}{1+(k-2)\operatorname{erf}\left(\dfrac{\sigma \log t_2}{m_1 - m_0} - \dfrac{m_1 - m_0}{2\sigma}\right)},$$

and

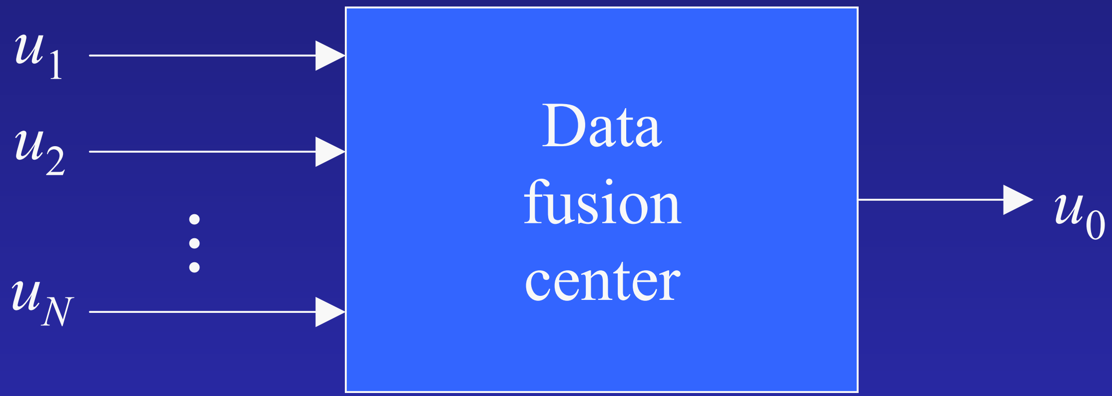
$$t_2 = \frac{(k-1)+(2-k)\ erf\left(\dfrac{\sigma \log t_1}{m_1 - m_0} + \dfrac{m_1 - m_0}{2\sigma}\right)}{1+(k-2)\ erf\left(\dfrac{\sigma \log t_2}{m_1 - m_0} - \dfrac{m_1 - m_0}{2\sigma}\right)}.$$

- Assume that $m_0 = 0$, $m_1 = 1$, and $\sigma = 1$.
- For $1 \leq k < 4.528$, there is only one solution $t_1 = t_2 = 1$.
- For $k \geq 4.528$, there are three solutions. One of the solutions is $t_1 = t_2 = 1$ but it does not yield the minimum value of $\Re$. The other two solutions need to be used in a pair.



Threshold values as a function of *k*

Fusion Center



Design of Fusion Rules

Input to the fusion center: u_i, i=1, …, N

$$u_i = \begin{cases} 0, & \text{if detector } i \text{ decides } H_0 \\ 1, & \text{if detector } i \text{ decides } H_1 \end{cases}$$

Output of the fusion center: u_0

$$u_0 = \begin{cases} 0, & \text{if } H_0 \text{ is decided} \\ 1, & \text{otherwise} \end{cases}$$

Fusion rule: logical function with N binary inputs and one binary output

Number of fusion rules: 2^{2^N}

Possible Fusion Rules for Two Binary Decisions

Input			Output u_0															
u_1	u_2		f_1	f_2	f_3	f_4	f_5	f_6	f_7	f_8	f_9	f_{10}	f_{11}	f_{12}	f_{13}	f_{14}	f_{15}	f_{16}
0	0		0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
0	0		0	0	0	0	1	1	1	1	0	0	0	0	1	1	1	1
1	0		0	0	1	1	0	0	1	1	0	0	1	1	0	0	1	1
1	1		0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1

The optimum fusion rule that minimizes the probability of error is

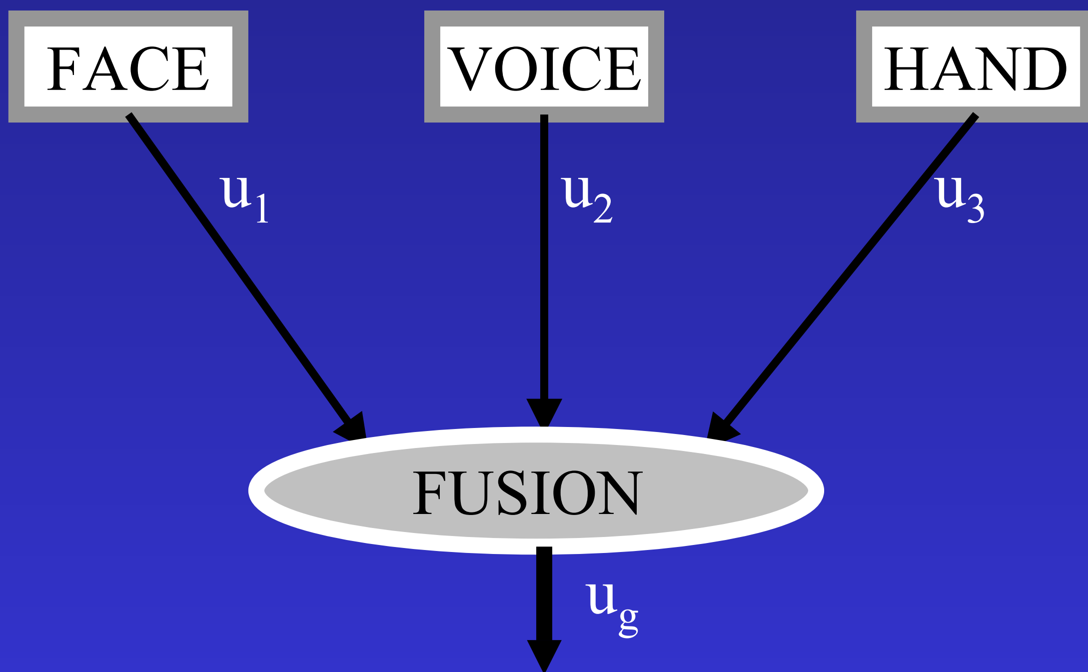
$$\sum_{j=1}^{N}\left[u_i \log\frac{1-P_{Mi}}{P_{Fi}} + (1-u_i)\log\frac{P_{Mi}}{1-P_{Fi}}\right] \underset{u_0=0}{\overset{u_0=1}{\gtrless}} \log\eta .$$

For more information, please refer to

Pramod K. Varshney, *Distributed Detection and Data Fusion*, Springer-Verlag New York, Inc., 1997.

