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Multisensor Integration

TUTORIAL T22

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Multisensor Integration

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Generic Multisensor System

Software Systems

if Enemy Tank present,
then Fire!

Artificial Intelligence
Knowledge Engineering

Data Structures
Object-Oriented
Design

Soviet T-73
position:
range:

Probability
Statistics
Geometry

Interfacing
Control

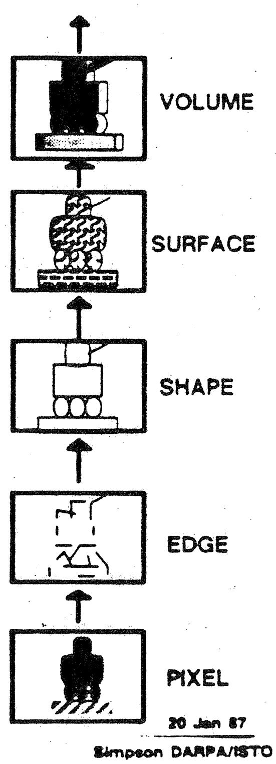
Computer Vision
Graph Theory
Computer Science

Computer
Architecture

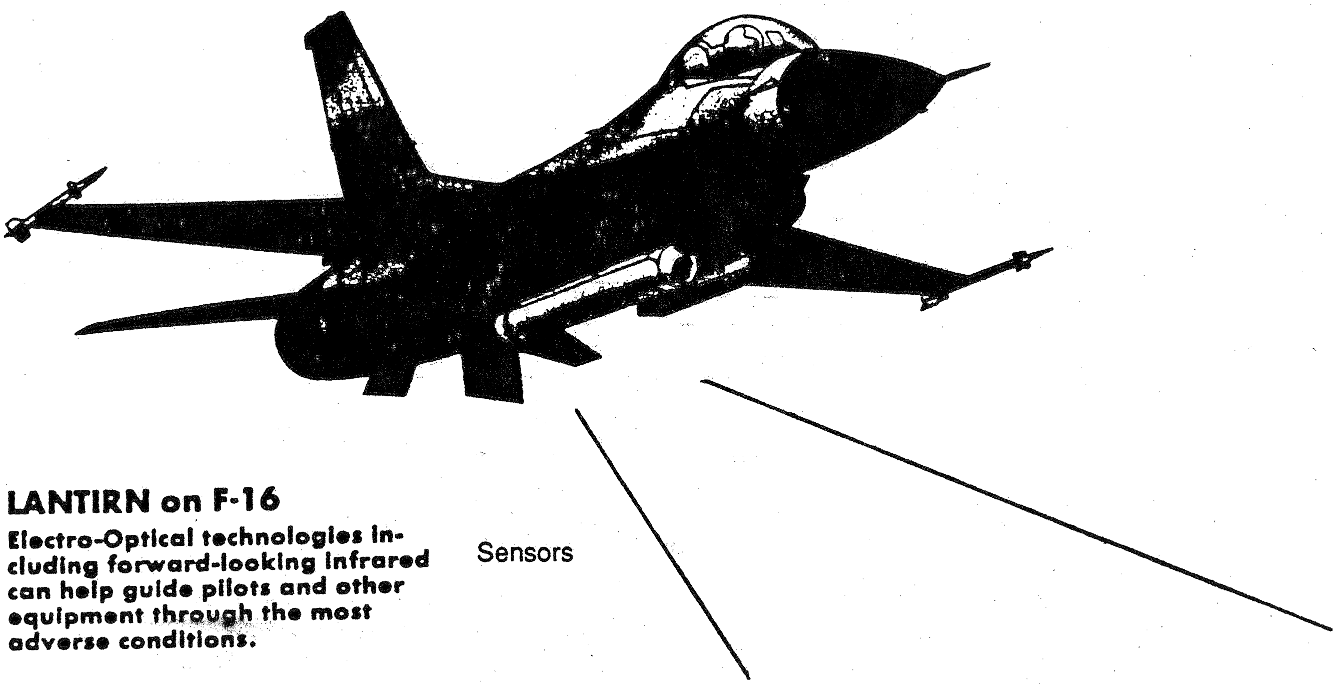
Pattern Recognition
Detection
Estimation

VLSI
Architecture
Sensors

Signal Processing
Adaptive Filtering
Physics
Sensor Design



IR   Gray Level   Range



LANTIRN on F-16
Electro-Optical technologies including forward-looking infrared can help guide pilots and other equipment through the most adverse conditions.

Not just integration, but **Coordination** of sensing for extraction of **Complementary** information.

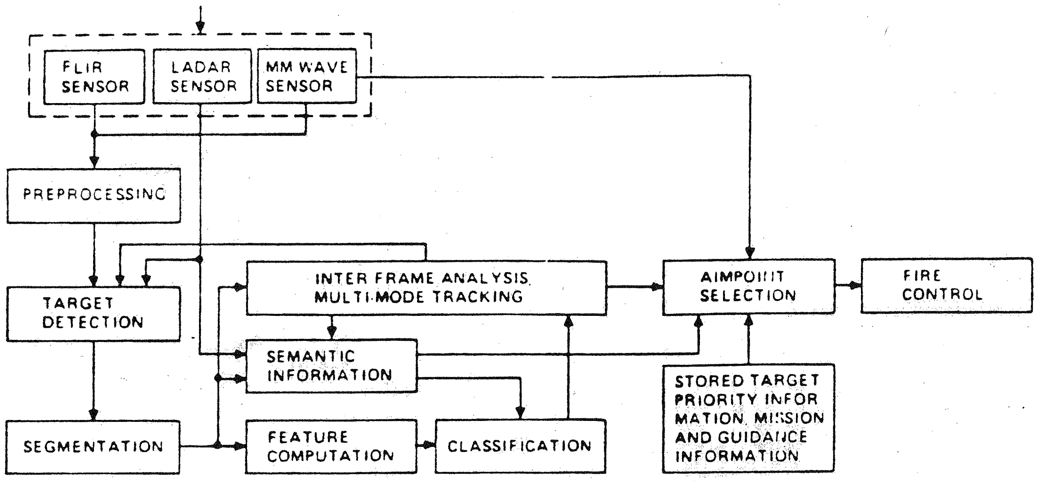
A Multisensor Automatic Target Recognition System

Components of an ATR System:

- Preprocessing
- Target Selection
- Segmentation
- Feature Computation

- Classification
- Aim Point Selection

Multisensor ATR System (from Bhanu):



System Modules

Sensors

- FLIR (8 - 12 micron)
- LADAR (10.6 micron)
- mm Wave (3.2 micron)

When FLIR and LADAR sensors are not operational, a mm wave sensor is used to determine target.

Preprocessing and Target Selection

- Use target's intensity, texture and slant range (reduces image area by 80% or more using multiple sensor input)
- Use relaxation scheme based on size, contrast and SNR.

Feature Computation

- Geometric, moment and intensity features are correlated across sensors
- Features chosen using standard pattern recognition techniques.

Classification:

- Use interframe analysis
- Use range image from LADAR sensor
- Use multi-mode tracker.

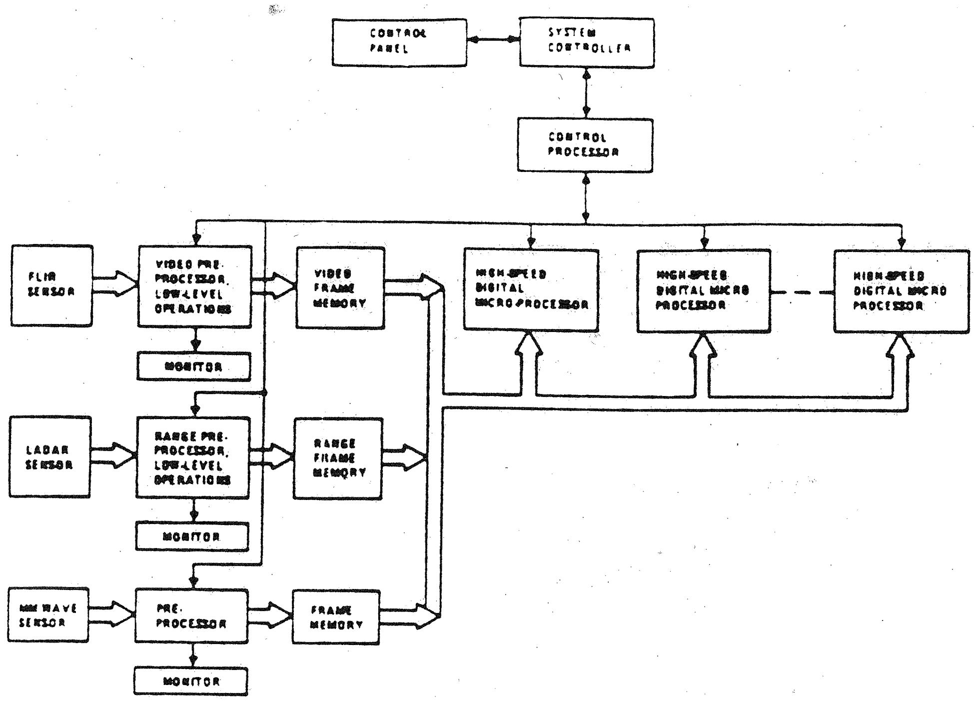
Aimpoint Selection

- Use mm wave sensor, semantic information and interframe analysis
- Target prioritization, mission guidance information stored as feature vector for each target class
- Aimpoint selection on actual target from aspect data acquired from sensors.

