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Simultaneous Bearing and Number of Sensors Estimation using Finite Set Statistics

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Simultaneous Locations and Number of Sensors Estimation using Finite Set Statistics

with distributed systems application in mind

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Why Distributed?

- Cost
  - Usually in hundreds – thousands of $$
- Portable
  - Easier deployment – “if done right”
  - Reuse, reconfigure
- Popular
  - Crossbow, Gumstix, etc
  - Potential commercial application

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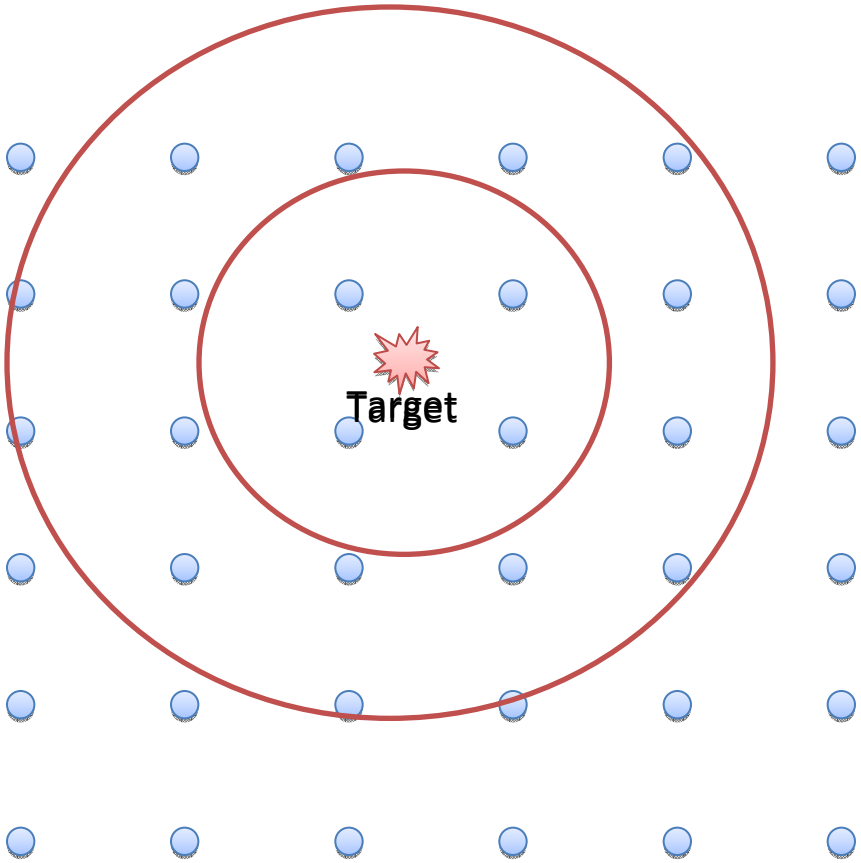
System Setup



Sensor Grid

- N sensors in a uniform grid
- The signal received at each sensor is corrupted by an AWGN

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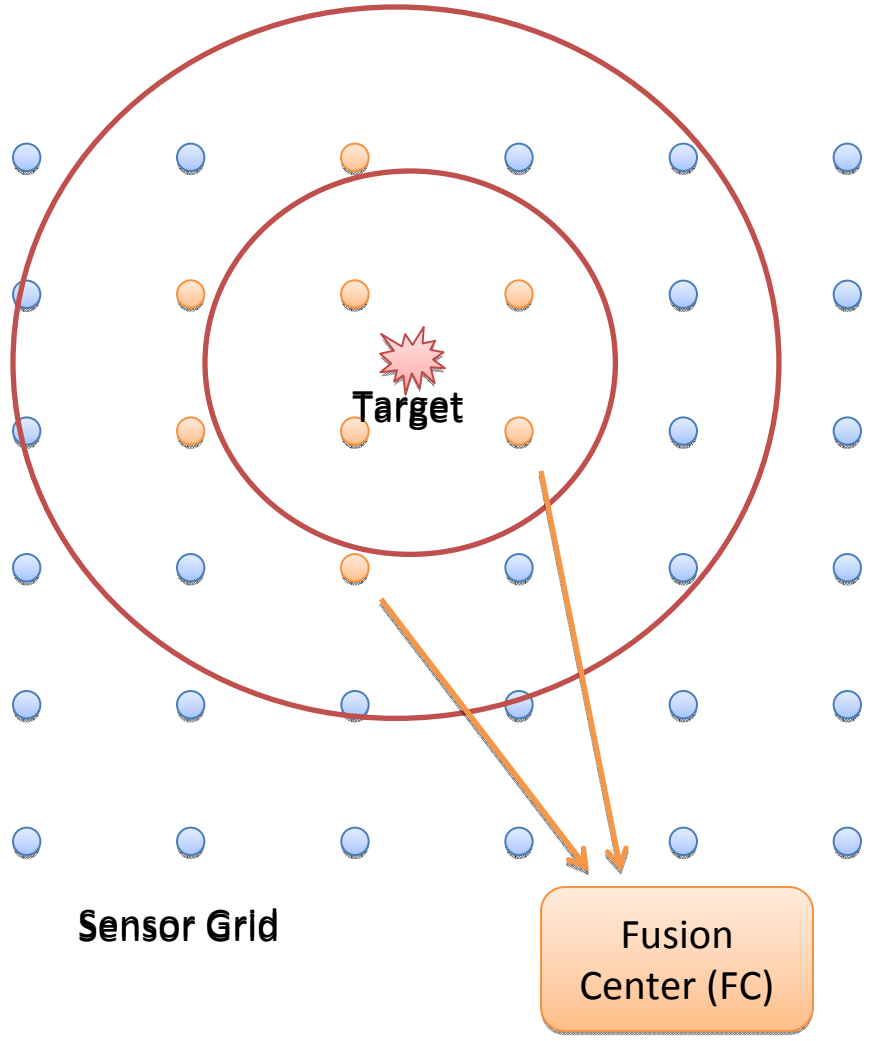
System Setup



- N sensors in a uniform grid
- The signal received at each sensor is corrupted by an AWGN
- Sensor sends data to the FC if signal received is above the threshold

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Problem with Sensors

- Sensor will eventually fails
  - Run out of battery
  - Install n
  - You sh
  - The wi
- Failing sensors can
  - Produce nothing
  - Produce noisy or erroneous reports