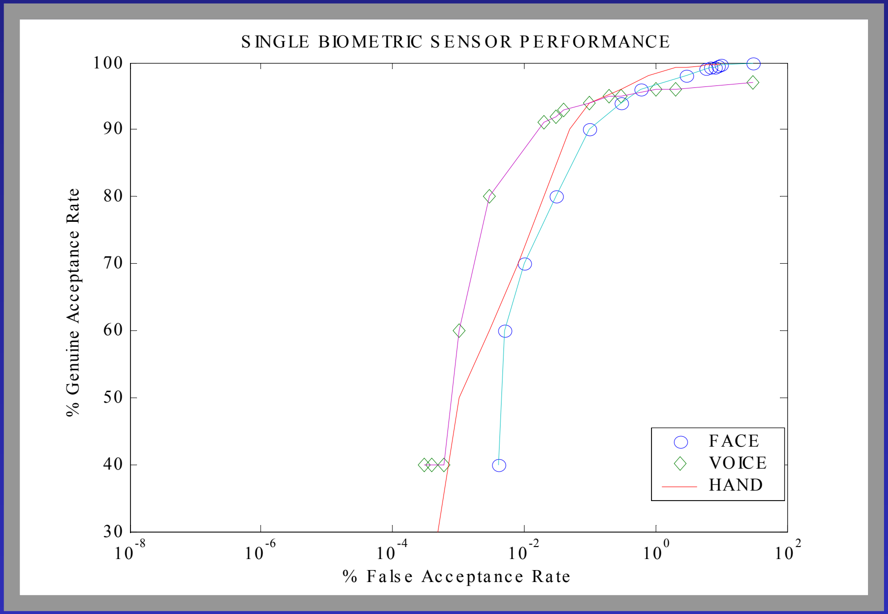
Decision Level Fusion
Access Control Using Biometrics

- Each sensor decides to accept or reject the individual prior to fusion .
- A global decision is made at the fusion center.



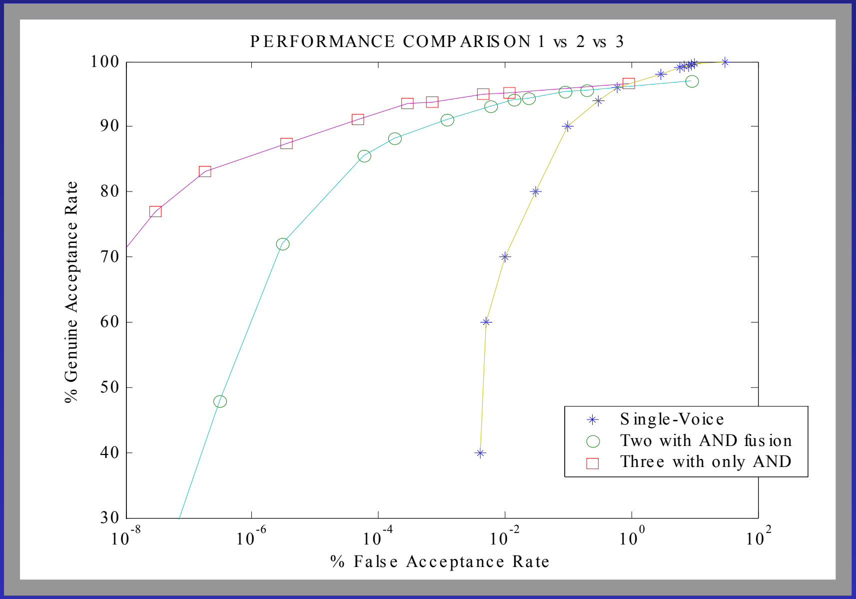
Performance Improvement Due to Fusion

Genuine Acceptance Rate→



False Acceptance Rate →

Genuine Acceptance Rate→



False Acceptance Rate →

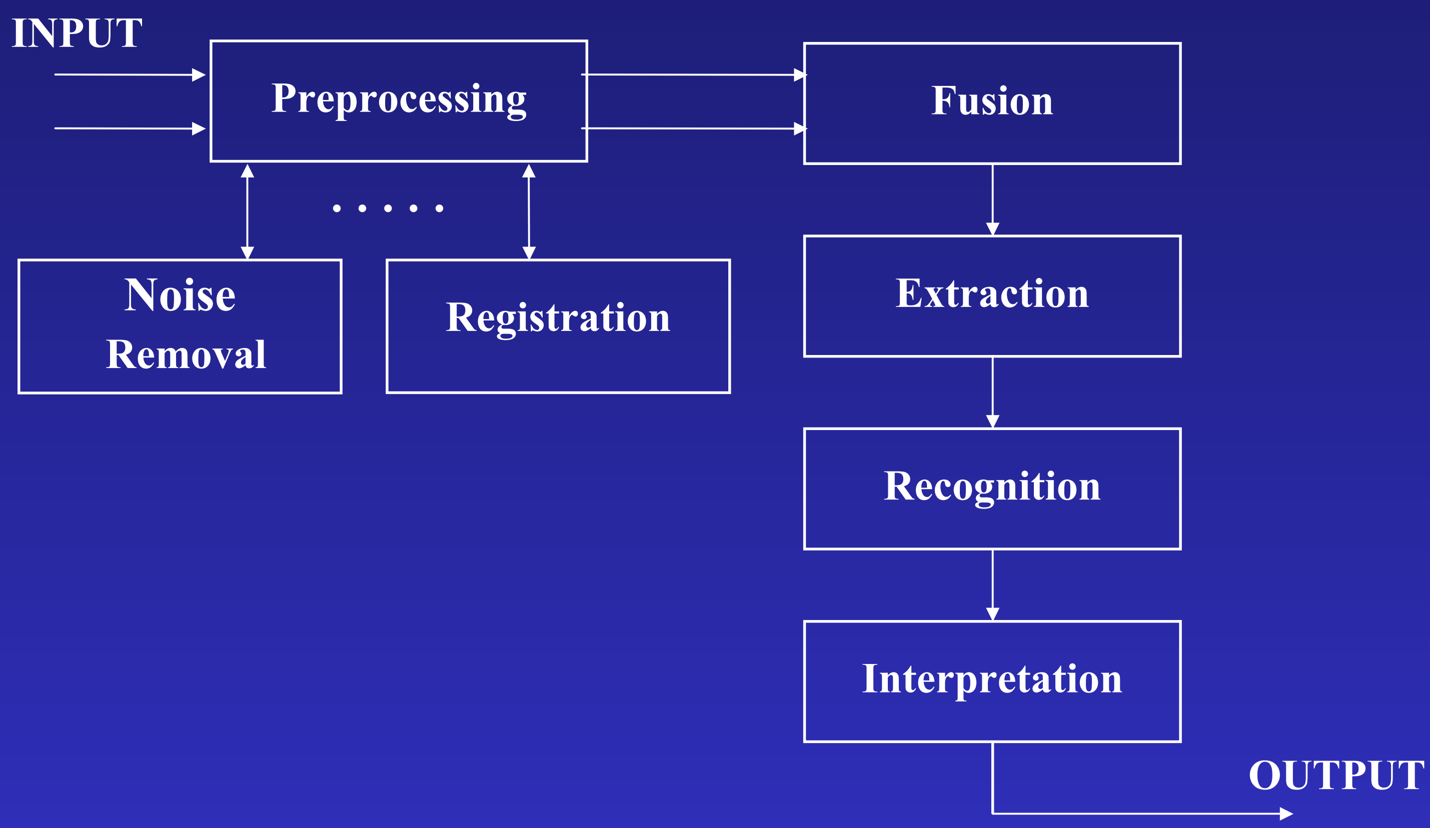
The graph is a illustration of a single sensor , two sensors with AND rule and three sensors with AND between all of them.

Wireless Sensor Networks

- Typically consist of a large number of low-cost, densely distributed, and possibly heterogeneous sensors.
- Suitable for battlefield surveillance and environment monitoring.
- Sensor nodes are battery driven and hence operate on an extremely frugal energy budget.
- Sensor nodes have limited sensing and communication ability.

- Many recent results on detection/classification for this scenario.