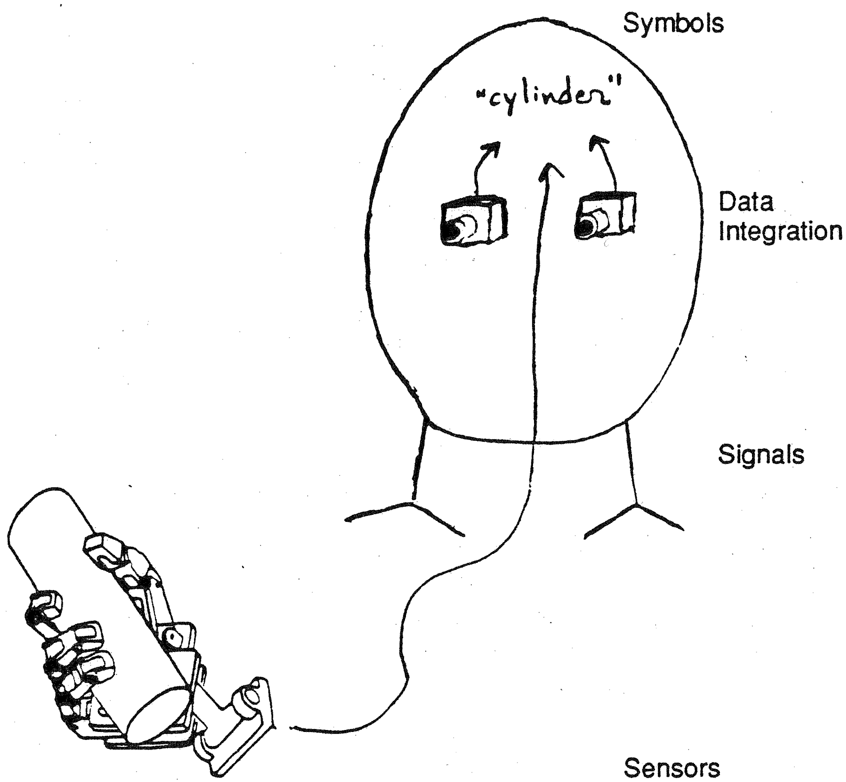
Semantic Information

- Produces type and aspect of target from LADAR (reduces aimpoint selection time and improves accuracy)
- Uses input from interframe analysis and multi-mode tracking
- Uses any specific information regarding target type and mission scenario.

System Implementation



Manufacturing Automation



Robot Schemas

One approach to organizing the robot's worldview is given here. As described by Overton, a schema is an abstract data type which monitors certain aspects of the current situation and becomes active when the situation matches the expected state. The current situation is defined by sensory input, the ensemble of schema activity and by the goals of the system. There are both perceptual schemas and motor schemas. The major components of a schema are:

Activation Section

- Sensory Monitors
- Goal Monitors
- Activation Level Calculation

Event Section

- Sensing

Action
Both Serial and Parallel Activity

Memory Section

The Activation Section turns the Event Section on and off according to the present situation. Sensory and goal monitors are used to judge the fit of the schema to the present situation. The Event Section specifies the action and sensing to be performed when the schema activates. The Memory Component is intended as a place holder for an adaptation mechanism.

The Role of Knowledge

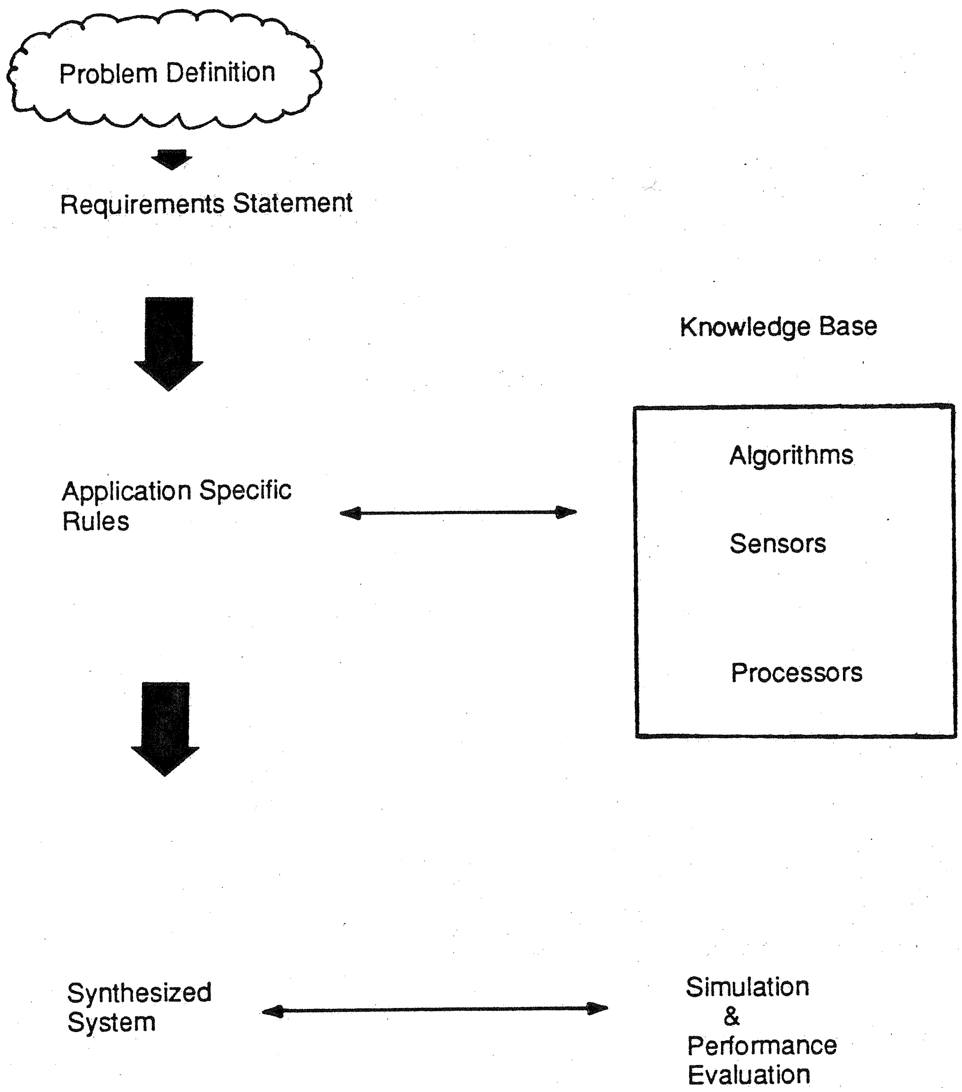
Key Issue: How to Use Specific Knowledge

E.g., of:

- Application
- Sensors
- Algorithms
- Computer Architecture
- Distributed Systems
- System Specifications
- Knowledge Engineering Techniques

to construct required system.

Multisensor Knowledge System



Signals and Sensors

Unfortunately, several issues must be addressed to make sensors more available, reliable and usable. Sensors are presently not well modeled, and obtaining reliable and accurate performance data for a particular sensor is a problem. With respect to sensors being designed and produced, it is useful to have a "spec sheet" for a sensor that addresses the following sensor parameters:

- dynamic range
- localization
- hysteresis
- repeatability
- accuracy vs. precision
- bandwidth
- calibration needs
- error detection
- multi-dimensionality
- sensitivity

A specification sheet with respect to these parameters should be available for any new sensor being developed and released to the community.

A number of key sensors for robotics are:

- **cameras**: Present visible light imaging systems are adequate and available. The TV industry driving this technology cannot be counted on to develop sensors for robotic and military applications. For example, no serious development of foveated retina cameras for robotics exists.
- **tactile**: presently not reliable or robust. Spec sheet a must here.
- **range**: laser scanners are slow, expensive and inaccurate.
- **proximity**: both near and far proximity sensors are extremely noisy and unreliable, usually as a function of the sensed object's geometry.
- **infra red**: an increasingly important sensing modality.

A second area of concern is the development of integrated arrays of detectors for process control. The areas of interest are: chemical, gas, flow, olfactory and thermal.

INTEGRATED SOLID-STATE SENSORS

Combinations of:

* Custom Thin Films
* Precision Microstructures
* High-Performance Interface Circuits
* Microcomputer-based Signal Processing

Present Status:

* Dedicated for Specific Processes
* Largely Open-Loop
* High-Volume Systems
* Very Expensive
* Sensor-Limited

Goal: **Sensor-Driven Flexible Systems**

Challenges in Sensor-Driven Systems

Sensor Issues:

* Availability
* Reliability
* System Compatibility
* Cost

System Issues:

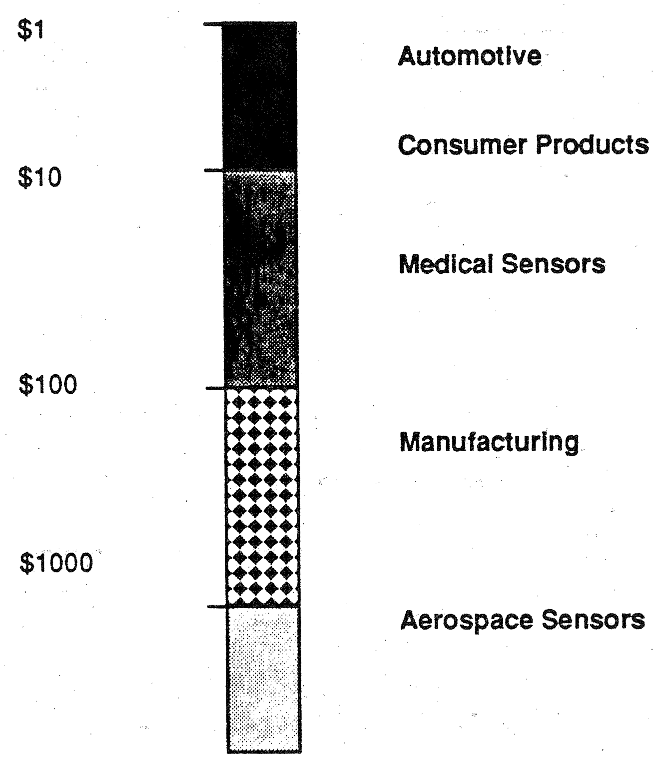
* Reliability

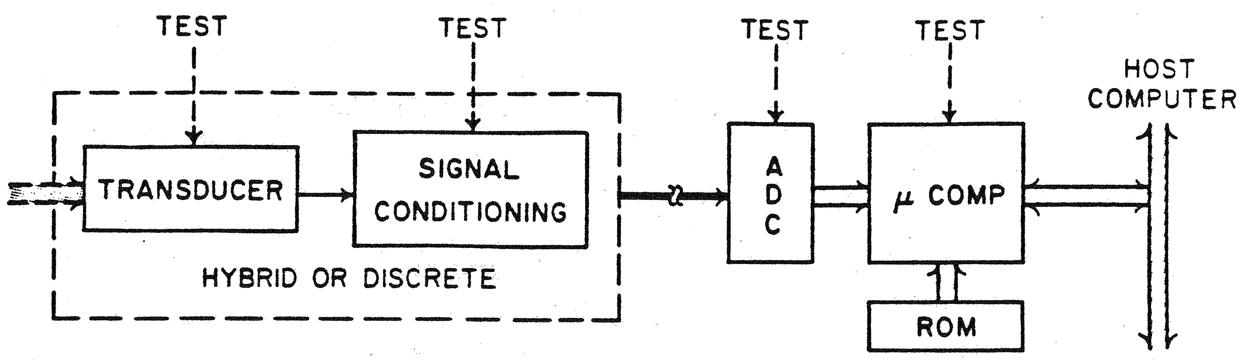
* Adaptability

* Control Architecture

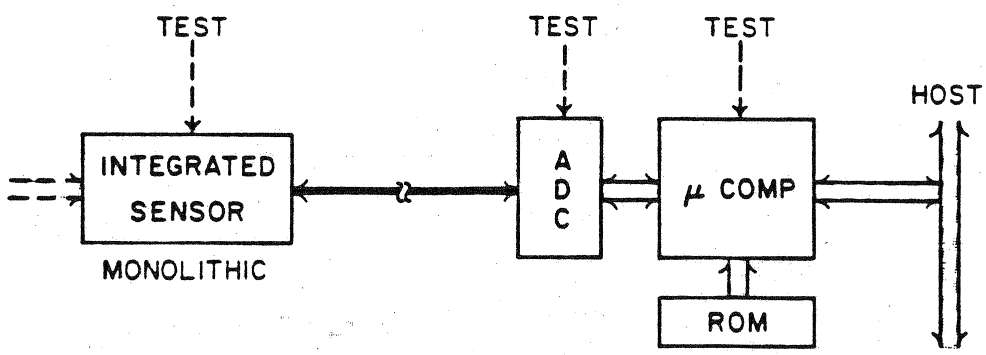
* Information Extraction

Typical Sensor Cost for Various Applications

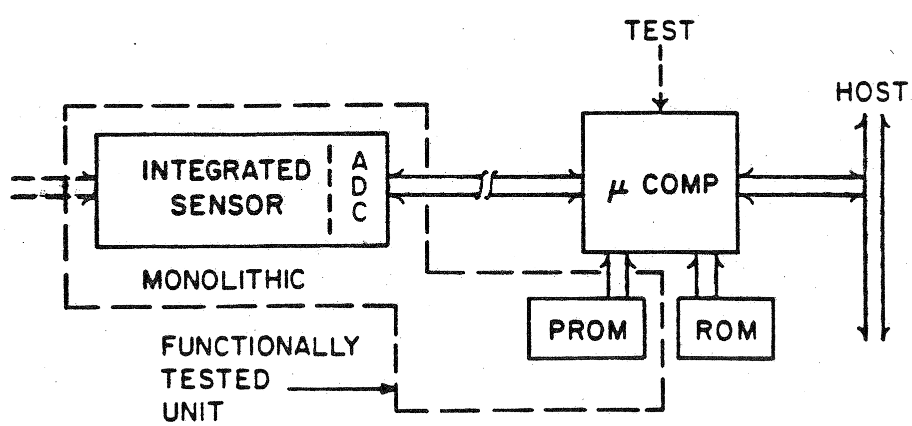




THIRD GENERATION

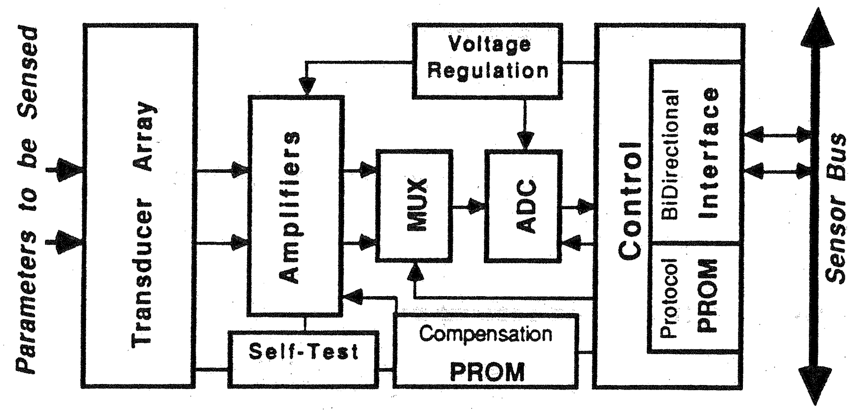


FOURTH GENERATION



FIFTH GENERATION

VLSI 5th Generation Integrated Sensor



VLSI 5th GENERATION INTEGRATED SENSOR

ADDRESSABLE * SELF-TESTING * DIGITAL OUTPUT
DIGITALLY-COMPENSATED
STANDARDIZED INTERFACE

Features:

* Standardized Interface
* Addressable, Bidirectional Bus-Compatible
* Selt-Testing and Autoranging
* Digitally Compensated, 12 bit accuracy
* Operating Temperature Range: -40 to 175C
* Single 5V Supply

Internal Storage of:

* Interface Protocols

* Nonlinearity Compensation

* Offset/Slope Compensation

Current Research Challenges in Sensors

* **Silicon Micromachining Techniques**

* **New Sensing Microstructures**

* Interface Circuit Techniques

* PROM-Based Digital Compensation

* Sensor Standardization

* Microcomputer-Based Signal Processing

Future Research Challenges in Sensors

Improved Micromachining Techniques

* Electrochemical Etch-Stops
* Laser-Assisted Etching

New Sensing Materials and Structures

* Biosensors
* GaAs-on-Si
* Optoelectronic Sensors

Standardized Interface Circuits

* Digitally-Compensated
* Self-Testing
* Addressable

Sensor Modeling and Simulation

* Sensor Science
* High-Level Sensor Compiler

Expert Local Control Structures

Models for Sensor Integration

To integrate multiple sensor observations effectively, we must be able to describe the information that can be provided by a sensor. We consider a sensor model as a description of the sensor's ability to observe and extract descriptions of the environment in terms of some prior world model. This model should provide an *a priori* description of capabilities through which observations can be aggregated, strategies developed, and coordination between sensor systems provided for. Therefore, models are needed for a number of components of the multisensor system.

Models Required for:

- **Geometry**. Multisensor systems will deal mainly with the perception of space. The placement, shape, and spatial relationships of objects are of great importance in space perception. The relevant geometry needs to be identified and modeled.
- **Physics of the Environment**. Models of the physics of the sensed environment (e.g., irradiance) can provide useful relations in the sensor response.
- **Sensor**. A model specifies the sensor function, operation, and response performance.
- **Uncertainty**. The evaluation of uncertainty, and more importantly, the integration of uncertainty over the multisensor system, are crucial in the process of evaluation and validation of a system.
- **Sensor System**. A model describes the coordination and regulation of the various sensor activations.

Two important aspects of sensor models:

- **Levels of Representation**
    - Irradiance Equations
    - Geometry
    - Symbolic Descriptions
- **Description of Capabilities**
    - Ability to provide observations of geometric features in the environment
    - Ability of a sensor to change its location or operating state
    - Dependence between observations made by different sensors

Control Strategies

A control strategy specifies the interface between the different models in the multisensor system and regulates their activation. The question must be addressed as to which properties of a control strategy are most appropriate for a given system. One has also to decide whether to commit each component of the system to the same set of properties, or to distribute properties as needed over the system components. Some of the control properties to consider are:

- Sequential / Parallel
- Probabilistic / Deterministic
- Cooperative / Competitive
- Feedback / Open Loop
- Modular / Hierarchical
- Goal-Directed / Data-Driven

An important advantage of using multiple sensor over single sensor systems is that cooperating observation sources provide more information than is available from a single source. The modeling of this cooperation and its use in developing sensor control strategies is very important. Elements of this problem are:

- Distributed control and system integration
- The exchange of information between sensor modules
- Resolving disagreements between systems
- The use of many sensors in a control loop
- The integration of complementary or competetive information.

Many of these considerations arise at all levels of model representation.

Levels of Representation

An important part of sensor modeling is the representation of the information supplied by the sensor. Indeed the representation of the environment can be considered as the dual of the sensor modeling problem. Three basic levels of representation were considered:

- **Data level**: reflectance properties, physical laws, etc.
- **Feature level**: surfaces, edges, etc. Of particular interest are mechanisms which allow many levels of geometric descriptions.
- **Task level**: planning and motion descriptions.

In a multisensor system, several different representations are likely to be used, each particularly suited to a given sensor. Compatibility between these representations is to be considered carefully in order to allow smooth fusion of multiple sensor information. The choice of a representation is tightly dependent on the level of sensor fusion (data level, feature level, and task level).

