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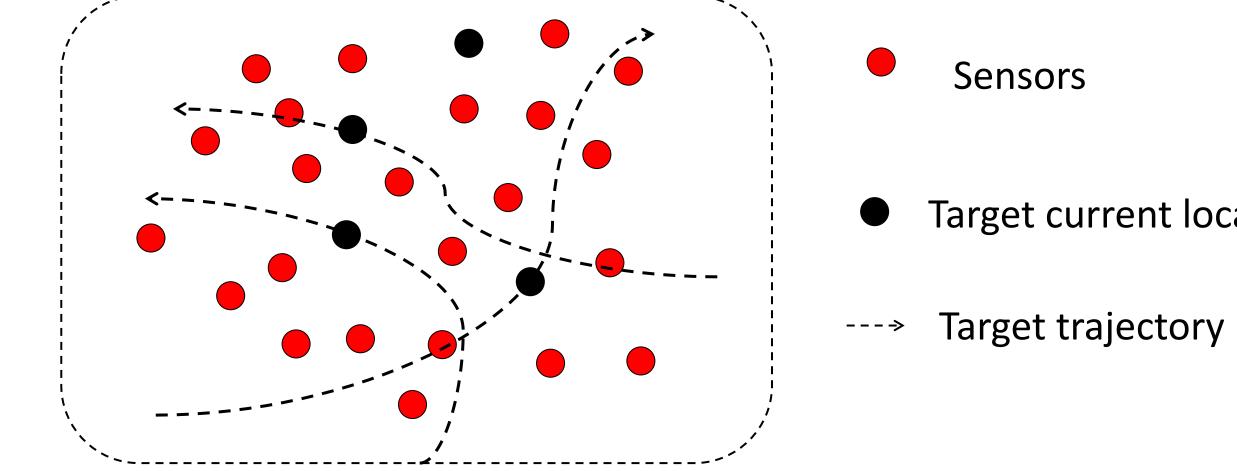
Distributed Fault Detection and Isolation for Kalman Consensus Filter

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Overview

OBJECTIVE – Track targets in a distributed manner via a sensor network in the presence of faults (cyber-attacks)



Faults/Cyber attacks in Sensor Network

Cyber attacks can cause an unacceptable performance in the surveillance parameter of the sensor.

Surveillance Parameter	Fault	Stochastic Language
Latency	Delayed transmission/reception	Bias
Accuracy	Transmission of states with noise	Covariance
Integrity	Incorrect Data	Spike
Continuity	No transmission/ reception	No data

- Target current location

Current Algorithms for Target Tracking

Target Dynamic Equation

 $x(k+1) = A(k)x(k) + B(k)\gamma(k);$ $x(0) \sim \mathcal{N}(0, \mathbf{P}_0), \gamma(k) \sim \mathcal{N}(0, \mathbf{Q})$

Sensor Model z(k) = H(k)x(k) + v(k)**CENTRALIZED KALMAN FILTER**

Update Phase $\begin{bmatrix}
\hat{x}^{+}(k) = \hat{x}^{-}(k) + M(y - S\hat{x}^{-}(k)) \\
S = (H_{1})^{T}(R_{1})^{-1}H_{1} + (H_{2})^{T}(R_{2})^{-1}H_{2} \\
y = (H_{1})^{T}(R_{1})^{-1}z_{1} + (H_{2})^{T}(R_{2})^{-1}z_{2}
\end{bmatrix}$

 $M = (W + S)^{-1}$

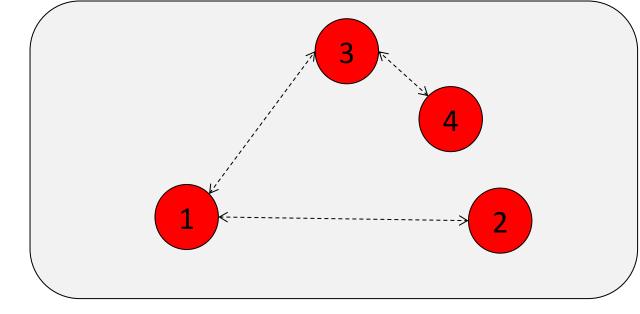
KALMAN CONSENSUS FILTER

 $v(k) \sim \mathcal{N}(0, \mathbf{R})$

Step 1: Each node will calculate u_i and U_i and transmit it to the neighbor.

 $\left[W(k+1) = (AMA^T + BQB^T)^{-1}\right]$ Predict Phase $\hat{x}^{-}(k+1) \leftarrow A\hat{x}_{i}^{+}(k)$

Notation: (x^+) and (x^-) : It denote estimate of x after and before kth time step



 $u_{i} = (H_{i})^{T} (R_{i})^{-1} z_{i}$ $U_{i} = (H_{i})^{T} (R_{i})^{-1} H_{i}$

Step 2: Fuse information: . $y_i = \sum_{i' \in \mathcal{N}_{C_i} \cup \{i\}} u_{i'}$ $S_i = \sum U_{i'}$ $i' \in \overline{\mathcal{N}_{C_i}} \cup \{i\}$

Step 3: Update the estimate and add a consensus term Standard Kalman $\hat{x}_{i}^{+}(k) = \hat{x}_{i}^{-}(k) + M_{i}(y_{i} - S_{i}\hat{x}_{i}^{-}(k)) \leftarrow$ Update

Fault detection Techniques

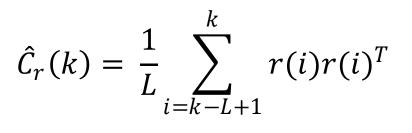
Method 1: Covariance Matching

Step 1: Calculate residue and **theoretical covariance** of the residue.