Multisensor Image Processing Steps



Multisensor Image Registration

- Goal: Alignment of images
- Techniques
  - Feature based techniques
    - Involve feature extraction, feature matching…
    - Case dependent
  - Intensity based techniques
    - Mutual information based image registration
- Applications
  - Concealed Weapons Detection (CWD) application
  - Remotely sensed images
  - Brain image registration

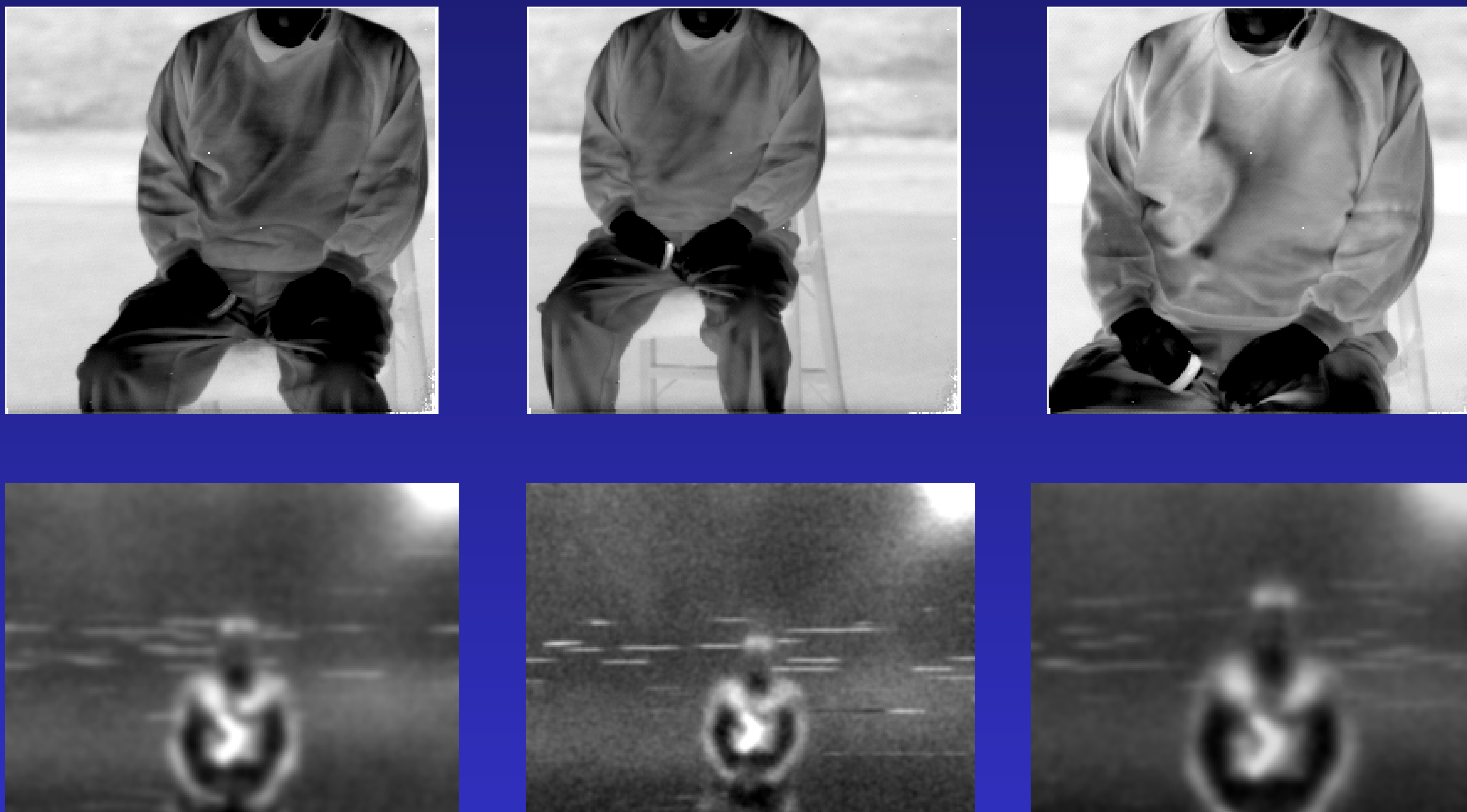
Mutual Information Based Registration

- Use the mutual information between two images as a similarity measure
- Proposed independently by Viola, Wells and Maes, Collignon in 1995
- It is a very general similarity measure because it does not rely on any specific relationship between the intensities of the two given images.
- It is assumed that the mutual information reaches its maximal value when images A and B are registered.

