Introduction to Multiple Sensor Fusion in Mobile Robotics

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Outline

- Brief Introduction
- Taxonomy of Algorithms
- Data Association
- Estimation
- Identity Declaration
- Decision Level Fusion
- Summary and Conclusions

Brief Introduction

- Multiple Sensor Fusion?
- Mobile Robotics?
- Sensor Fusion in Mobile Robotics.

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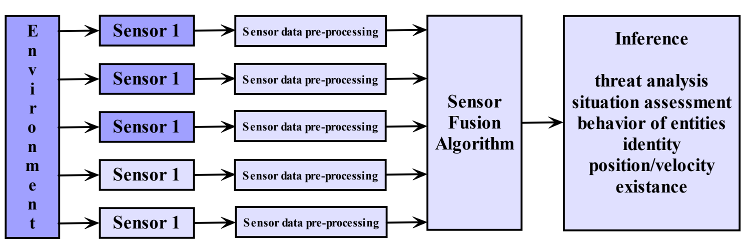
Brief Introduction

- Sensor Fusion?



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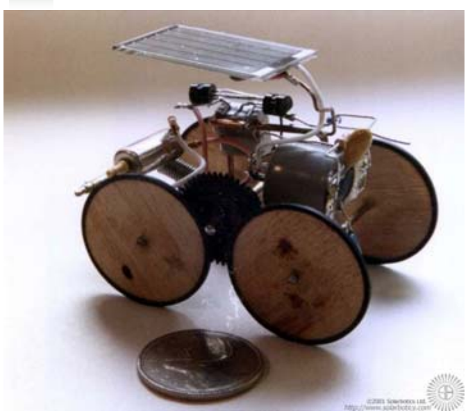
Brief Introduction

- Mobile Robotics?
  - Mechanical engineering
  - Computer science
  - Electrical engineering
  - Cognitive psychology, perception, and neuroscience

Brief Introduction:Example1



Brief Introduction: Example2

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Brief Introduction: Example3

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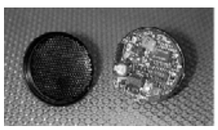
Brief Introduction: Sensor Fusion in Mobile Robotics

- Encoder

- Gyroscope

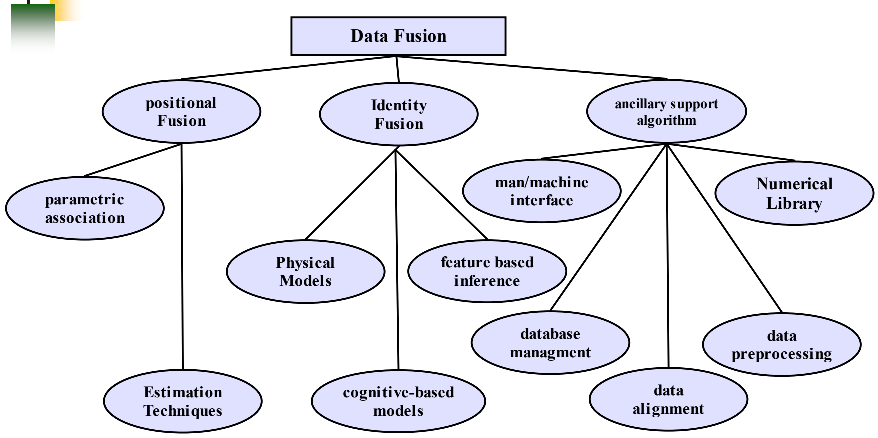
- Ultrasonic Sensor



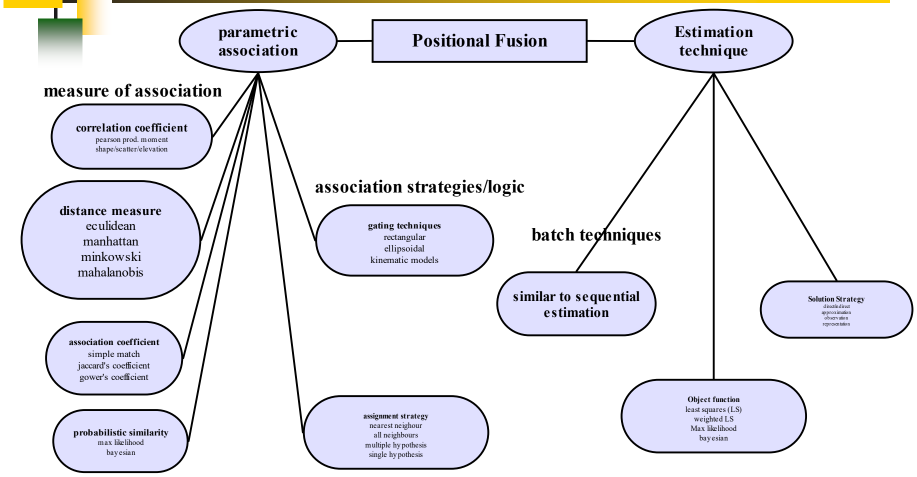
- Global Positioning System (GPS)