Representation of Uncertainty

A system theory is needed that can cope with uncertainty since uncertainty is intrinsic to the use of sensory information. In general, uncertainty should be treated explicitly and represented at all levels of modeling. The use of feedback theory which incorporates uncertainty has been suggested. Three problems raised are:

- What formal description of uncertainty should be used: feedback theory, probability, Dempster-Shafer, etc.
- Development of mechanisms to move uncertainty information between locations and representations.
- The validity of uncertainty models: e.g., the Gaussian noise model.

There seems to be general agreement on the use of probability models at the physics and geometry level. Other methods may be more appropriate at the symbolic level. Within probability, justification of existing methods for describing and manipulating uncertain geometric features was considered essential. There is some concern about the validity of Gaussian noise models (e.g., in laser range finding).

Algorithm Specification

A multisensor system is likely to require a large collection of algorithms which will often communicate through requests for information. As with any software package, it is necessary to follow strict specification guidelines to describe, for each algorithm, the input, output, side effects, complexity, stability, and relation to other algorithms. Specification is needed for algorithm development, testing and use. Appropriate specification can lead to the development of off-the-shelf algorithms.

Logical Sensor Specifications have been proposed as the basis for a multisensor system specification methodology. LSS permits sensor systems to be defined abstractly in terms of computational processes operating on the output from other sensors. Fault tolerance and dynamic reconfiguration of the computation can also be specified by naming alternative logical sensors which produce the same result. Finally, it is possible for control information to flow from more centralized processing to more peripheral processes and to be generated locally in the logical sensor by means of a micro-expert system specific to the interface represented by the logical sensor.

Parallel and Multiprocessing

Many issues of multiprocessor systems arise in multisensor systems, too:

- Combining distributed processes
- Interfacing, Contention, Compatibility
- Dedicated special purpose vs. general purpose systems
- Parallel algorithms, connectionism
- System resource allocation, scheduling, load balancing
- Monitoring, debugging, tuning
- Reliability, redundancy, fault tolerance
- Heterogeneous systems
- System abstraction, High-level models of multisensor systems (dataflow, Ada, object-based, etc.)

Artificial Intelligence

At the highest level of processing, artificial intelligence and knowledge engineering play a significant role:

- What information is appropriate to sense?
- Knowledge integration, knowledge-based approach
- Goal-directed sensing
- Numeric vs. symbolic crunching
- Inference techniques
- Data structures, algorithms, system design
- Intelligent control

Sensor Models and Multisensor Integration

Durrant-Whyte has proposed to model the world as a set of uncertain geometric objects and to describe each sensor by its ability to extract descriptions of these objects from the environment. We outline his approach in the pages that follow. A sensor model has three components:

- an **observation model** which describes a sensor's measurement characteristics,
- a **dependency model** which describes a sensor's dependence on information from other sources, and
- a **state model** which describes how a sensor's observations are affected by location and internal state.

Each model is represented as a probability distribution on observed geometric objects. This provides a powerful mechanism with which to manipulate, transform and integrate uncertain sensor observations. He has shown that these sensor models can deal effectively with cooperative, competitive and complimentary interactions between disparate information sources.

The key to efficient integration of multisensory information is to provide a purposeful description of the environment and to develop effective models of a sensor's ability to extract this information.

The environment is represented as features, all described by functions of the form $g(\mathbf{x},\mathbf{p}) = 0$, together with a probability distribution $f_p(\mathbf{p})$ on the parameter vector $\mathbf{p}$, describing the likelihood of observing or locating a particular instance of the feature. This representation provides sufficient detail so that each sensor or cue can contribute information, while allowing communication between sensors to be at a more functional level. This level of information corresponds closely to the division of information among different sensor algorithms. This type of feature description can be easily manipulated, transformed and compared providing a basis for the development of sensor integration policies.

Sensor Integration Considerations

- **Intra-Sensor Model**
  - Uncertainty in Sensor Components - e.g., a range finder has a CCD camera, lenses, and laser positioning
  - Nature of Features Produced - e.g., edges recovered from images are a complex function of the physically measured variables
- **Features**
  - Plethora of Features - e.g., many edges detected and hypothesis selection is expensive
  - Complementary Relations between Features - e.g., exploit the relation between surface normals and edges

- **Inter-Sensor Model**

  - Common Coordinate Frame - e.g., to combine observations
  - Control of Sensor Parameters - e.g., camera position, focus, filter and redundancy

Geometry

Any geometric object will be described as:

$$g(\mathbf{x},\mathbf{p}) = 0 \qquad \mathbf{x} \in \mathbf{R}^n \quad \mathbf{p} \in \mathbf{R}^m$$

e.g., lines on a plane expressed as:

$$g(\mathbf{x},\mathbf{p}) = x\cos(\theta) - y\sin(\theta) + r = 0$$

$$\text{with } \mathbf{x} = [x\ y]^T \quad \mathbf{p} = [r\ \theta]^T$$

If $\mathbf{p} = [0\ 0]$, then g is the y axis.

Uncertainty is described by:

$$f_p(\mathbf{p})$$

a distribution function on the parameter vector.

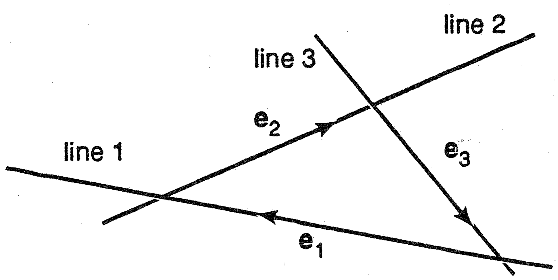
Two necessary operations:

1. Describe a feature in terms of another, and
2. Change a feature's coordinate system.

Both can be described by a transformation of $f_p(\mathbf{p})$.

Topology

Topology associated with objects and geometric features has properties invariant to distortions of **p**. Relations between uncertain features remain consistent. E.g., consider the random placement of 3 lines in the plane:



$\mathbf{p}_1 + \mathbf{p}_2 + \mathbf{p}_3 = 0$
with probability 1

This can be extended to any topological network of geometric features as follows:

Let N be a connected digraph with n nodes and m arcs and r cycles. Let T be the set of all such graphs. Let $\mathbf{e}_j$ label arc j.

Let C be an r by m matrix defining the loops in N. I.e., C[i,j]=1 if $\mathbf{e}_j$ is in loop i.

Let M be the n by m arc incidence matrix defined as:

$$M[i,j] = \begin{cases} 1 \text{ if } \mathbf{e}_j \text{ exits node i} \\ -1 \text{ if } \mathbf{e}_j \text{ enters node i} \\ 0 \text{ otherwise} \end{cases}$$

For the 3 lines shown above:

$$M = \begin{bmatrix} 1 & 0 & -1 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} \quad \text{and} \quad C = [1\ 1\ 1]$$

For every $N \in T$, we have:

$$CM^T = 0 \quad \text{and} \quad MC^T = 0$$

Let $\mathbf{e} = [e_1 \ldots e_m]^T$ and $\gamma = [\gamma_1 \ldots \gamma_r]^T$ where $\mathbf{e}$ is the arc labeling and γ is the loop lengths. I.e.,

$$C\mathbf{e} = \gamma$$

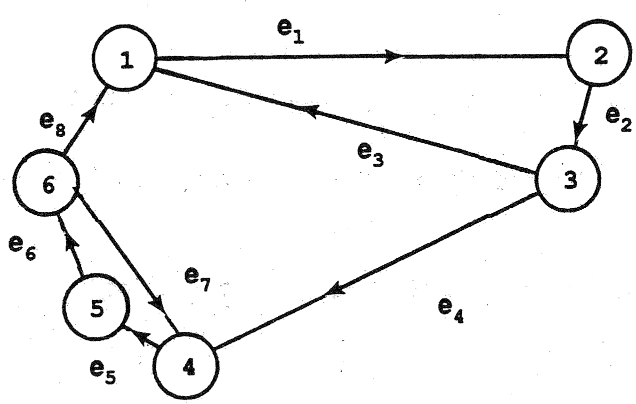
characterizes the structure of the graph.

$N \in T$ is <u>constrained</u> if we add a new node (n+1) to N and n arcs $\mathbf{x}_i$ such that $\mathbf{x}_i$ is an arc from node (n+1) to node i. We have then:

$$\mathbf{e} = M^T\mathbf{x}$$

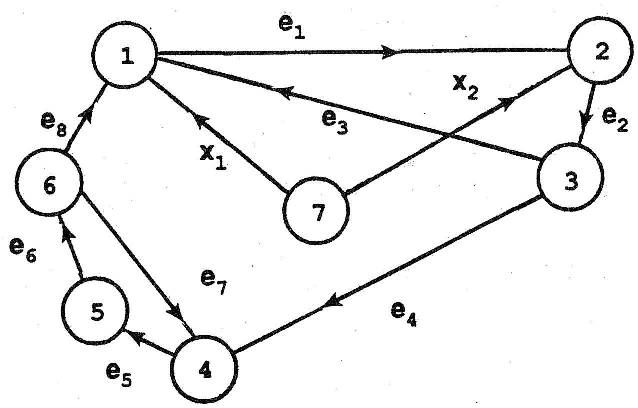
An Example

Let N be (with n=6, m=8 and r=3):



$$M = \begin{bmatrix} 1 & 0 & -1 & 0 & 0 & 0 & 0 & -1 \\ -1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & -1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & -1 & 1 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & -1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & -1 & 1 & 1 \end{bmatrix} \qquad C = \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 1 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \end{bmatrix}$$

N can be made into a constrained network:



It is clear that:

$$\begin{bmatrix} e_1 \\ e_2 \\ e_3 \\ e_4 \\ e_5 \\ e_6 \\ e_7 \\ e_8 \end{bmatrix} = \begin{bmatrix} 1 & -1 & 0 & 0 & 0 & 0 \\ 0 & 1 & -1 & 0 & 0 & 0 \\ -1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & -1 & 0 & 0 \\ 0 & 0 & 0 & 1 & -1 & 0 \\ 0 & 0 & 0 & 0 & 1 & -1 \\ 0 & 0 & 0 & -1 & 0 & 1 \\ -1 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \\ x_7 \\ x_8 \end{bmatrix}$$

E.g., $e_1 = x_1 - x_2$.