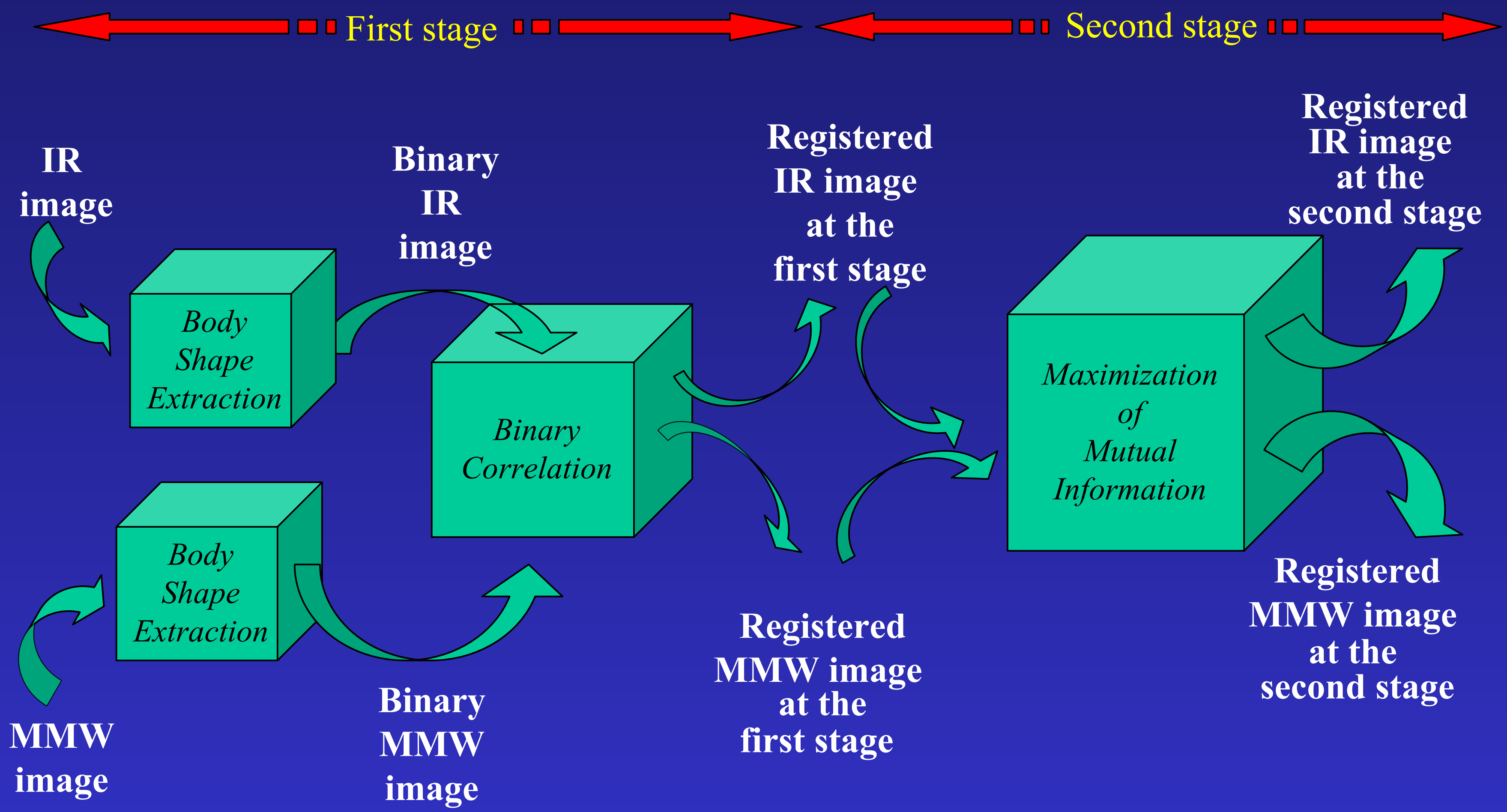
CWD Application

- Images taken from the same sensor but different viewpoints

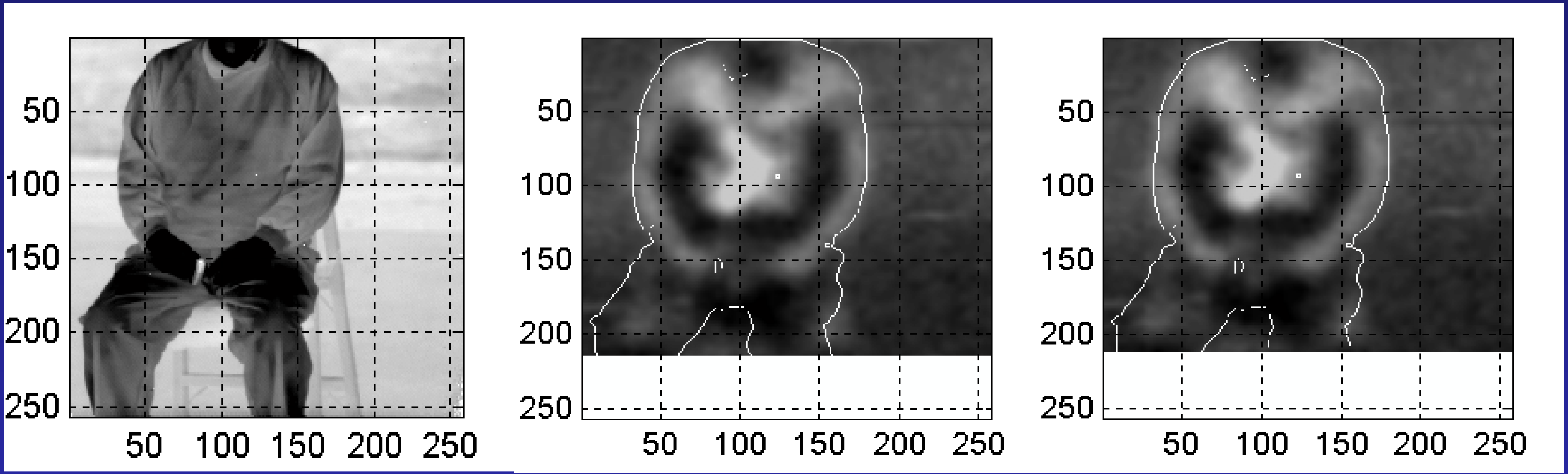
- Images taken at the same time, but from different type of sensors



Registration Algorithm



Results

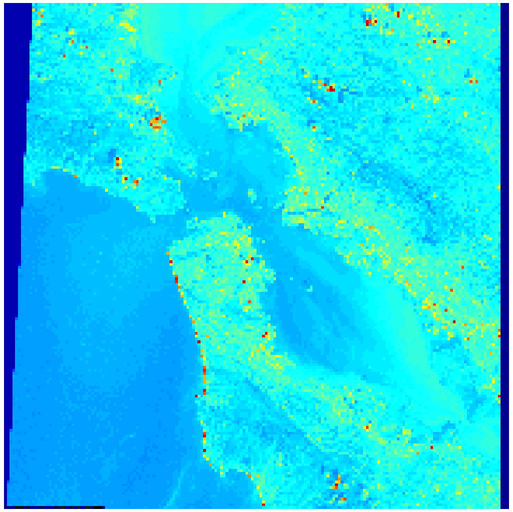


	x-displacement	y-displacement	Rotation	Scale
First Stage	62.5	12.5	0	0.40
Second Stage	64.10	14.21	3.15	0.414

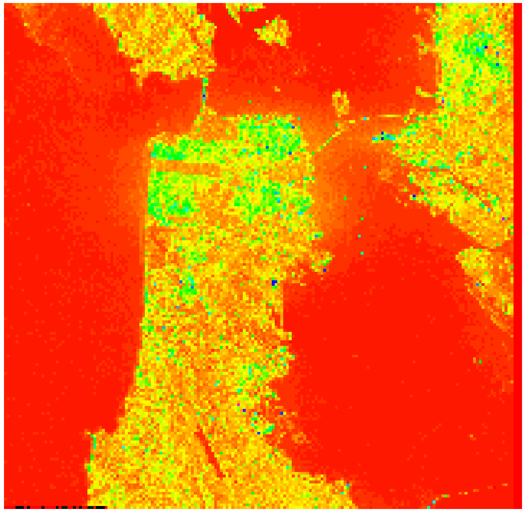
Registration of Remotely Sensed Images

- Many sensors are commonly used for remote sensing:
  - Landsat
  - IFSAR
  - IRS
  - Aviris
  - Radarsat
- The goal is to develop a general, robust registration algorithm based on mutual information