Randomness in the number of sensors and their reports

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Problems with Targets

- Multiple targets can occupy the same time and frequency space
- We have
- Target m
- Transmit
- Target m sence
- Intentional/unintentional jammer may exists

Randomness in the number of target and their state

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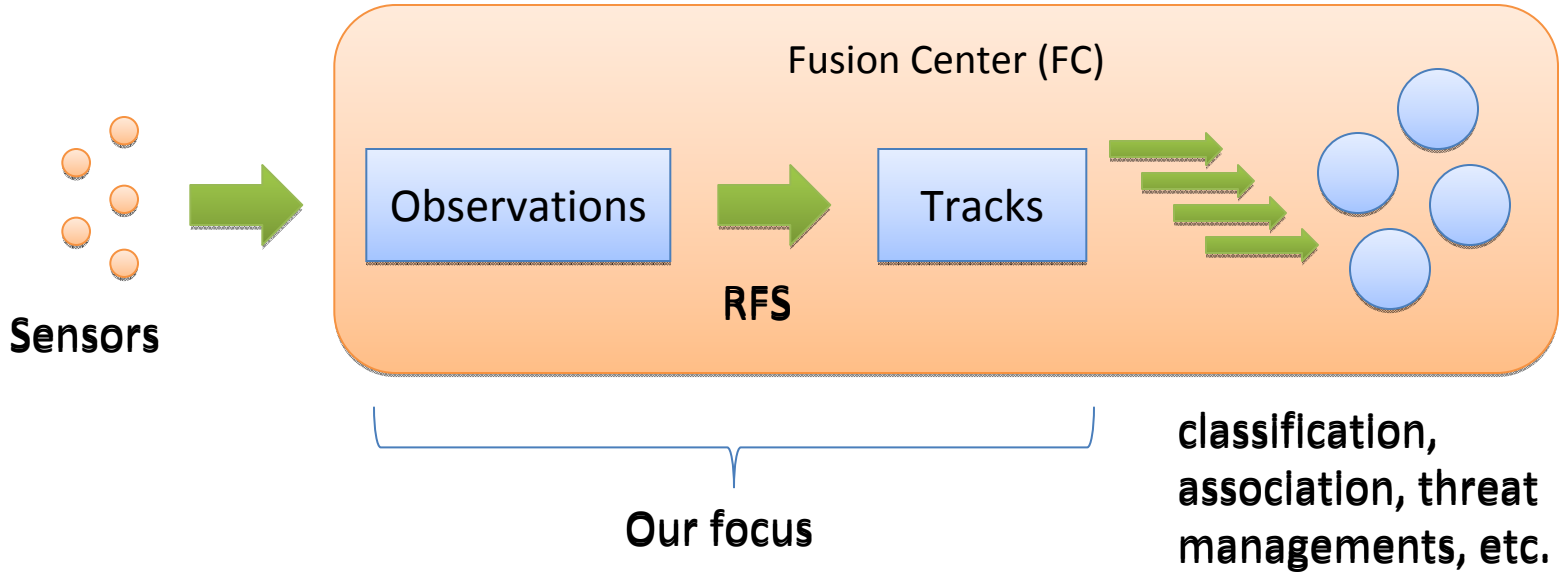
Big Picture

- Assume discrete timing
- Fusion Center sees
  - Random list of observations from
  - Random sensors that can randomly fails
- Apply Random Finite Set (RFS) approach to filter the observation into multiple target tracks



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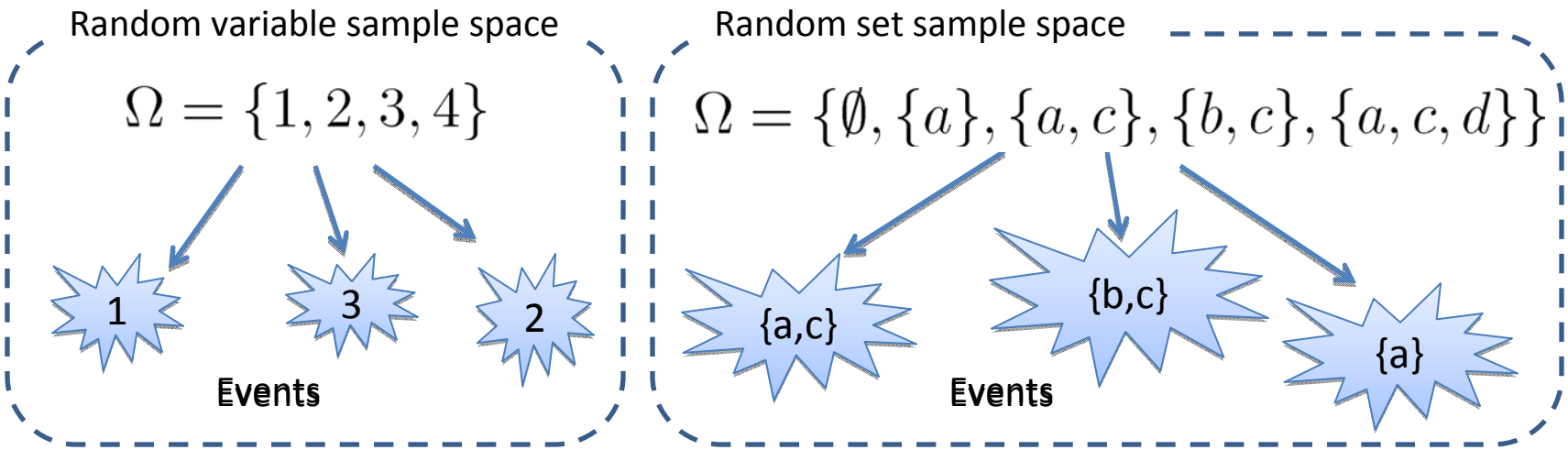
Random Finite Set

- A generalization of probability theory



- A sample of a random set (r.s.) is a set
- A sample of a r.s. can be an empty set
- A r.s. with finite cardinality is called RFS

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Random Variable

- Distribution function
- Density function
- Statistics
  - Crammer-Rao Bound
  - Bayesian Recursive Prediction Filtering
  - Maximum Likelihood

Random Finite Set

- Belief function
- Set density function
- Finite Set Statistics (FISST)
  - Crammer-Rao Bound
  - Bayesian Recursive Prediction Filtering
  - Maximum Likelihood