Useful Properties

Lemma 1: If **e** is the vector of random variables labeling a constrained network, then:

$$\mathbf{Ce} = 0 \qquad (1)$$

E.g., If we want to estimate the value of three parameter vectors describing edges that meet at a corner, Equation (1) ensures that when any one vector is chosen, the others are constrained by it.

Lemma 2: The variance-covariance matrix Λ_e of the vector **e** is singular, since:

$$CE[(\mathbf{e}-E[\mathbf{e}])(\mathbf{e}-E[\mathbf{e}])^T]C^T = C\Lambda_e C^T = 0$$

where $E[\cdot]$ is the expected value.

which defines the relation between the constraints and determines the allowable distortions or uncertainty in ensuring consistency.

Lemma 3: For any symmetric matrix Σ, the matrix $M^T\Sigma M$ is singular.

I.e., the plane surface parameters can be chosen independently and whatever the resulting estimate **x**, it is guaranteed to find edges which are consistent and which meet at a corner.

Representing Uncertainty

Let:

i,j	be coordinate frames
$^i\mathbf{p}$	be a geometric feature wrt i
$f^i(\mathbf{p})$	be a prob. density function of **p** in i
^jD_i	transforms $^i\mathbf{p}$ to $^j\mathbf{p}$ (assume 1-1)
^iJ_i	be the associated Jacobian

then

$$f^j(^j\mathbf{p}) = \frac{f^i(^jD_i^{-1}(^j\mathbf{p}))}{|\det(^jJ_i)|_\mathbf{p}}$$

Also, we have that:

$$^jE[\mathbf{p}] = E[^j\mathbf{p}] = E[^jD_i(^i\mathbf{p})] = {}^jD_i(E[^i\mathbf{p}]) = {}^jD_i(^iE[\mathbf{p}]) \qquad (2)$$

and

$$ {}^{j}\Lambda_{p} \approx \left(\frac{\partial^{j}D_{i}}{\partial^{i}\mathbf{p}}\right){}^{i}\Lambda_{p}\left(\frac{\partial^{j}D_{i}}{\partial^{i}\mathbf{p}}\right)^{T} \qquad (3) $$

Assuming location and feature vectors to be jointly Gaussian, then **p** and Λ_p completely define the feature density functions and Equations (2) and (3) permit transformation between coordinate systems.

Changes in Position

Consider a 6-dimensional pose vector consisting of position and orientation. We have:

Λ_p variance-covariance matrix

Λ_p^{-1} information matrix

Suppose ${}^{j}D_i$ is a homogeneous transform:

$$ {}^{j}T_i = \begin{bmatrix} \mathbf{n}\ \mathbf{o}\ \mathbf{a}\ \mathbf{p} \\ 0\ 0\ 0\ 1 \end{bmatrix} $$

Then $\quad {}^{j}\Lambda_p = {}^{j}J_i{}^{i}\Lambda_p{}^{j}J_i{}^{T} \quad (4)$

Let $\quad \mathbf{r} = [\mathbf{n}^T\ \mathbf{o}^T\ \mathbf{a}^T]^T$

$\mathbf{m} = [(\mathbf{pxn})^T\ (\mathbf{pxo})^T\ (\mathbf{pxa})^T]^T$

then

$$ J_T = \begin{bmatrix} \mathbf{r} & \mathbf{m} \\ 0 & \mathbf{r} \end{bmatrix} \qquad J_T{}^T = \begin{bmatrix} \mathbf{r}^T & 0 \\ \mathrm{m}^T & \mathbf{r}^T \end{bmatrix} $$

and

$$ {}^{j}\Lambda_p = J_T{}^{i}\Lambda_p J_T^T $$

$$ {}^{i}\Lambda_p = J_T^{-1}{}^{j}\Lambda_p J_T^{-T} \qquad (5) $$

$$ {}^{j}\Lambda_p^{-1} = J_T^{-T}{}^{i}\Lambda_p^{-1} J_T^{-1} $$

$$ {}^{i}\Lambda_p^{-1} = J_T^{T}{}^{j}\Lambda_p^{-1} J_T \qquad (6) $$

An Example

Let $\mathbf{x}$ be a 6D pose vector

$${}^{i}\Lambda_x = \begin{bmatrix} {}^{i}\Lambda_{11} & {}^{i}\Lambda_{11} \\ {}^{i}\Lambda_{12}^{T} & {}^{i}\Lambda_{22} \end{bmatrix} \quad \text{its variance}$$

We obtain:

$${}^{j}\Lambda_x = J_T {}^{i}\Lambda_x J_T^T$$

which is:

$$\begin{bmatrix} \mathbf{r}{}^{i}\Lambda_{11}\mathbf{r}^T + \mathbf{m}{}^{i}\Lambda_{22}\mathbf{m}^T & \mathbf{m}{}^{i}\Lambda_{22}\mathbf{r}^T \\ \mathbf{r}{}^{i}\Lambda_{22}\mathbf{m}^T & \mathbf{r}{}^{i}\Lambda_{22}\mathbf{r}^T \end{bmatrix}$$

Consider the term ${}^{j}\Lambda_{11}$. Then:

$\mathbf{r}{}^{i}\Lambda_{11}\mathbf{r}^T$ is the position variance rotated to a new position, and

$\mathbf{m}{}^{i}\Lambda_{22}\mathbf{m}^T$ is the magnification of the orientation uncertainties due to interframe distance.

In the case of partial information, it's better to work with the information matrixes, $\Sigma = \Lambda^{-1}$, which have 0 entries where uncertainty is infinite:

$${}^{j}\Sigma_x = \begin{bmatrix} \mathbf{r}{}^{i}\Sigma_{11}\mathbf{r}^T & \mathbf{r}{}^{i}\Sigma_{11}\mathbf{m}^T \\ \mathbf{m}{}^{i}\Sigma_{11}\mathbf{r}^T & \mathbf{m}{}^{i}\Sigma_{11}\mathbf{m}^T + \mathbf{r}{}^{i}\Sigma_{22}\mathbf{r}^T \end{bmatrix}$$

Consider ${}^{j}\Sigma_{22}$.

$\mathbf{m}{}^{i}\Sigma_{11}\mathbf{m}^T$ is the extra information gained from position info, and

$\mathbf{r}{}^{i}\Sigma_{22}\mathbf{r}^T$ is the rotated orientation information.

Combining Different Features

Goals:

- Represent one feature in terms of another
- Combine observations of different kinds of features

Let $g_i(\mathbf{x},\mathbf{p}_i) = 0$ and $g_j(\mathbf{x},\mathbf{p}_j) = 0$

(with $\mathbf{p}_i \in \mathbf{R}^l$, $\mathbf{p}_j \in \mathbf{R}^m$ and $\mathbf{x} \in \mathbf{R}^n$) describe two distinct kinds of features. Suppose:

$$\mathbf{p}_j = {}^jh_i(\mathbf{p}_i)$$

gives the geometric relation between the two features. Given g_i, $\mathbf{p}_i$, ${}^jh_i(\mathbf{p}_i)$ and

$${}^iJ_i\left(\frac{\partial {}^jh_i^{-1}}{\partial \mathbf{p}_i}\right)\Big|_{\mathbf{p}_i=E[\mathbf{p}_i]}$$

and $\quad \mathbf{p}_i \approx N(E[\mathbf{p}_i],\Lambda_i)$

then $\quad \mathbf{p}_j \approx N(E[\mathbf{p}_j],\Lambda_j)$

with $\quad E[\mathbf{p}_j] = {}^jh_i(E[\mathbf{p}_i])$

$$\Lambda_j^{-1} = {}^iJ_i\Lambda_j^{-1}\,{}^iJ_i^T$$

An Example

Consider the polyhedral world of edges and surface normals:

- **Each edge** describes a possible family of surface normals,
- **Two edges** may describe a planar surface $\mathbf{e}_i x \mathbf{e}_j = \mathbf{n}_{ij}$.

Given an edge description $\mathbf{e}_i \approx N(E[\mathbf{e}_i],\Lambda_i)$ and $\mathbf{e}_j \approx N(E[\mathbf{e}_j],\Lambda_j)$, the surface normal estimate is then:

$$\mathbf{n}_{ij} \approx N(E[\mathbf{n}_{ij}],\Lambda_{ij})$$

where $\quad E[\mathbf{n}_{ij}] = E[\mathbf{e}_i]xE[\mathbf{e}_j]$

and $$\Lambda_{ij}^{-1} = \left(\frac{\partial(\mathbf{e}_i x \mathbf{e}_j)}{\partial \mathbf{n}_{ij}}\right) D \left(\frac{\partial(\mathbf{e}_i x \mathbf{e}_j)}{\partial \mathbf{n}_{ij}}\right)^T$$

where D is diagonal with

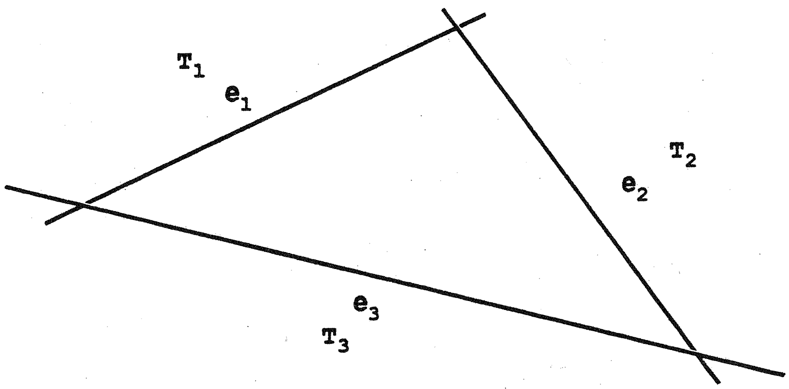
$$D_{11} = \Lambda_{e_i} \text{ and } D_{22} = \Lambda_{e_j}$$

Gaussian Topology

How can sensed information be propagated? It is essential to:

- **Combine** uncertainty measures, and
- Compute cumulative effects.