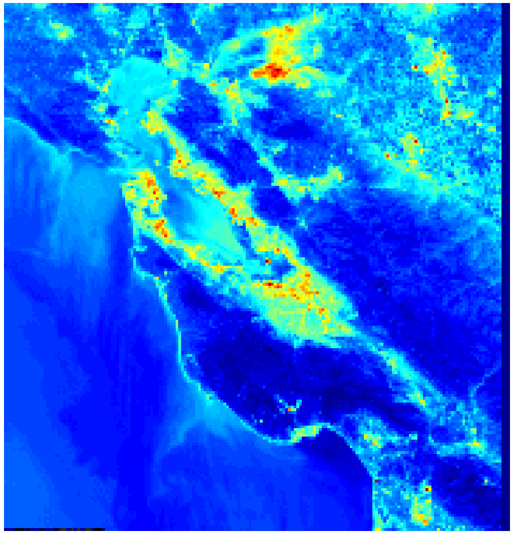
Typical images from different sensors



IRS

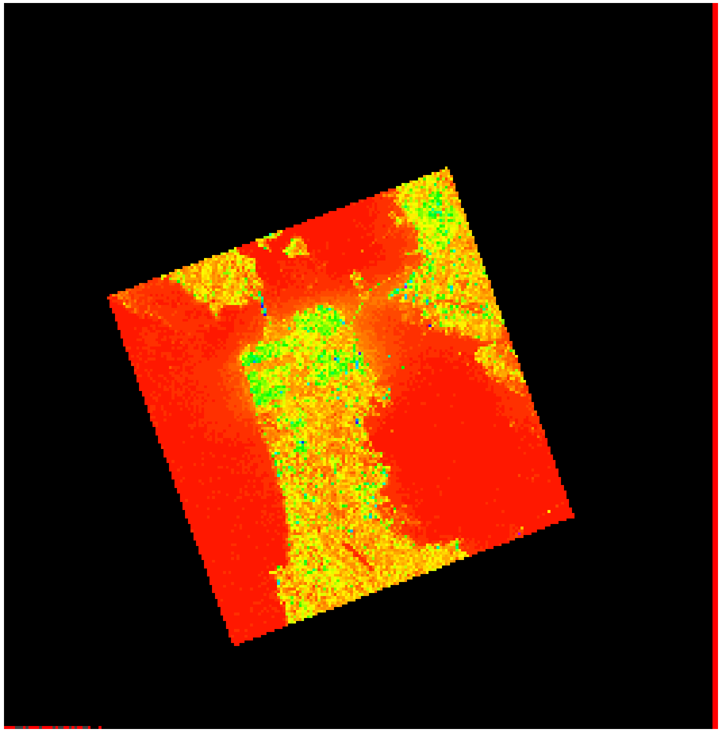


Radarsat

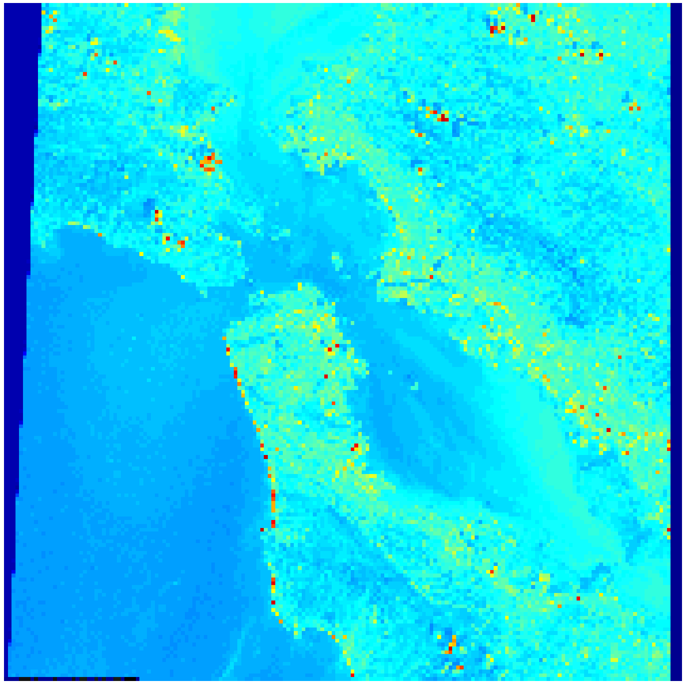


Landsat

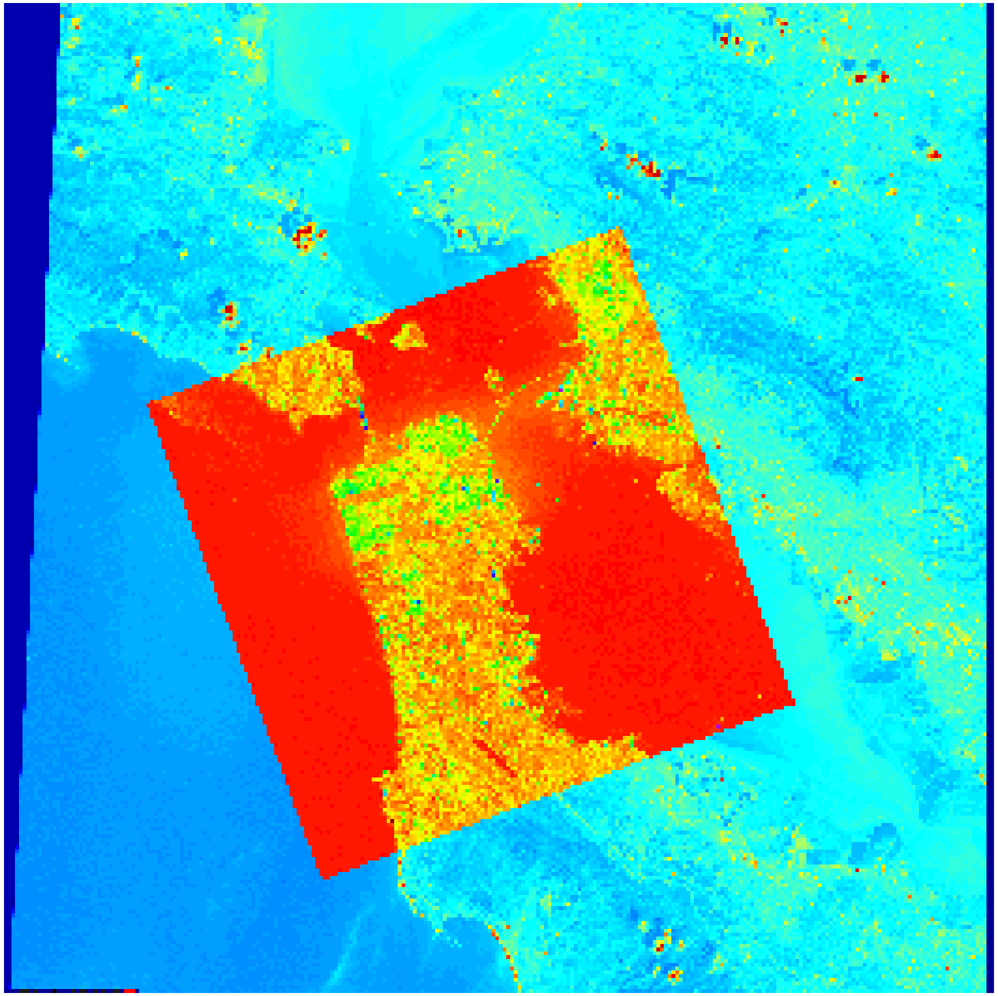
Registration Results



Radarsat

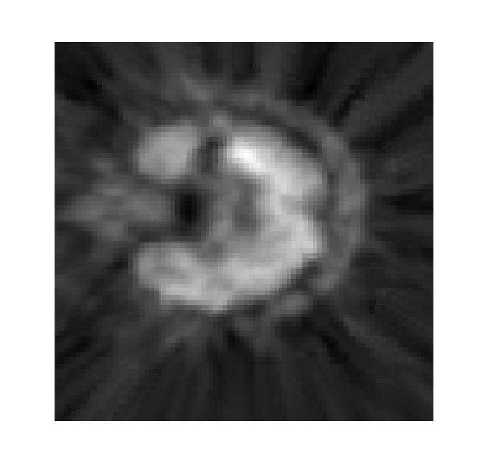


IRS

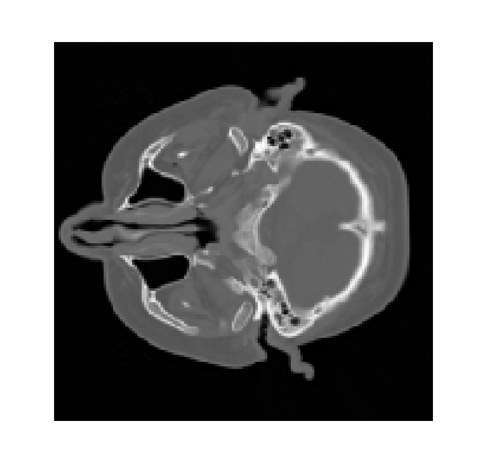


Registration of Brain Images

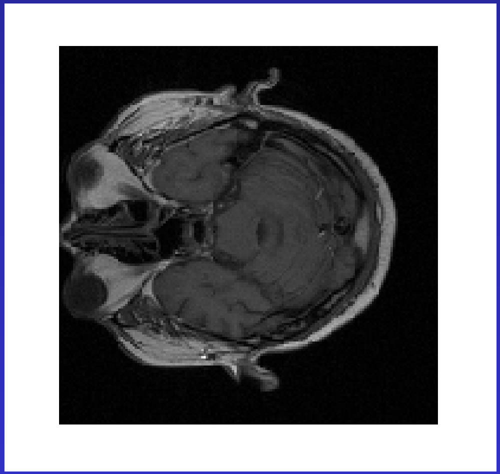
- Modalities
  - PET image
  - CT image
  - MR_T1 image
