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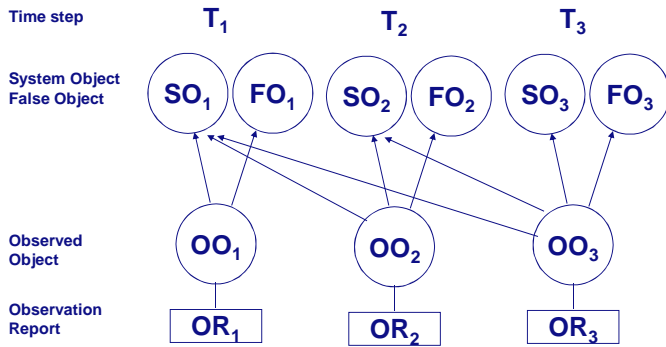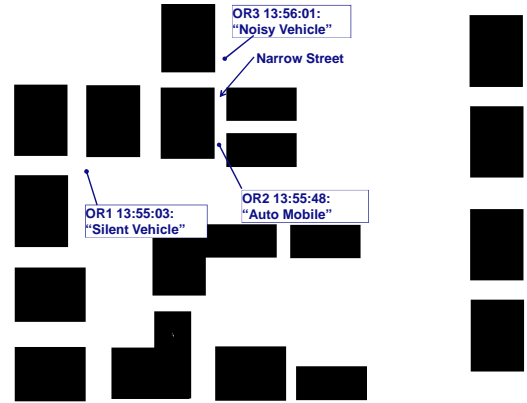# Association of Sparse Sensor Data
Applying Bayesian networks (BN)

K. Wallenius (Saab)

Definitions and Hypotheses
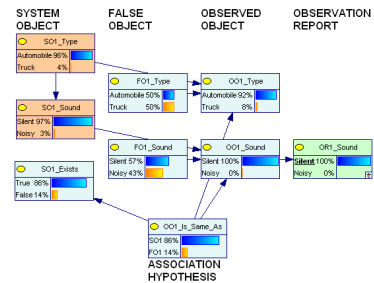
Time step: T_1 T_2 T_3

System Object / False Object: SO_1 FO_1 SO_2 FO_2 SO_3 FO_3

Observed Object: OO_1 OO_2 OO_3

Observation Report: OR_1 OR_2 OR_3

Scenario

OR3 13:56:01: "Noisy Vehicle"
Narrow Street
OR1 13:55:03: "Silent Vehicle"
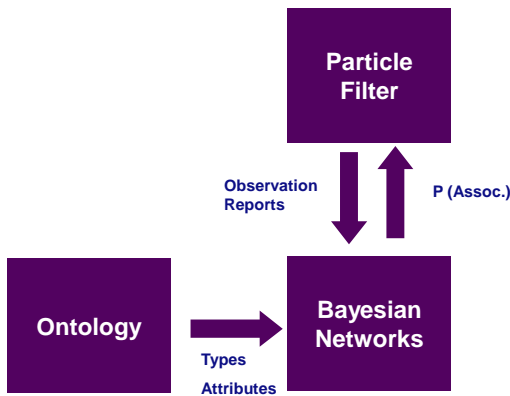OR2 13:55:48: "Auto Mobile"

Demonstration

- 1. Type estimation
- 2. Association based on semantic information
- 3. Suppressing false reports
- 4. Association based on spatial-temporal information
- 5. Solving an example scenario

TIME STEP 1

| SYSTEM OBJECT | FALSE OBJECT | OBSERVED OBJECT | OBSERVATION REPORT |

SO1_Type — Automobile 96%, Truck 4%
FO1_Type — Automobile 50%, Truck 50%
OO1_Type — Automobile 92%, Truck 8%
SO1_Sound — Silent 97%, Noisy 3%
FO1_Sound — Silent 57%, Noisy 43%
OO1_Sound — Silent 100%, Noisy 0%
OR1_Sound — Silent 100%, Noisy 0%
SO1_Exists — True 86%, False 14%
OO1_Is_Same_As — SO1 86%, FO1 14%
ASSOCIATION HYPOTHESIS

Introduction

Particle Filter
Observation Reports / P (Assoc.)
Ontology → (Types, Attributes) → Bayesian Networks

- Problem: Difficult to associate sparse sensor data
  - Take uncertainties into account: semantic similarities, frequencies of types and attributes, sensor accuracies
  - Possible to complement ontologies and particle filters with Bayesian Networks (BN)

- We have designed concepts using BN for
  - Type estimation
  - Association based on semantic information
  - Suppressing false reports
  - Association based on spatial-temporal information
  - Solving an example scenario

Conclusions

- Possible to use BN to support association
- Remaining issues
  - Generate BN according to the ontology?
  - Connection to particle filters?
  - Complexity aspects?

- The models were created using the GeNIe modelling environment developed by the Decision Systems Laboratory of the University of Pittsburgh

D-FUSE