Topological constraints can be interpreted as a set of constrained topological neworks. Consider a 3-node graph:



From Lemma 1: $C[e_1, {}^1D_2(e_2), e_3]^T = 0$

Fix vectors in a common frame such that:

$$^0e_1 + {}^0e_2 - {}^0e_3 = 0.$$

For the variance matrix:

$$\Lambda_3 = \Lambda_1 + J_{T_1}\Lambda_2 J_{T_1}^T$$

which describes how geometric uncertainty measures can be propagated between different frames.

For the information matrix:

$$\Sigma_3 = J_{T_1}^{-T}\Sigma_2 J_{T_1}^{-1}[J_{T_1}^{-T}\Sigma_2 J_{T_1}^{-1}+\Sigma_1]^{-1}\Sigma_1$$

These results may be applied sequentially to any number of inferences providing the transforms are not perturbed in doing so.

Multisensor Integration

Durrant-Whyte has also developed a team structured approach to integrating observations from multiple sensors:

- **Individual Sensors**
    - Make local decisions
    - Cooperate with other sensors
- **Team Structure Permits:**
    - Information exchange
    - Validation of Sensors
    - Resolution of differences
    - Broader information base
    - Greater result than just sum of parts
- **Information Structure**
    - Stochastic geometry as common language
    - Model of sensor capabilities (i.e., information required and observations produced)
    - Explicit sensor dependencies

Comparing Sensor Observations

Basis of Comparison: Local Utility Functions

If $\delta_i(\mathbf{z}_i)$ is a sensor's decision about a feature based on observation $\mathbf{z}_i$ and $E[\mathbf{p}]$ is some consensus parameter of the associated object, then the utility of the decision to the consensus for each sensor i is:

$$u_i(\delta_i(\mathbf{z}_i), E[\mathbf{p}]) \in \mathbf{R}$$

E.g., suppose

S_1 observes edges $\mathbf{z}_1$
S_2 observes surface normals $\mathbf{z}_2$

both of the same surface parameterized by $\mathbf{p}$. Furthermore, $\delta_1(\mathbf{z}_1)$ and $\delta_2(\mathbf{z}_2)$ are the best estimates given $\mathbf{z}_1$ and $\mathbf{z}_2$. To find a surface which best explains δ_i, find a parameter $E[\mathbf{p}]$ that maximizes $u_i(\delta_i(\mathbf{z}_i), E[\mathbf{p}])$ for every i.

Note:

1. The comparison is on the dimensionless u_i's, and
2. Interest centers on when a $E[\mathbf{p}]$ exists which satisfies all sensors and what consensus value it takes.

Specification of Multisensor Systems

The Problem:

Currently there is no formal methodology for sensor system design. Sensor system design is carried out in an *ad hoc* fashion for a particular application ... This does not generally lead to an optimal design, nor does it allow flexibility of application ...

Goal: Sensor System Design and Specification (including sensing and control issues).

Approach:

A methodology for system configuration requires the identification of an abstraction that can be used as a building block.

Key Abstraction: Logical Sensors

Benefits:

- Separates specification from implementation
- Permits redundancy in systems
- Permits fault tolerant systems, and
- Permits dynamic reconfiguration of systems.

Logical Sensors

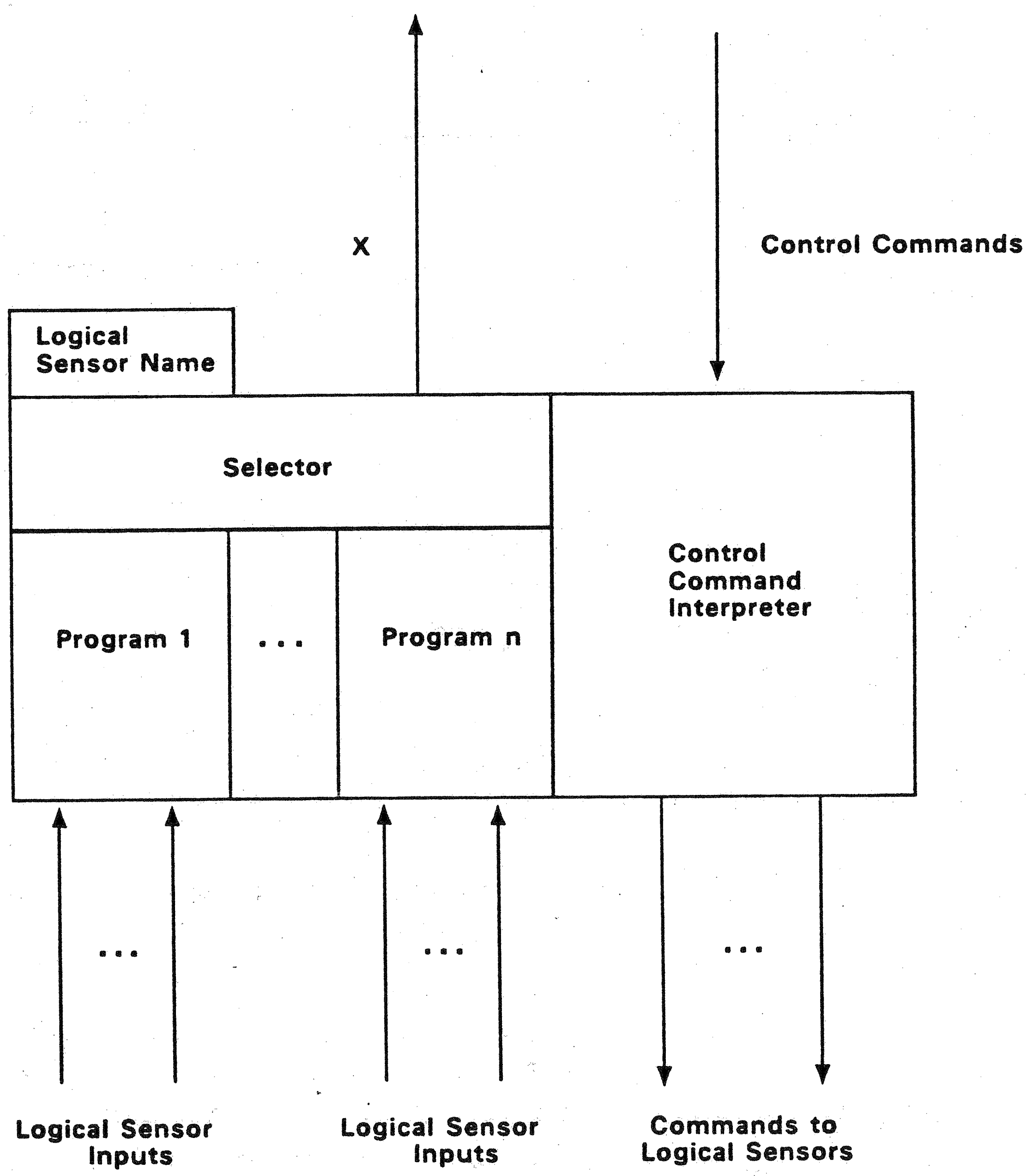
A methodology for the explicit characterization of the data to be sensed and the processing of that data.

Motivations:

- Emergence of multisensor systems - complex systems are crucial to technical progress: nuclear power plants, automatic target recognition systems, flexible robotics workcells
- Benefits of data abstraction - separate specification from implementation
- Availability of smart sensors - lower hardware cost; implement algorithms directly in hardware
- Reconfiguration - replication of subsytems and replacement.

A logical sensor is an object with a type (which characterizes the output). This means that sensor system design can be viewed as function application or dataflow.

Logical Sensor Building Block



Components of Logical Sensor

Logical Sensor Name: Uniquely identifies module.

Characteristic Output Vector (COV): A vector of types which serves as a description of the output vectors produced by the logical sensor.

Alternate Subnets: A set of one or more ways to produce the COV. Each alternate subnet is composed of (1) a set of input sources, and (2) a comptation unit over the input sources.

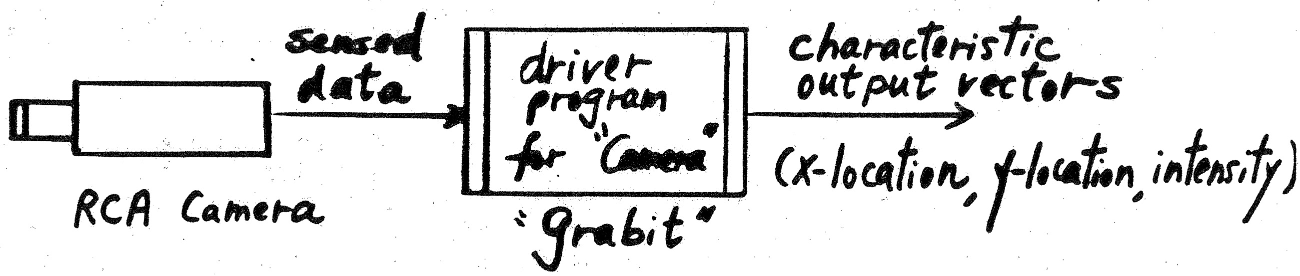
Control Command Interpreter: A program to interpret the control commands coming from a level up in the hierarchy, and to send commands down to logical sensors lower in the hierarchy. Thus, it acts as a "logical controller."