  - MR_T2 image
  - MR_PD image



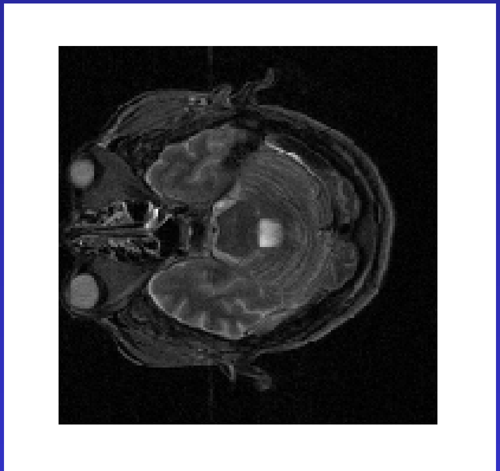
PET



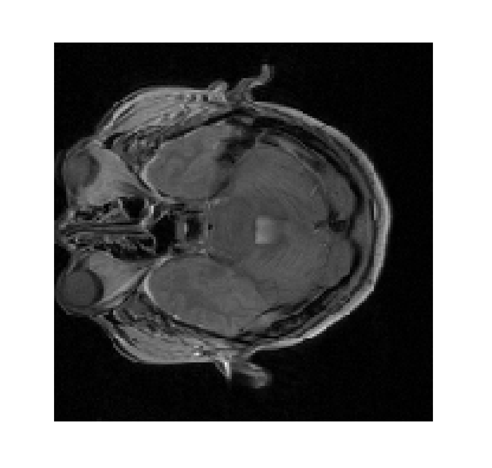
CT



T1



T2

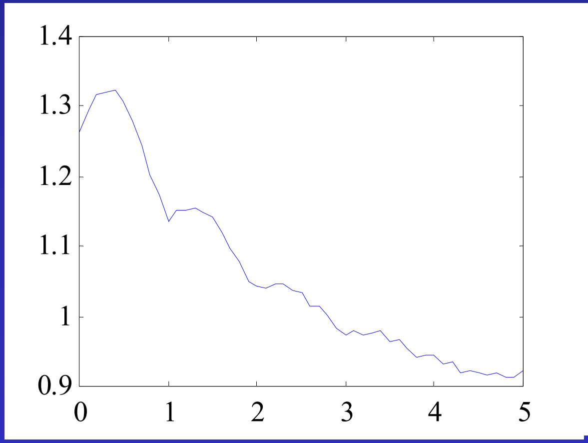


T3

Contributions

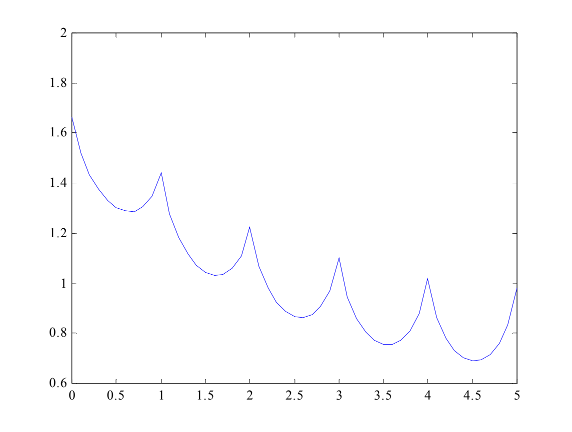
- Development of a new joint histogram estimation scheme to remove artifacts
- Improved accuracy when artifacts are present

(1)



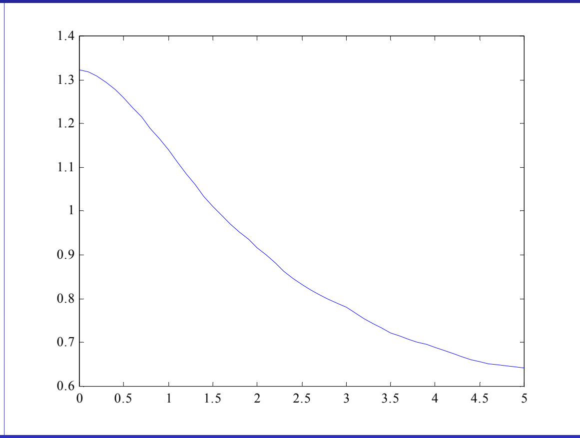
Linear interpolation

(2)



Partial Volume Interpolation

(3)