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Application of RFST

- Define model with random sets
- Write out the belief function, which is defined as a probability
- Derive the set densities using set derivative operation.
- Apply the statistics over the set densities
  - Maximum Likelihood
  - Cramer-Rao Bound

$$\Sigma = A \cup B \cup C$$

$$\beta_\Sigma(S) \triangleq P(\Sigma \subset S)$$

$$f_\Sigma(Z) = \frac{\delta}{\delta Z}\beta(S)\Big|_{S=\emptyset}$$
$$Z = \{z_1, \ldots, z_k\}$$

$$y_1 = MLE[f_\Sigma(Z)]$$
$$y_2 = CRB[f_\Sigma(Z)]$$

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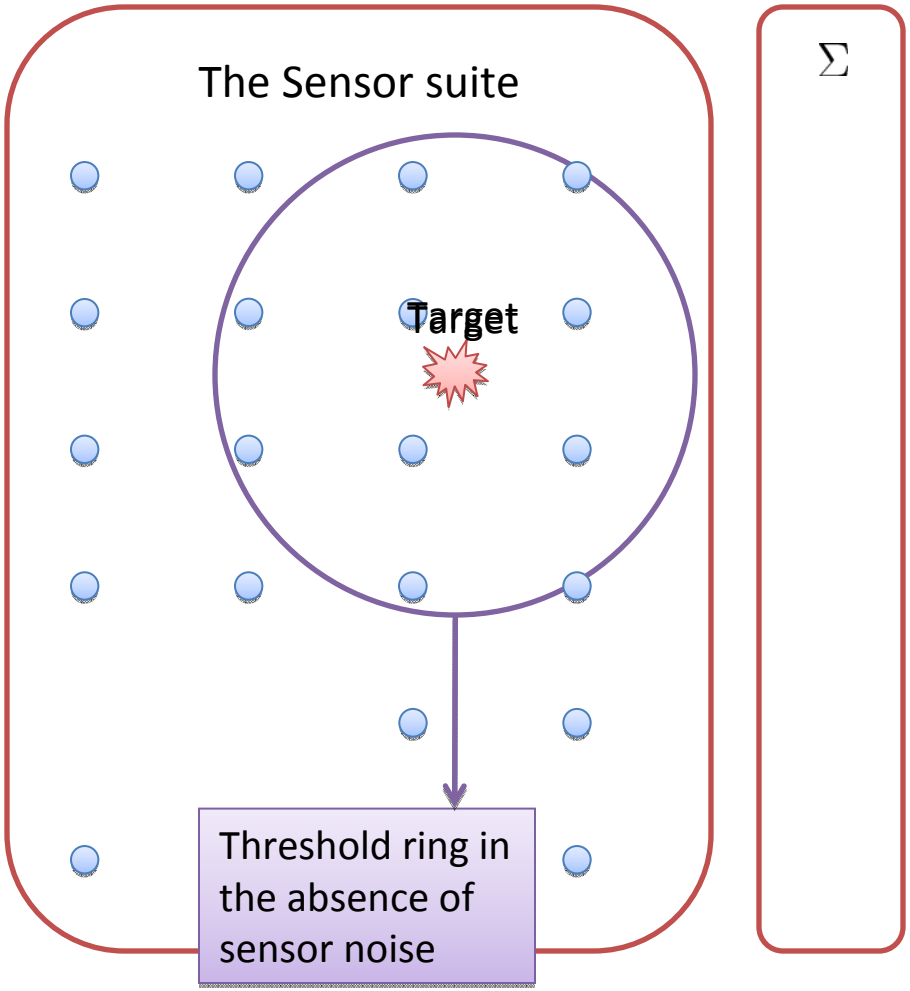
Observation Model



- Fusion center knows each sensor id
- Fusion center does not know the source that generates the report

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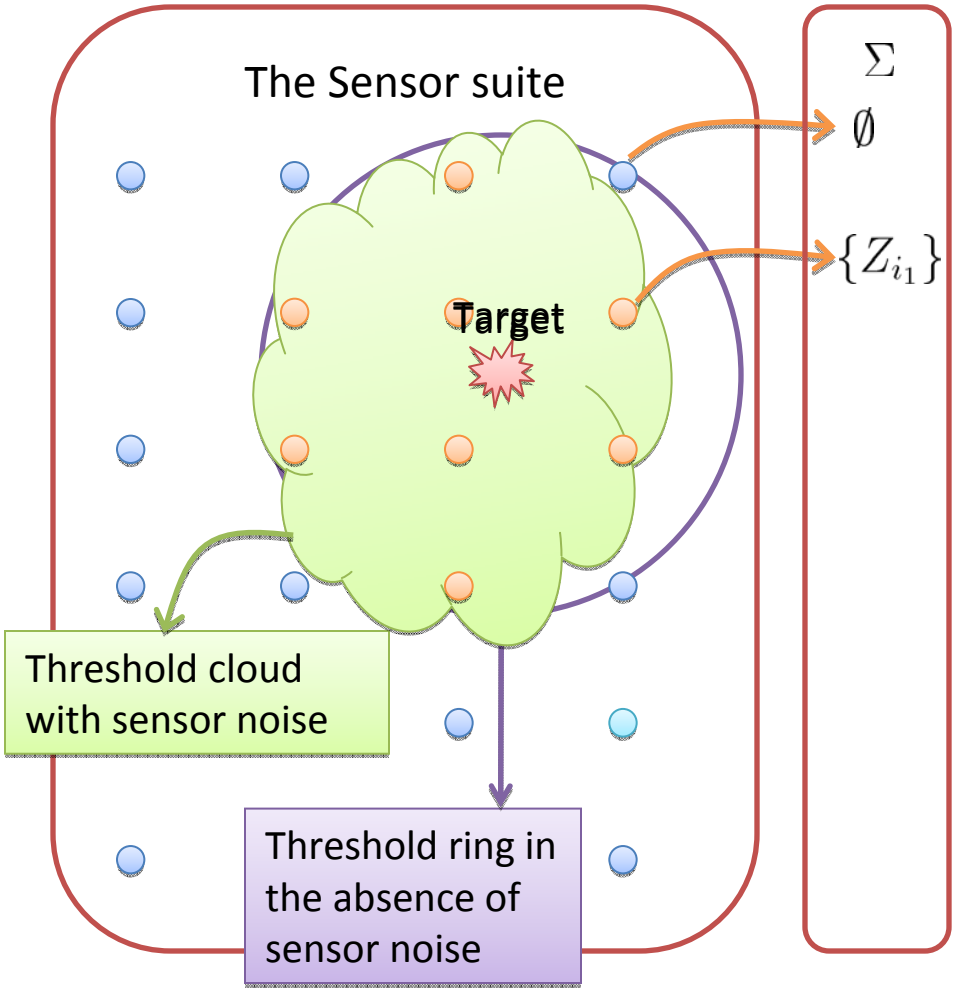
Observation Model