Selector: A function whose inputs are a set of alternate subnets and an acceptance test name. The role of the selector is to detect failure of an alternate and switch to a different alternate if possible. The select function monitors both the sensor data going up and the command stream. Given the control command and the local sensor data, the select function can short circuit the control commands to be issued. Such a function may be viewed as a µexpert system which knows all about the interface represented by the logical sensor in which it is located.

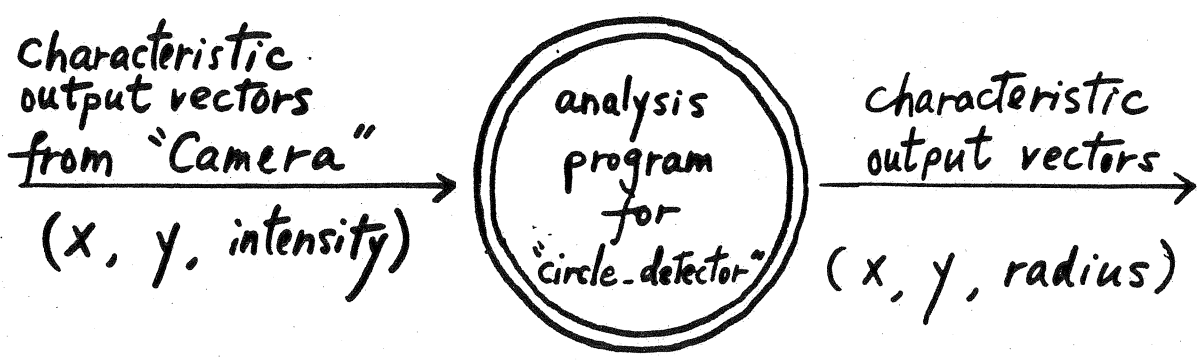
A logical sensor network is a network composed of subnetworks which are themselves logical sensors. (They can be viewed as dataflow networks.)

Examples of Logical Sensors :

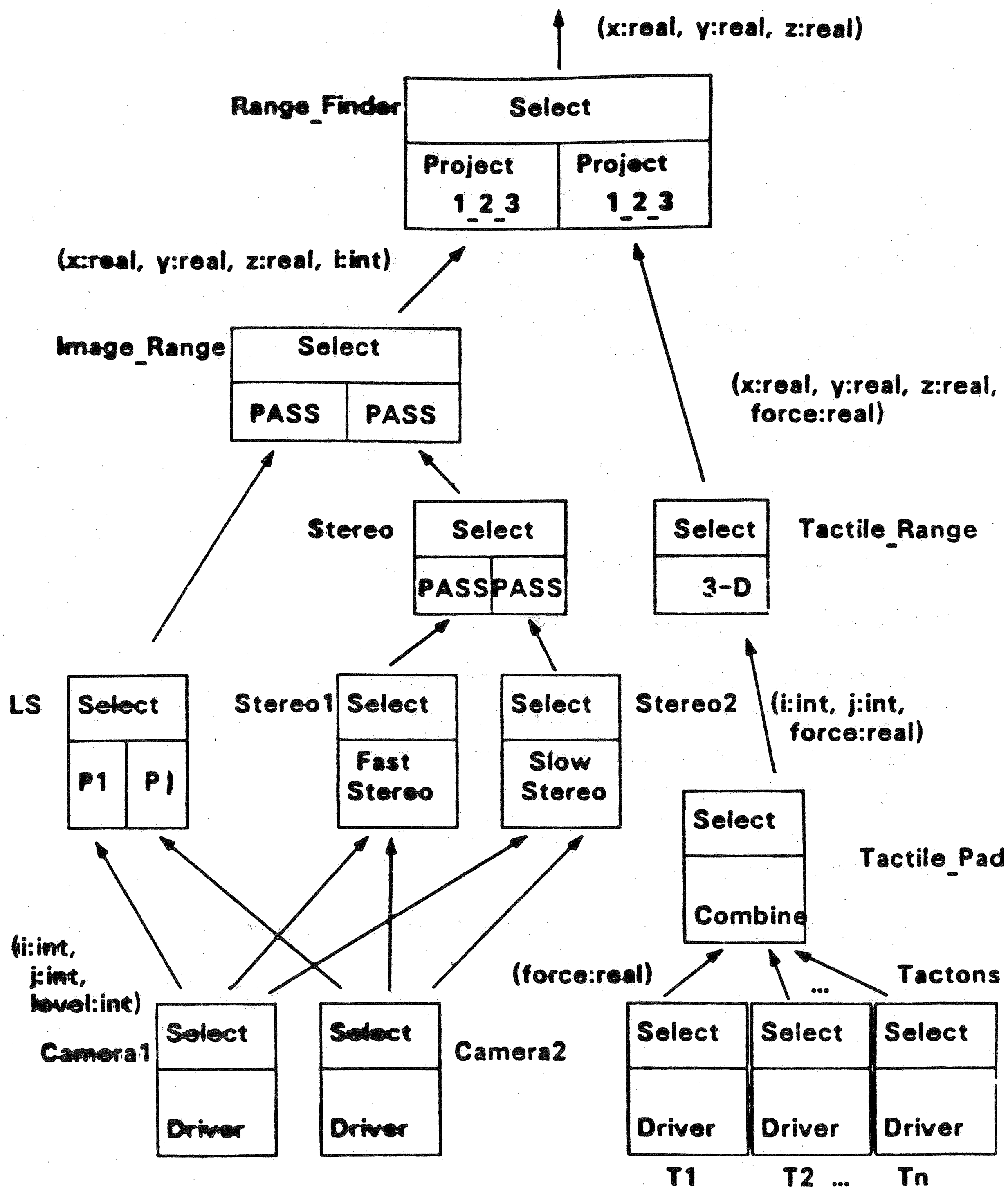
example 1 : "Camera"



example 2 : "Circle-Detector"



"Circle"


(x:real, y:real, z:real)
Range_Finder
Select
Project 1_2_3
Project 1_2_3
(x:real, y:real, z:real, i:int)
Image_Range
Select
PASS
PASS
(x:real, y:real, z:real, force:real)
Stereo
Select
PASS
PASS
Select
3-D
Tactile_Range
LS
Select
P1
P1
Stereo1
Select
Fast Stereo
Select
Slow Stereo
Stereo2
(i:int, j:int, force:real)
Select
Combine
Tactile_Pad
(i:int, j:int, level:int)
(force:real)
Tactons
Camera1
Select
Driver
Select
Driver
Camera2
Select
Driver
Select
Driver
Select
Driver
T1
T2 ...
Tn

Sensor System Reconfiguration

Why Reconfigure?

- Failure: hardware or software, and
- Dynamic Sensing Goals: change sensor configuration for particular task or environment.

We require an abstract view of sensor system equivalence. This allows:

- Replication: build in identical backup sensors/algorithms, or
- Replacement: use other sensors/algorithms to achieve the same result as another.

Logical Sensor Specifications facilitate error determination and recovery. A lgical sensor has a selector which monitors computational activity and upon detection of an error attempts recovery by switching to an alternate subnet. Selectors detect failures arising from either an input source or a computation unit. Thus, the selector together with alternate subnets constitute a failure and substitution device, that is, a fault tolerant mechanism, and both hardware and software fault tolerance is achieved.

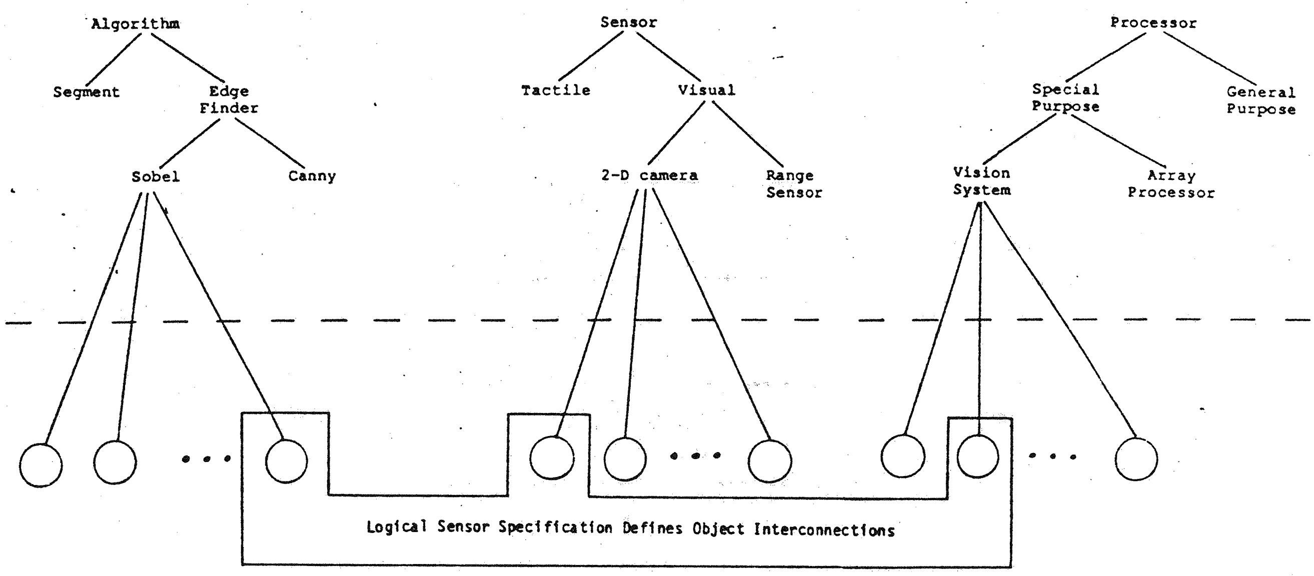
Multisensor Knowledge Base

The knowledge base serves two main purposes:

- **Describe Properties of System Components**
  - Sensors: E.g., accuracy, hysteresis, dynamic range, etc.
  - Algorithms: E.g., space and time complexity, numerical stability, etc.
  - Processors: E.g., cycle times, memory limits, addressing, etc.
  - Actuators: E.g., actuation principles, power required, etc.