Generalized Partial Volume Estimation

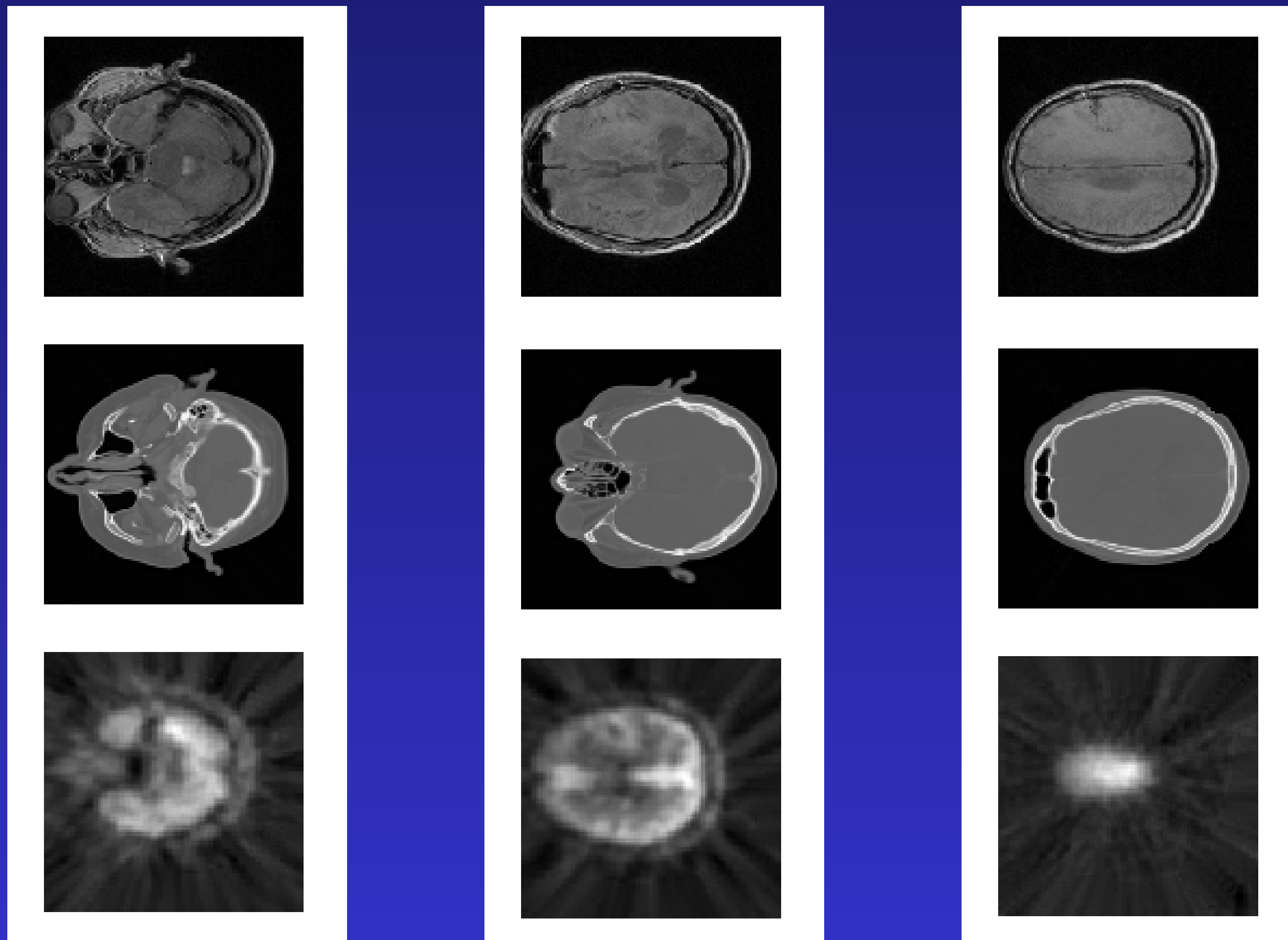
Results (Before Registration)

Slice 1 Slice 8 Slice 15

MR_PD

CT

PET



Results (After Registration)

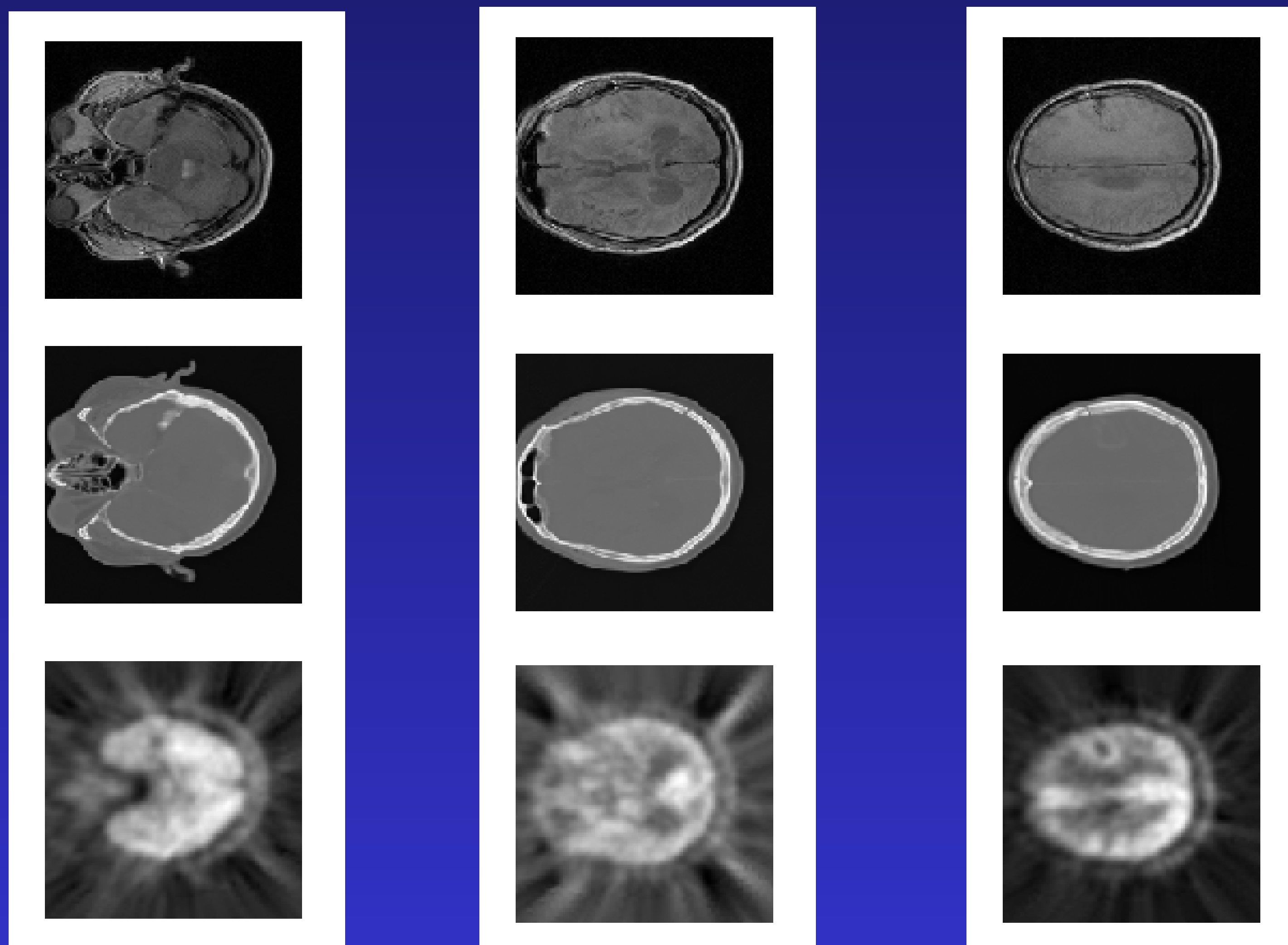
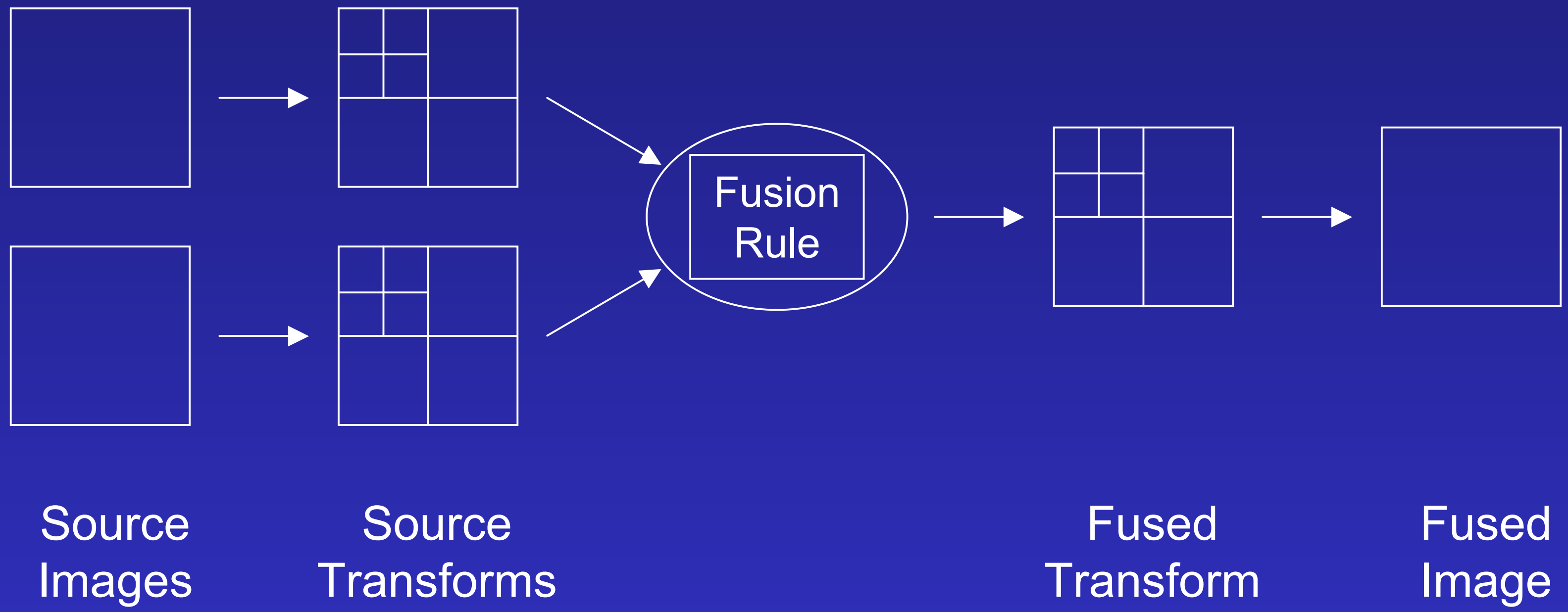