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  - Signal above threshold
  - Signal below threshold (no report)

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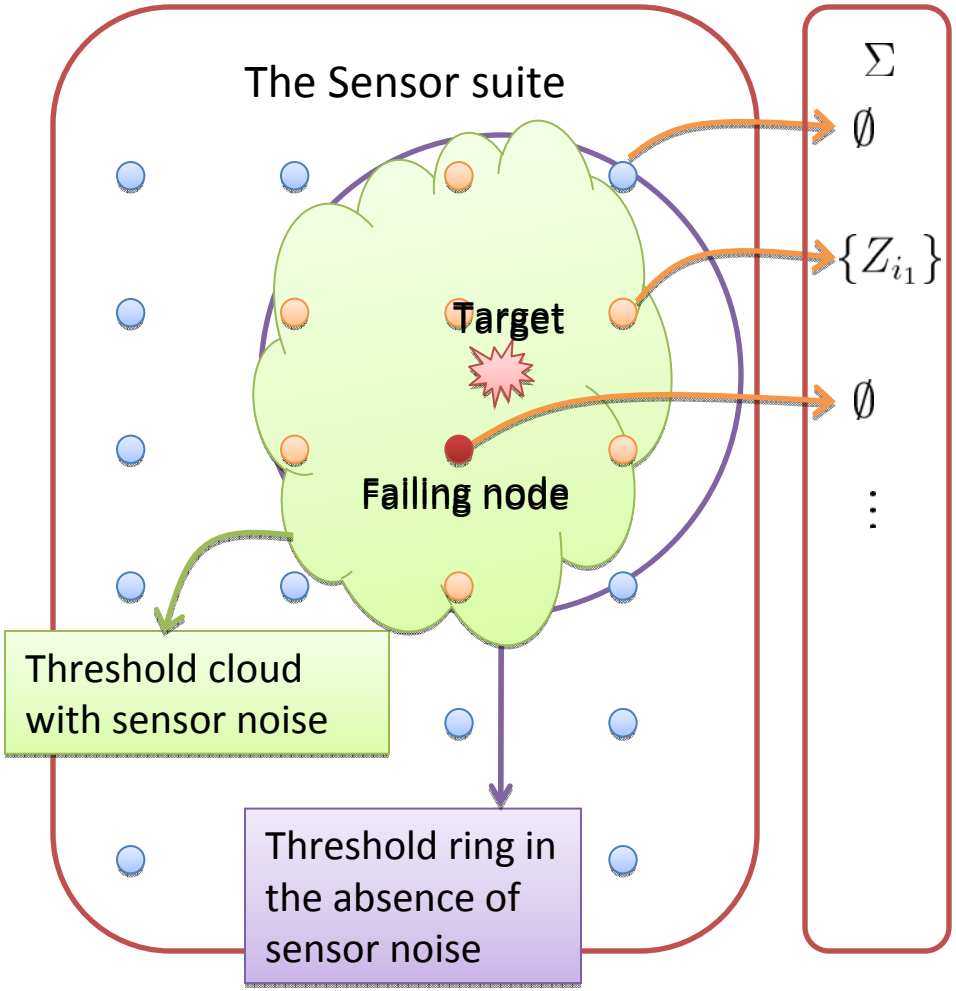

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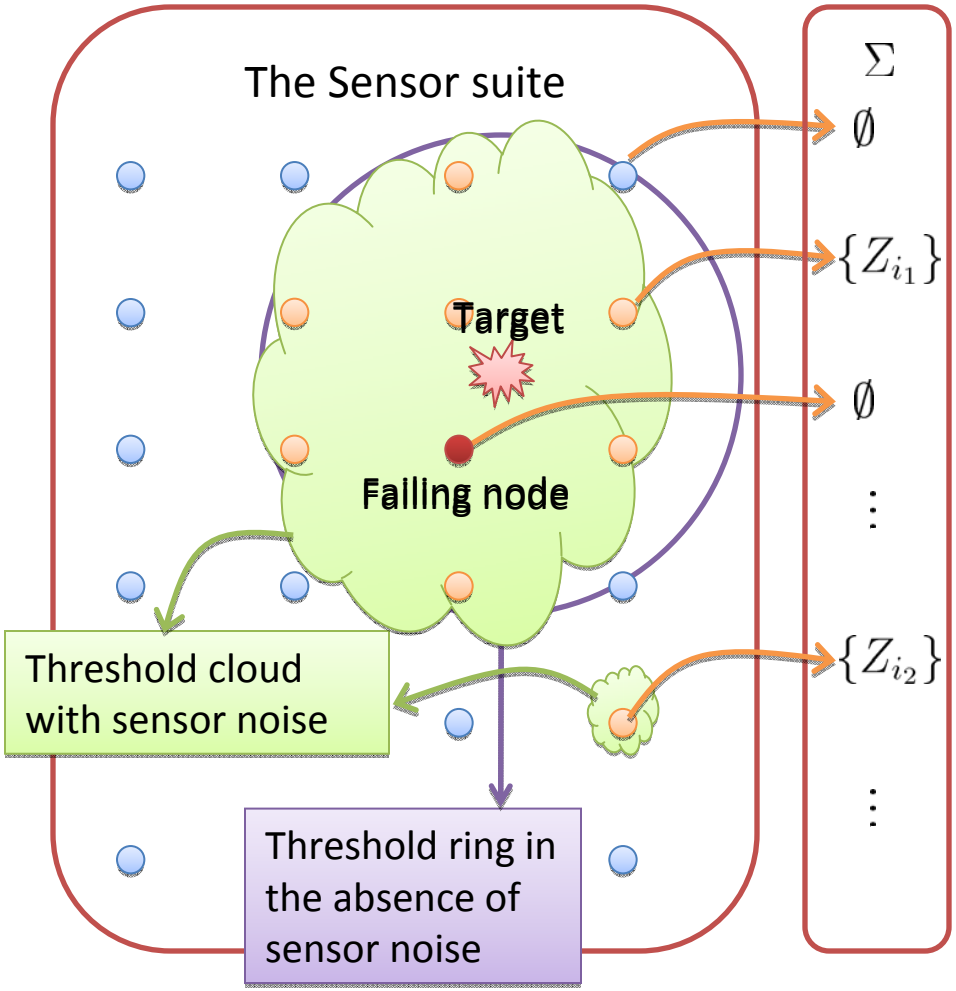
Observation Model