- **Provide Class Descriptions**
  - Actual Devices: these are just instances of the leaves in the frame-based knowledge structure;
  - Interconnect: they are interconnected by filling slots with messages to send to other instances of system modules.

Knowledge Organization



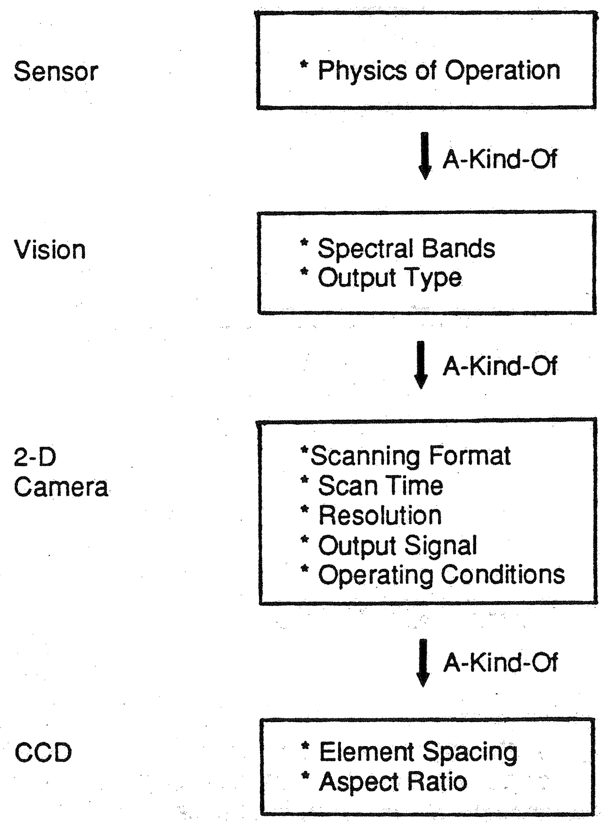
Frames and Objects

The object-based style takes the view that the major concern of programming is essentially the definition, creation, manipulation and interaction of objects; that is, a set of independent and well-defined data structures. In particular, a single data structure (or instance) is associated with a fixed set of operations (or functions), and those operations are the only ones defined on the object. Thus, an object is a structure whose internal state (slots comprised of name/value relationships) which are accessed through functions (methods) defined in association with the object.

A Multisensor Knowledge Base is implemented in a frame-like representation. Frames relate very naturally to object-based descriptions. Reasoning and inference takes place by accessing slot information.

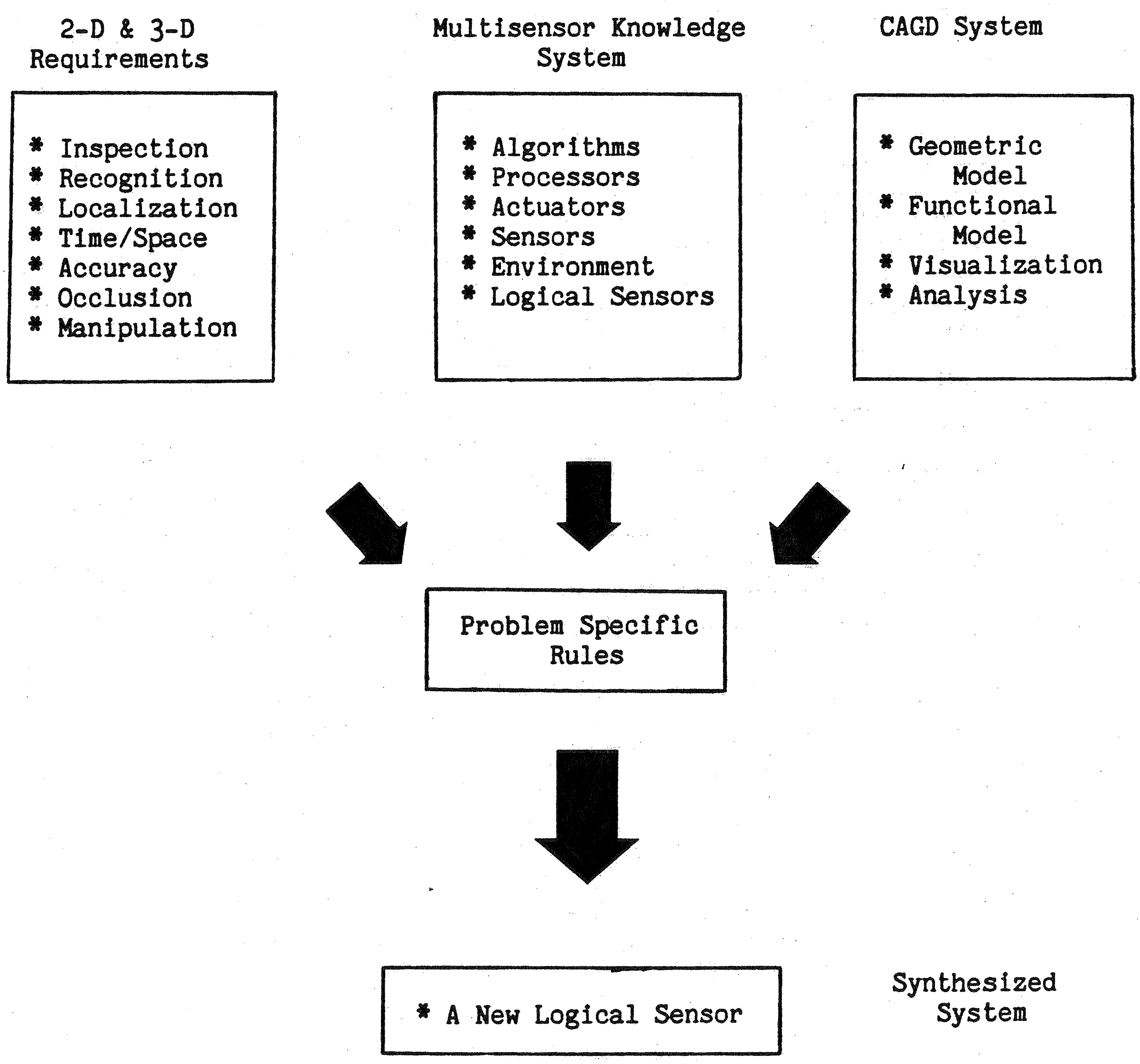
Example

A CCD camera hierarchy might be defined as:

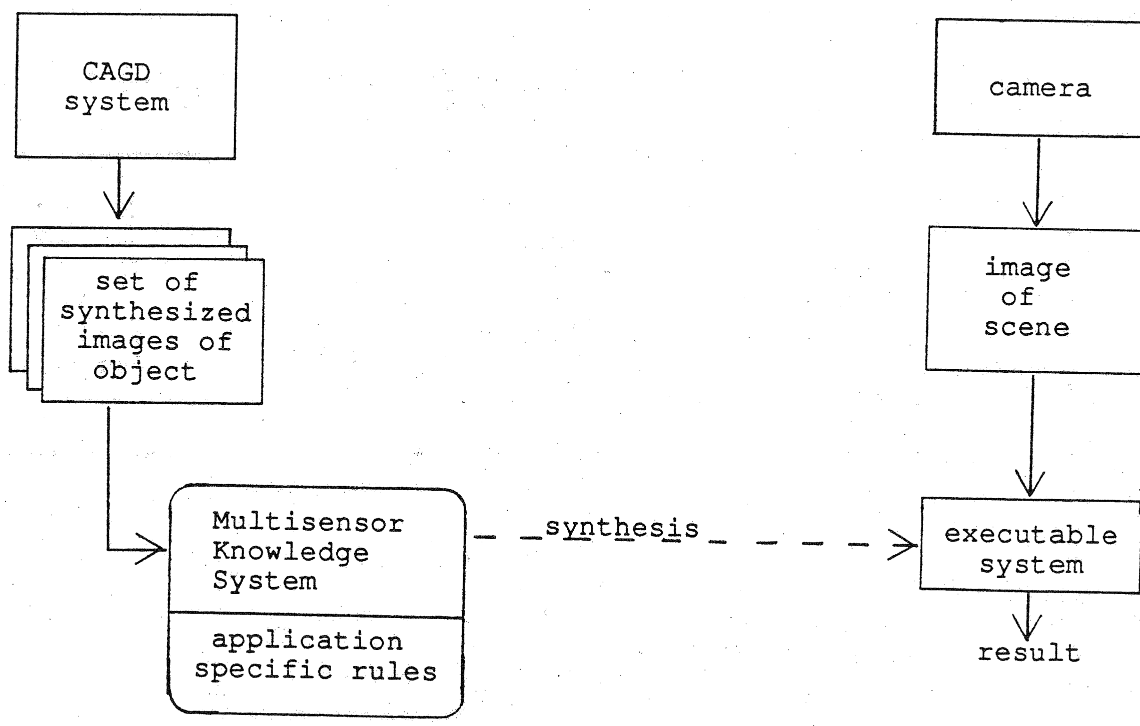


Automatic Sensor System Specification

It is possible to use the methods described previously to automatically synthesize sensor systems. A requirements statement can be analyzed by a set of application specific rules. These in turn take advantage of the knowledge in the frame system to reason about the characteristics of the components, and eventually the complete system. These are "hooked together" by filling in slots of instances of modules created from the knowledge base. Their slots are filled in with messages to the other modules comprising the system:



An Example: CAD-Based Computer Vision



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