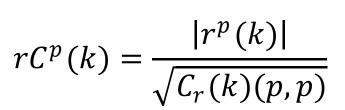
 $r(k) = z(k) - H\hat{x}^{-}(k)$

 $C_r(k) = H(W^-(k))^{-1}H^T + R$

Step 2: Calculate sample covariance of residue by some previous measurements (say k)



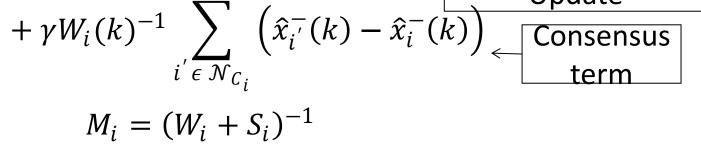
Step 3: Define a parameter called residual compatibility



Step 4: Check the conditions on rC (sensor is good if rC ~ 1)

Note: Measurement Data of only one sensor is required for this method

Method 2: Consistency Checking



Step 4: Predict the next position (same as KF)

 $H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}, R = \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix},$

 $A = \mathbf{I_4}, Q = \begin{bmatrix} 3\\3\\3 \end{bmatrix}$

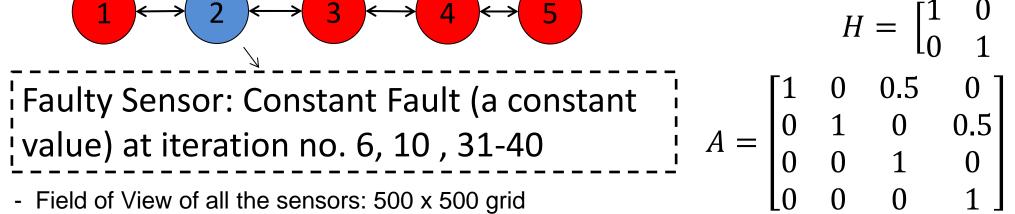
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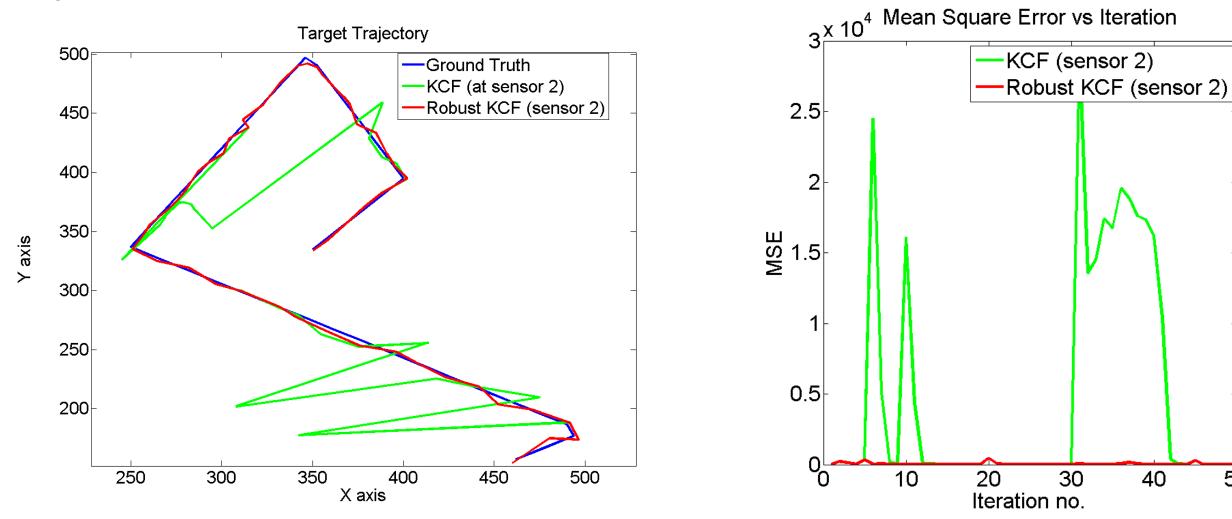
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Sensor Network

Results



- Target is tracked for 50 time instants



 $D_{12} = |z_1 - z_2|, D_{13} = |z_1 - z_2|, D_{14} = |z_1 - z_4|$ $D_{23} = |z_2 - z_3|, D_{24} = |z_2 - z_4|, D_{34} = |z_3 - z_4|$ Step 1: Calculate difference parameter

Step 2: if D₁₂, D₁₃ and D₁₄ are greater than a threshold then sensor 1 is faulty. Similar checks can be introduced for other sensors too.

Note: Measurement Data of more than one sensor is required for this method

ROBUST KALMAN CONSENSUS FILTER

Spike Detection: Use method 1 and method 2 on each node.

Covariance Detection: Introduce a separate Kalman Filter on each node and use method 2

No Data: KCF works with asynchronous communication

Contact and references

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