- Other Sensors
  - Video Sensor
  - CCD Camera
  - Infrared Sensor
  - Tactile Sensors

Taxonomy of Algorithms for Sensor Fusion



Taxonomy of Positional Fusion



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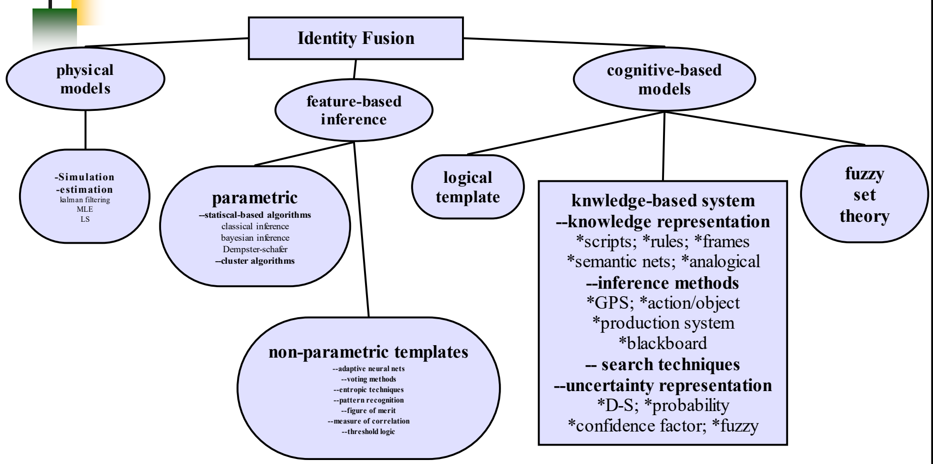
Taxonomy of Identity Fusion



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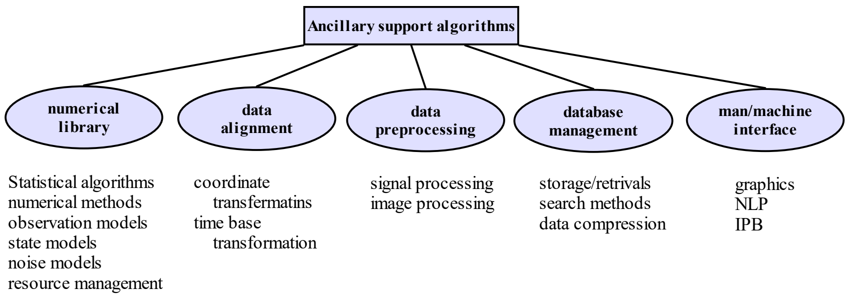
Taxonomy of Ancillary Support



Data Association

- Introduction
- A general association process
- Gating
- Association metrics
- Assignment
- Summary

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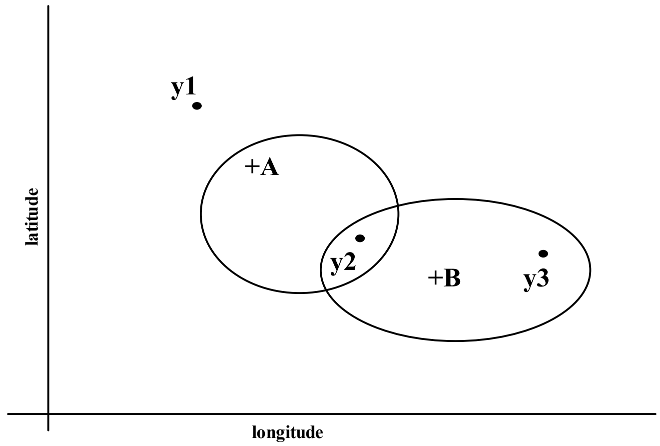
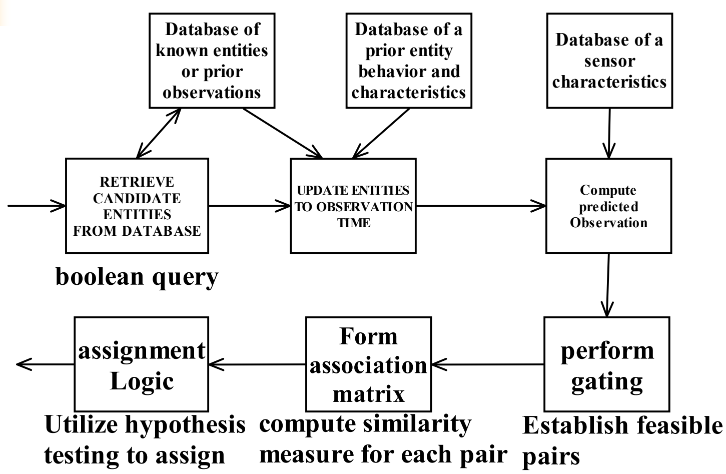
Data Association: Introduction