- Fusion center knows each sensor id
- Fusion center does not know the source that generates the report
- Observations types
  - Signal above threshold
  - Signal below threshold (no report)
  - Failing node (no report)
  - Noisy data (clutter report)

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Observation Model

Observations suite $\Sigma = \cup_{i=1}^{N} \Sigma_i$

Sensor failure state

Observation from sensor i $\Sigma_i = \Sigma_i' \cap F_i$

Detection state

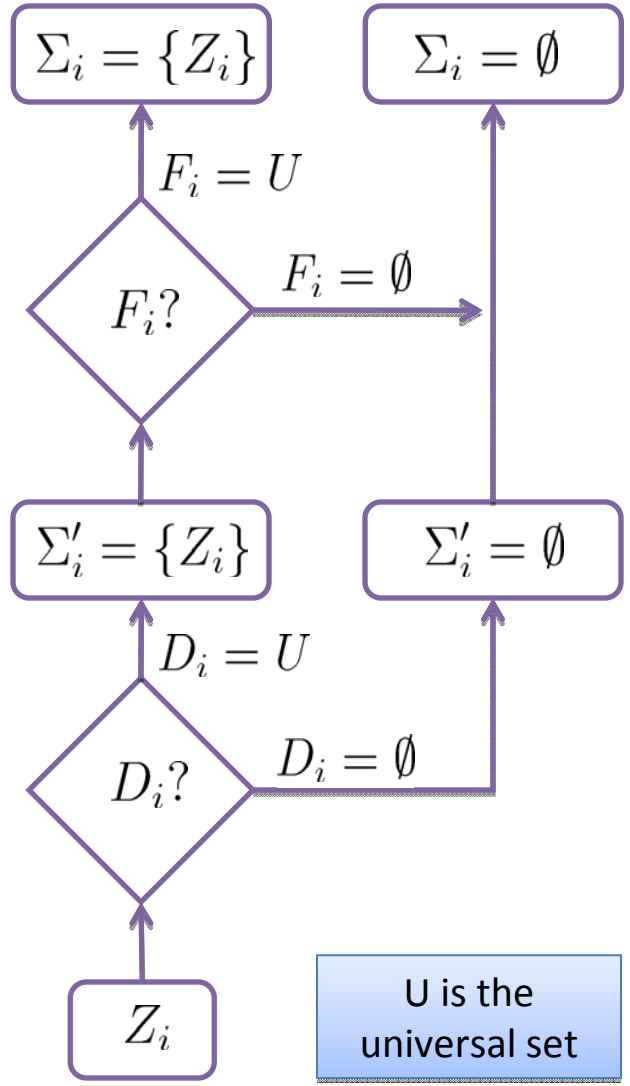
Report produced by sensor i $\Sigma_i' = \{Z_i\} \cap D_i$

A singleton (a random variable)

Sensor i noise

Observed signal at sensor i $Z_i = h_i(\Theta) + N_i$

Signal received model at sensor i



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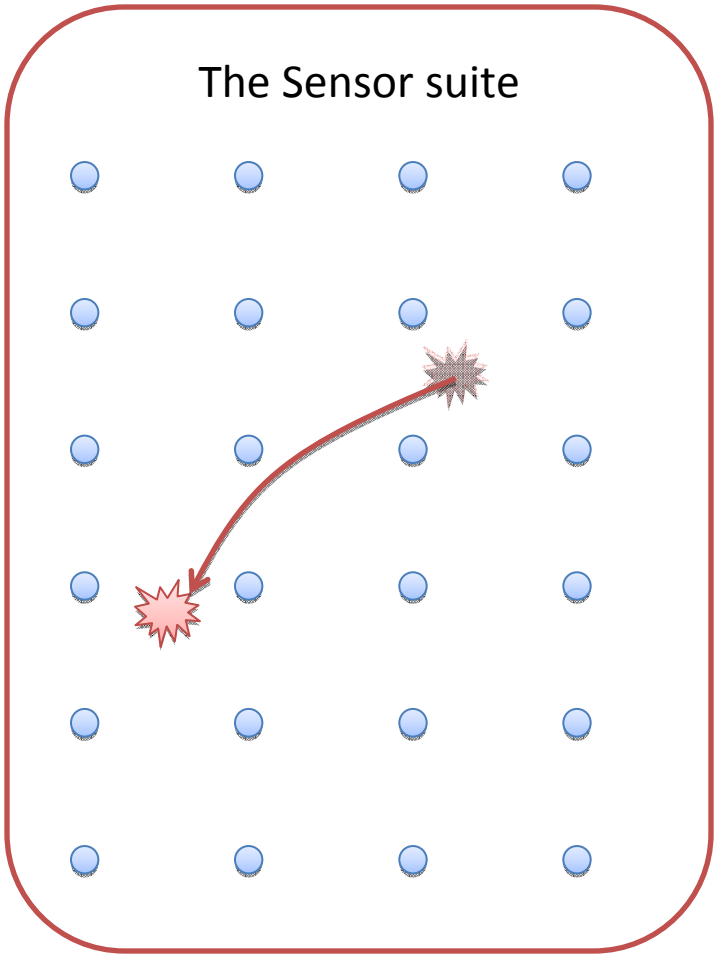
Motion Model



- Need to model target motion for:
  - Appearance of target (birth)
  - Disappearance of target (death)
  - Movement of surviving targets