Image Fusion

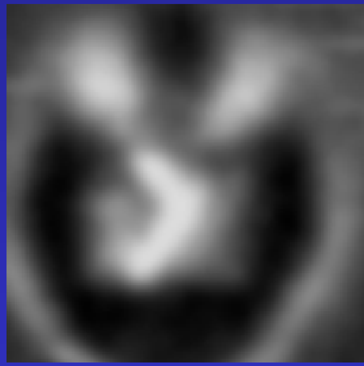
- Utilize images from multiple sensors to form a composite image with increased information content

General Fusion Process



Example 1: CWD application

IR

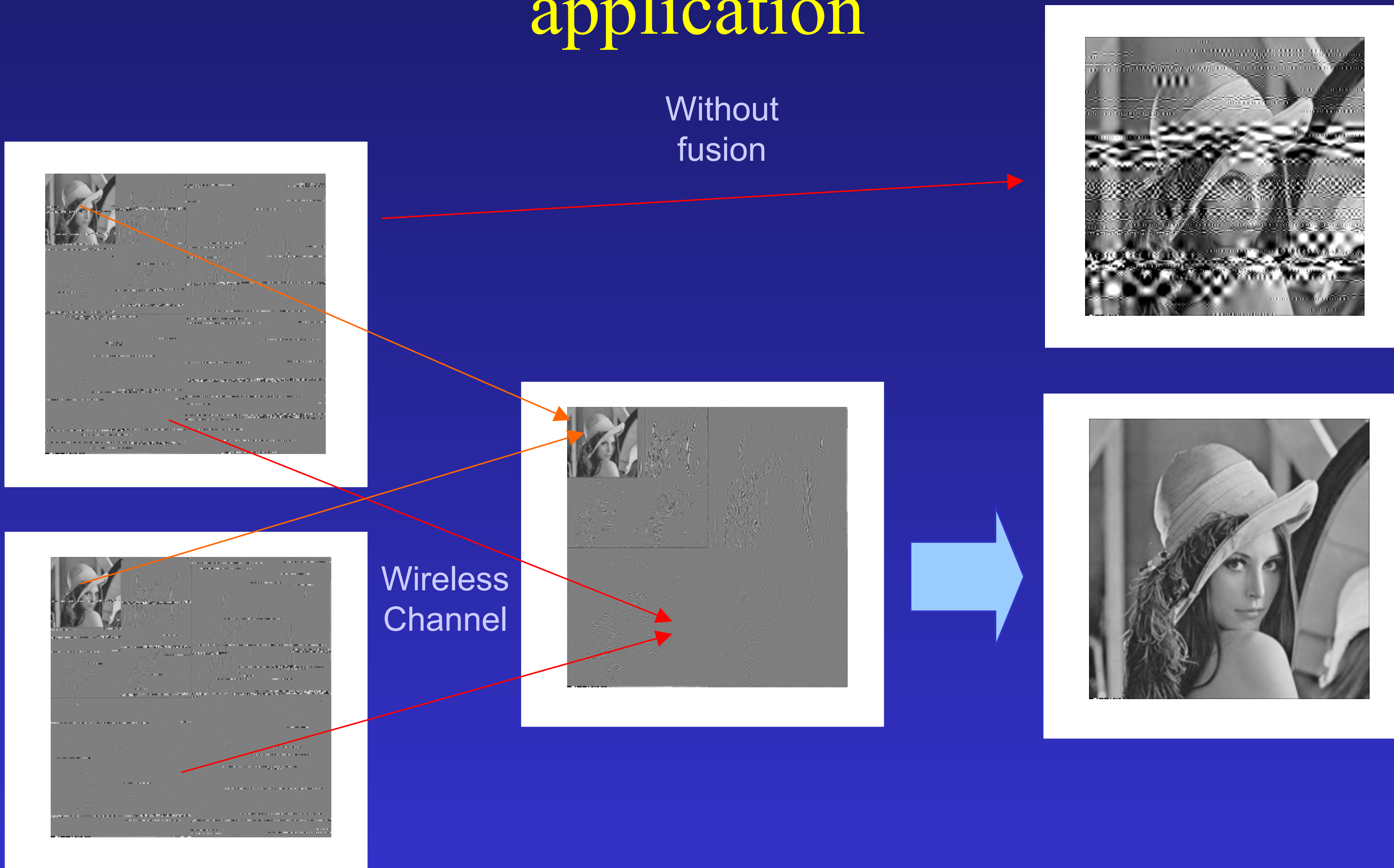


MMW

Fused

Segmented

Example 2: Wireless communication application



3. Some Ongoing Research Projects

Some Ongoing Research Projects

- Image Registration
  - MI based
  - Intelligent approach

- Multi/Hyperspectral Image Processing
  - Feature extraction
  - Classification
  - Target Detection
  - Spectral Unmixing

* P. K. Varshney and M.K.Arora, ***Advanced Image Processing Techniques for Remotely Sensed Hyperspectral Data***, Springer, 2004

Some Ongoing Research Projects

- Video Surveillance
  - Tracking
  - Activity Recognition
  - Multi-modal Fusion

  * G.L. Foresti, C.S. Regazzoni and P.K. Varshney (Eds.), ***Multisensor Surveillance Systems : The Fusion Perspective*** , Kluwer Academic Press, 2003.
- Fusion for Detection/Classification/Tracking
  - Wireless Sensor Networks
  - Vehicle Health Management
- Environmental Quality Systems
  - Center of Excellence in Environmental and Energy Systems (http://eqs.syr.edu/)


Thank You!