Data Association: A general association process



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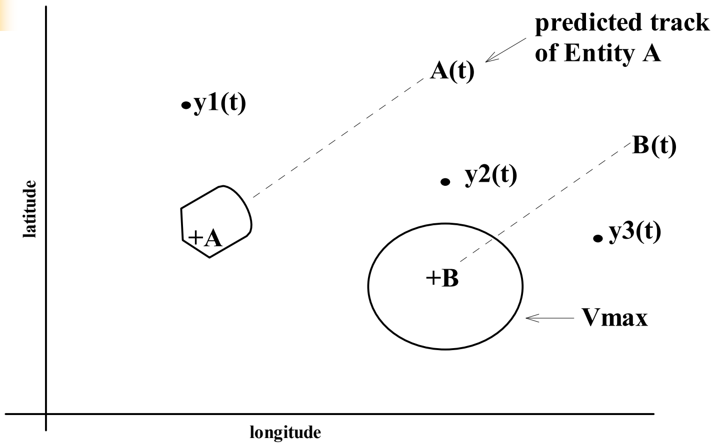
Data Association: Gating



Data Association: Association Metrics

- Metric rules:
  - D(a,b)=d(b,a)>=0 (symmetry)
  - D(a,b) <=d(a,c)+d(b,c) (triangle inequality)
  - If d(a,b) <>0 then a<>b (distinguish ability of nonidenticals)
  - D(a,a)=0 (indistinguishability of identical)
- Association measure
  - Distance measures
  - Correlation coefficients
  - Association coefficients
  - Probabilistic similarity coefficients

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Data Association: Assignment

- The final step in the association process is the actual assignment of observation to observation, or observation to tracks.

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Data Association: Summary

- Gating technique
- Association measures
- Assignment strategies

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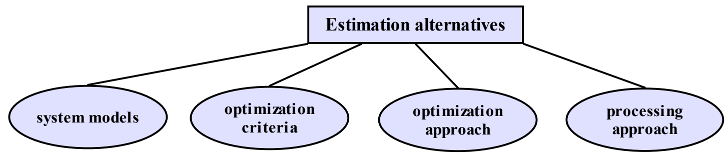
Estimation



System models:
observation equations
equations of motion
dynamic
state vector
implementation

Optimization criteria:
least squares
weighted LS
mean squares
maximum likelihood
bayesian

Optimization approach:
--direct methods
-non-derivative
downhill simplex
direction set
-derivative
conjugate gradient
variable metric
--indirect methods

Processing approach:
--sequential processing
--batch processing techniques
--covariance error formulation

Estimation: Kalman Filter

- What is a Kalman Filter and what can we do?
- Optimal in what sense?
- Why is it so popular?
- Formulating a Kalman filter
- State Definition

Estimation: state space representation

- State equation:
- X(k+1)=F(k)X(k)+G(k)U(k)+V(k)
  - E[V(k)V(k)']=Q(k)
- Measurement equation
- Z(k)=H(k)X(k)+W(k)
  - E[W(k)W(k)']=R(k)

Estimation: Falling Body Example

- Consider an object falling under a constant gravitational field. Y(t) denotes the height of the object,

$$\ddot{y}(t) = -g$$

$$\dot{y}(t) = \dot{y}(t_0) - g(t - t_0)$$

$$y(t) = y(t_0) - \dot{y}(t_0)(t - t_0) - \frac{g}{2}(t - t_0)^2$$

- As a discrete time system with time increment of
- $t-t_0=1$

Estimation: Falling Body Example

$$y(k+1) = y(k) + \dot{y}(k) - \frac{g}{2}$$

- The height y(k+1) depends on the previous velocity and height at time k.
- We can define the state as $x(k) = [y(k)\ \dot{y}(k)]$
- and then the state equation becomes

$$x(k+1) = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} x(k) + \begin{bmatrix} 0.5 \\ 1 \end{bmatrix} (-g) = Fx(k) + Gu \qquad z(k) = \begin{bmatrix} 1 & 0 \end{bmatrix} x(k) + w(k) = Hx(k) + w(k)$$

- The variance of w(k) needs to be known for implementing a Kalman filter

Estimation: State Estimation

- 1. Known are $\hat{x}(k|k),\ u(k),\ p(k|k)$ and the new measurement z(k+1)
- 2. State prediction $\hat{x}(k+1|k) = F(k)\hat{x}(k|k) + G(k)u(k)$
- 3. Measurement prediction $\hat{z}(k+1|k) = H(k)\hat{x}(k+1|k)$
- 4. Measurement Residual $v(k+1) = z(k+1) - \hat{z}(k+1|k)$
- 5. Updated state estimate: $\hat{x}(k+1|k+1) = \hat{x}(k+1|k) + W(k+1)v(k+1)$
- Where W(k+1) is called the Kalman gain defined next in the state covariance estimation