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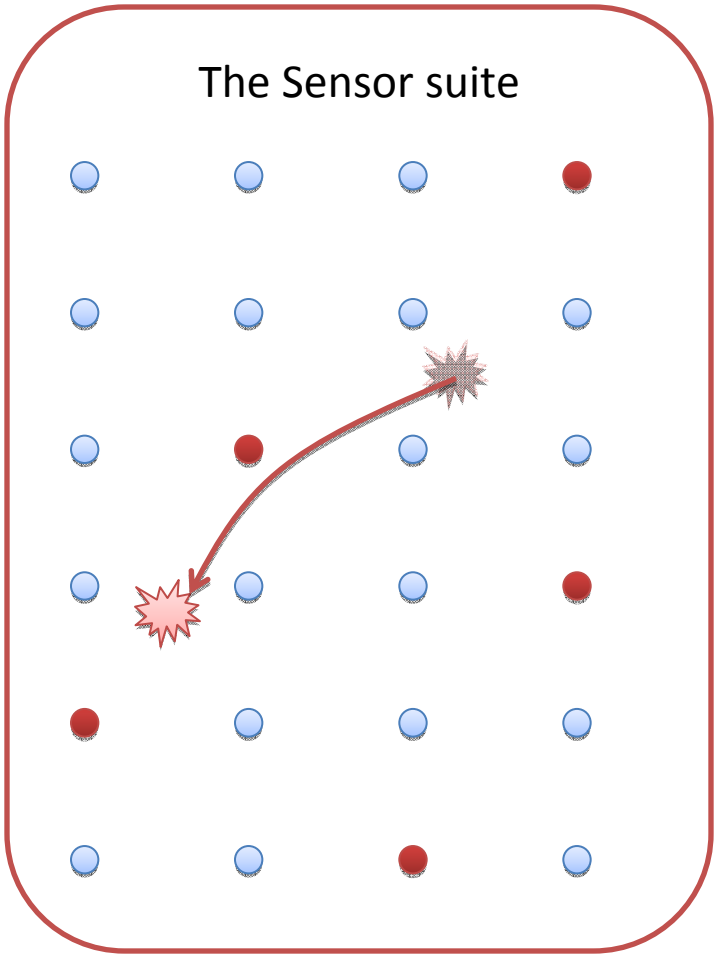
Motion Model



- Need to model target motion for:
  - Appearance of target (birth)
  - Disappearance of target (death)
  - Movement of surviving targets
- Need to model the sensor failure state at each time instant

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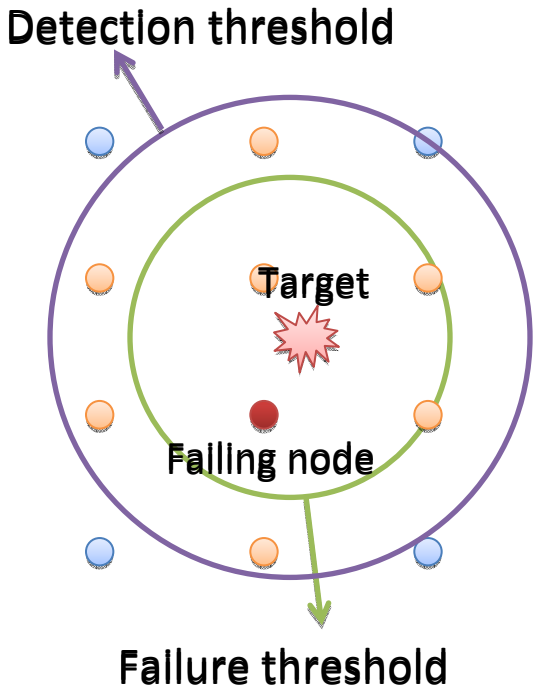
Failure Detection

- Estimate the target
- Check nearby sensor that fails to transmit
- Compare to a failure threshold to declare sensor failure
- Failure threshold:
  - More stringent to lessen sensitivity with sensor noise
  - Not too strict, since false sensor failure declaration is less damaging



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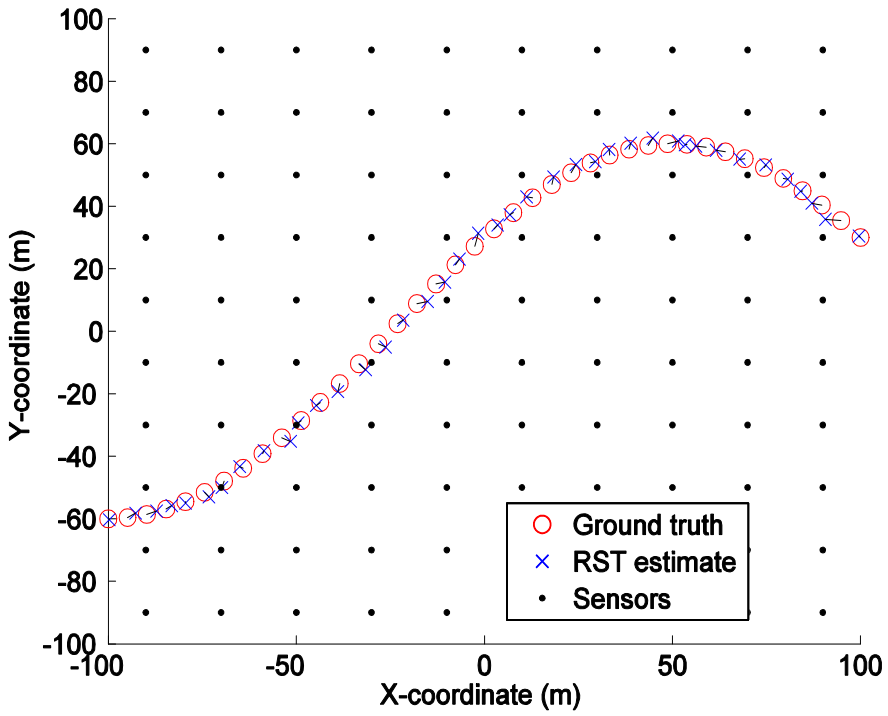
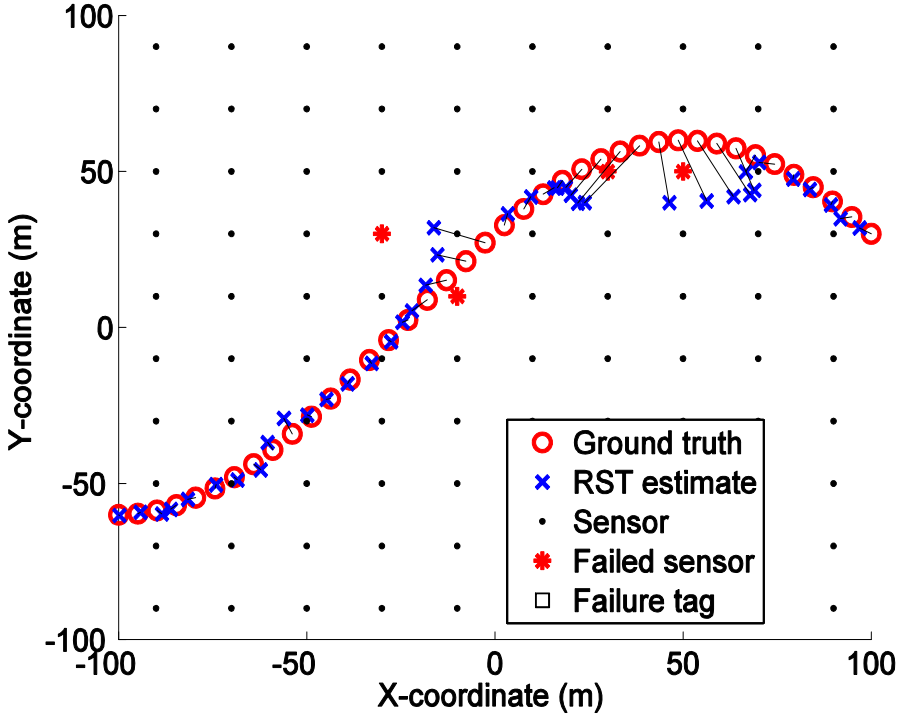
Failing Sensor Problem