Estimation: State Covariance Estimation

- 1. State prediction covariance:

$$P(k+1|k) = F(k)P(k|k)F(k)' + Q(k)$$

- 2. Measurement prediction covariance

$$S(k+1) = H(k+1)P(K+1|k)H(k+1)' + R(k+1)$$

- 3. Filter gain

$$W(k+1) = P(k+1|k)H(k+1)'S(k+1)^{-1}$$

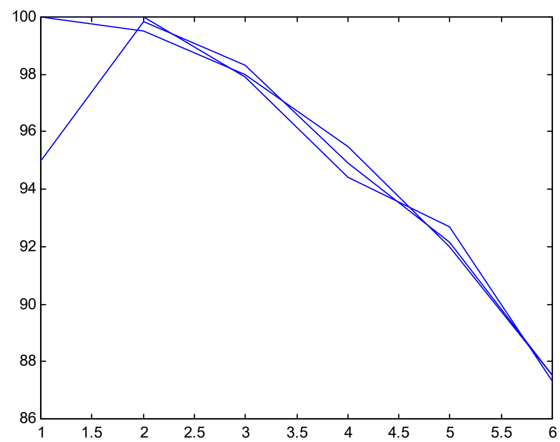
- 4. Updated covariance

$$P(k+1|k+1) = P(k+1|k) + W(k+1)S(k+1)W(k+1)'$$

Estimation: Falling Body Kalman Filter

- Assume an initial true state of position=100 and velocity =0, g=1
- We choose an initial estimate state and initial state covariance P(0) base on mainly intuition.
- The state noise covariance Q is zeros R is estimated from knowledge of predicted observation errors, chose 1 here.
- F,G,H are known

Estimation: plot



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Identity Declaration

- Identity Declaration and Pattern Recognition
- Feature Extraction ☺
- Parametric Templates
- Cluster Analysis Techniques
- Adaptive Neural Networks
- Physical Models
- Knowledge based Methods

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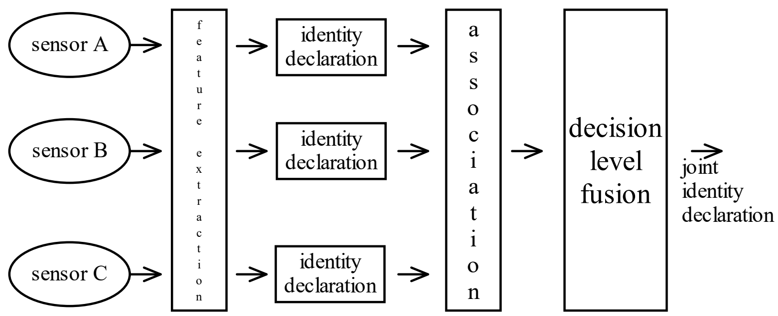
Decision Level Identity Fusion



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Decision Level Identity Fusion

- Classical inference
- Bayesian inference
- Dempster-shafer's method
- Generalized evidence processing theory
- Heuristic methods for identity fusion
- Knowledge based approach

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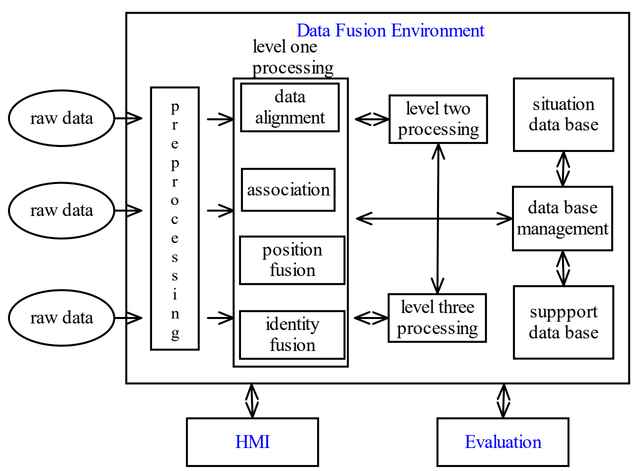
Some Approaches in Mobile Robots

Method	Sensor Type
Dempster-shafer	Laser range finder and camcorder
Rule based, LMS	Sonar and wheel encoder
Extended Kalman filter	Rotary encoders and gyroscope
Genetic Algorithms	Landmarks and dead-reckoning
Bayesian and neural network	Infrared range sensing and visual sensing
Maximum likelihood	Landmarks and dead reckoning
Kalman filter	Camera and dead reckoning

Summary and Conclusions



Questions and Comments

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