All sensors operates normally



Some sensors fails to report

- Sensor failures severely degrade tracking estimates
- Sensor failure detection is essential in a real system

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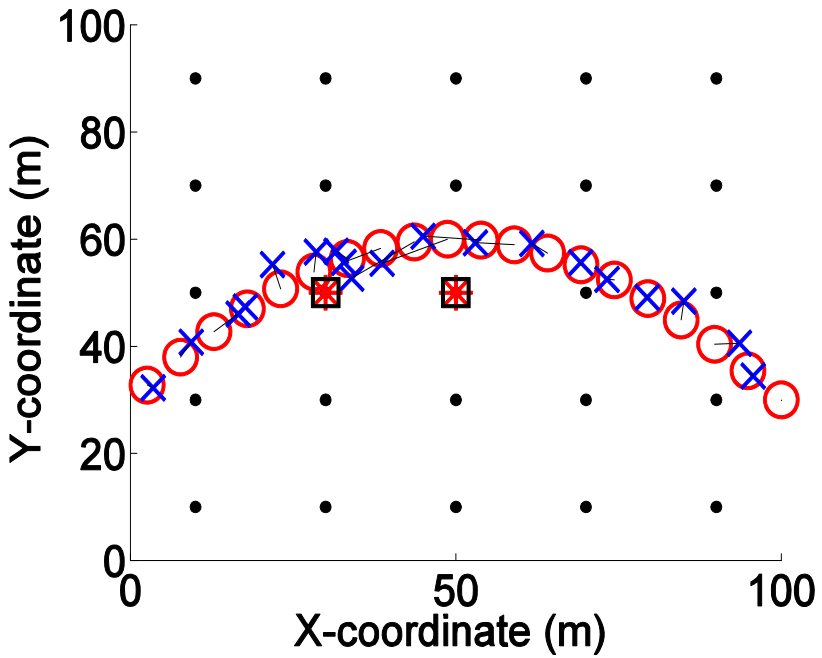
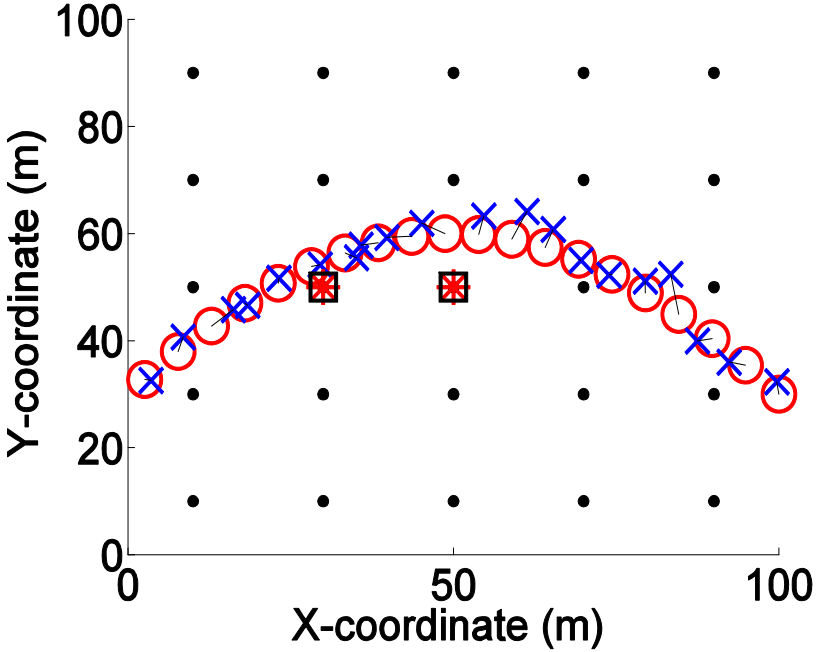
Tracking with Sensor Failure



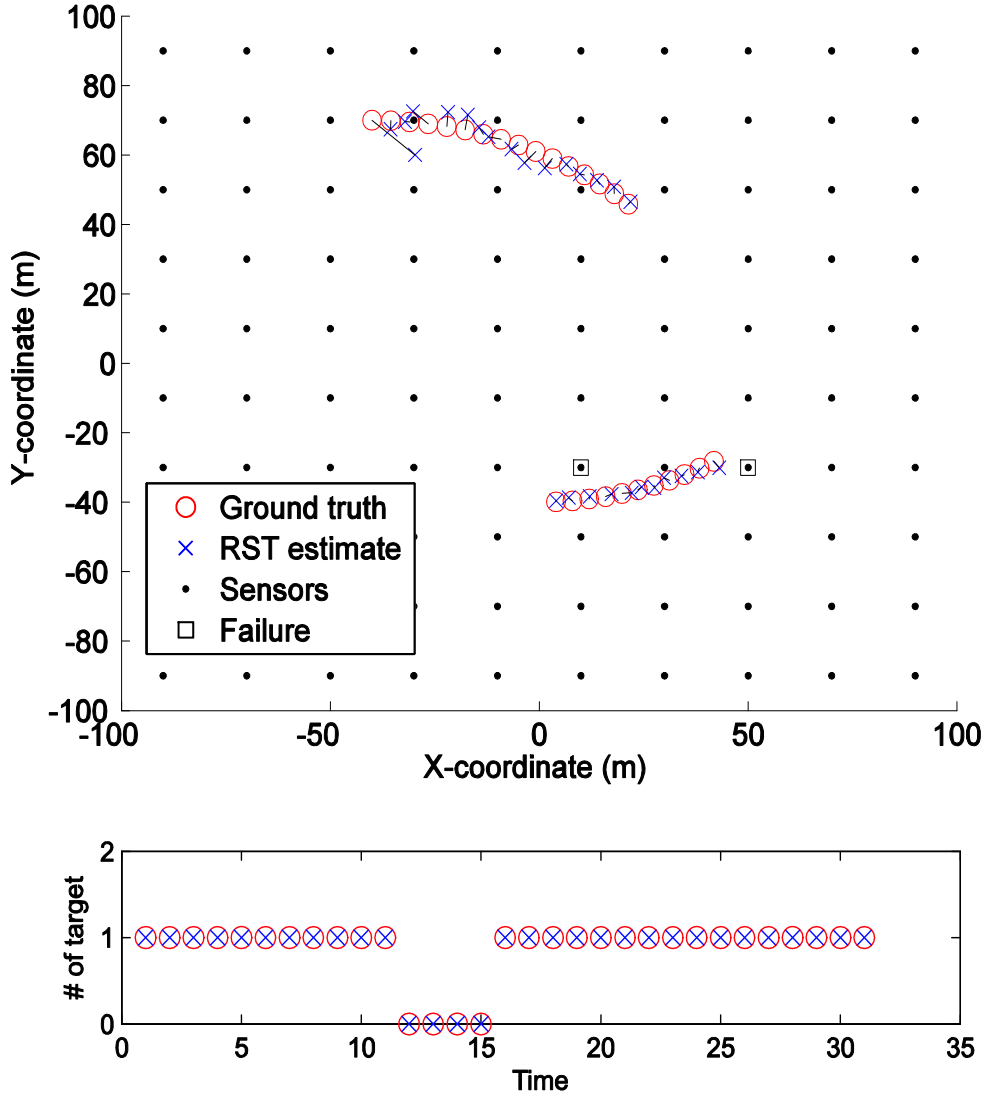
Sensor failure is detected



Future tracks

- After the failing sensor is detected, future tracks benefits from prior information
- Sensors that are mistakenly tagged as failing does not contribute much error because the report can be used immediately by the fusion center

UCLA Appearance and Dissapearance



- A target follows the bottom track for 11 time instant and suddenly disappear
- At time 16 a target appears at the top track
- The estimator is able to track simultaneously the number of target and the state of the target
- The second target may or may not be the same as the first target

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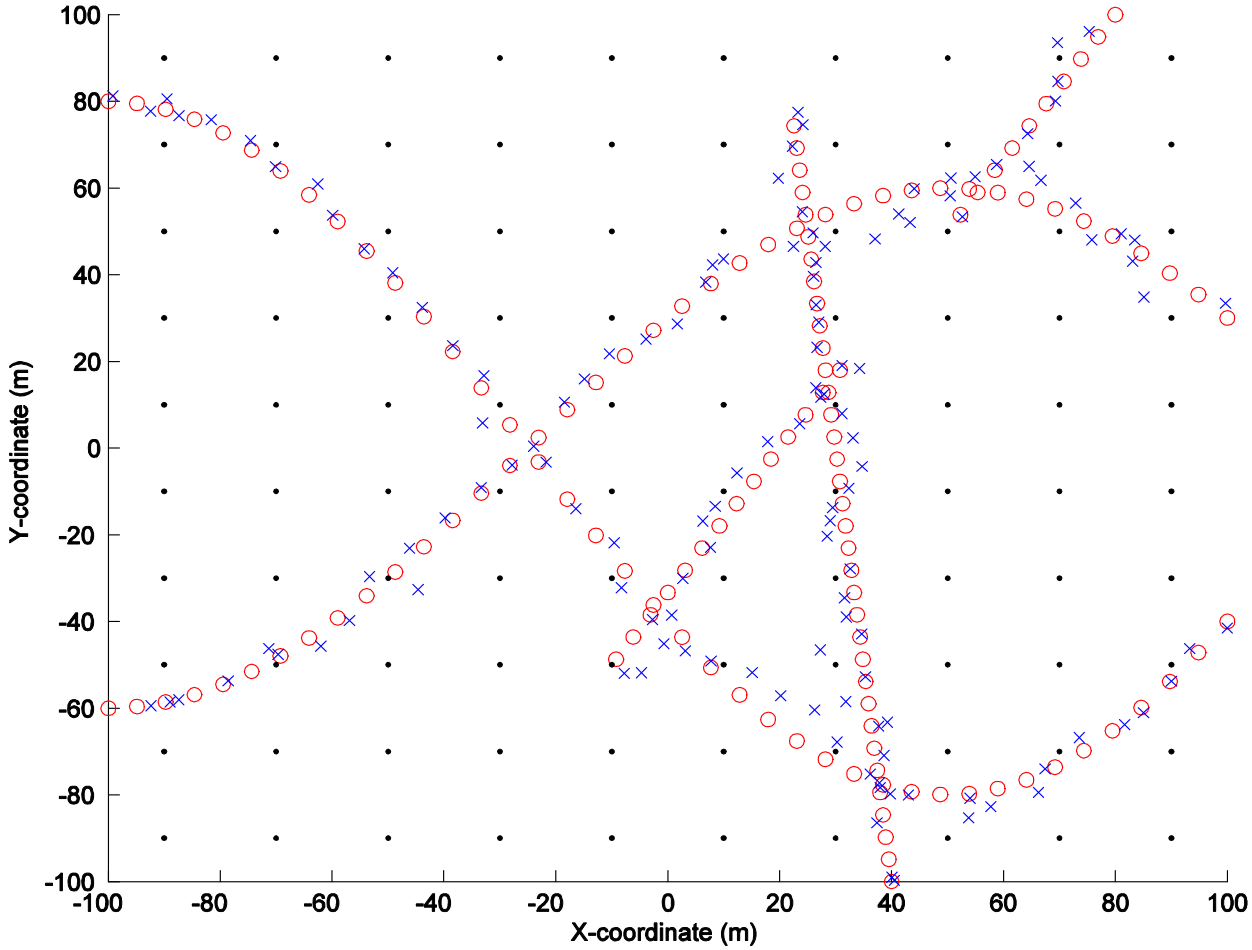
Multiple Target Tracking



Four simultaneous targets: two targets at straight line appears and reappears at various times, the two sinusoid target intersects at the same time

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Summary & Conclusion

- Random set theory allows the modeling of complex real life data and situation mathematically
- Finite Set Statistics can be applied to the set densities deriving optimum algorithms for joint detection and estimation
- Sensor failure tracking in a real system is necessary to avoid large estimation error
- Tracking multiple sources with random appearance and disappearance becomes practical with approaches like particle filtering

Thank you