PROBLEM DESCRIPTION

We consider distributed state estimation of a linear dynamic system, observed by various sensors, as a problem in information fusion.

We introduce a model of trust, using weights on the graph links and nodes that represent the sensor network. These weights can represent several interpretations of trustworthiness in sensor networks.

We show that by appropriate use of these weights the distributed estimation algorithm avoids using information from untrusted sensors.

MODEL

We consider a sensor network with N sensors, indexed by i. The network is used for the state estimation of a linear random process given by:

\[ x(k+1) = Ax(k) + w(k) \]

where \( x \in \mathbb{R}^n \) is the state vector and \( w \in \mathbb{R}^n \) is the state noise, assumed zero mean and with covariance matrix \( Q \). The initial state \( x_0 \) has a Gaussian distribution, with mean \( \mu_0 \) and covariance matrix \( P_0 \), We assume each sensor has a linear sensing model given by:

\[ y_i(k) = C_i x(k) + v_i(k) \]

where \( y_i \in \mathbb{R}^{p_i} \) is the observation of \( x(k) \) made by sensor \( i \) and \( v_i \in \mathbb{R}^{p_i} \) is the measurement noise assumed Gaussian with zero mean and covariance matrix \( R_i \). Let \( N_i \) denote the communication neighborhood of node \( i \) and let \( T_{ij} \) represent a measure of the trust sensor \( i \) has in the information received from sensor \( j \).

References


ALGORITHM AND SIMULATIONS

Algorithm 1: Trust Based Distributed Kalman Filtering Algorithm

Input: \( \mu_0, P_0 \)
Initializations: \( \mu_i = \mu_0, P_i = P_0 \)

while new data exists

Compute the intermediate Kalman estimate of the target state:

\[
M_i = P_i^{-1} + C_i R_i^{-1} C_i^\top \\
L_i = M_i C_i R_i^{-1} \\
\phi_i = \mu_i + L_i (y_i - C_i \phi_i) \\
\]

Compute locally the belief divergence:

\[
d_{ij} = \frac{1}{N_i - 1} \sum_{k \in N_i} \| \phi_j - \phi_k \|^2
\]

Compute the trust values:

\[
T_{ij} = c_i - d_{ij}, \quad j \in N_i
\]

Compute the normalized trust values:

\[
p_{ij} = \frac{T_{ij}}{\sum_{k \in N_i} T_{ik}}
\]

Eliminate insufficiently accurate data by setting \( T_{ij} \) to zero if \( p_{ij} < p_{min} \)

Compute the consensus weight values:

\[
w_{ij} = \frac{T_{ij}}{\sum_{k \in N_i} T_{ik}}
\]

Estimate the state after a consensus step:

\[
\hat{x}_i = \sum_{j \in N_i} w_{ij} \hat{x}_j
\]

Update the state of the local Kalman filter:

\[
P_i = A_i P_i A_i^\top + Q
\]

\[
\xi_i = A_i \xi_i
\]

We consider a perturbed oscillatory linear system:

\[ x(k+1) = Ax(k) + w(k) \]

where,

\[
A = \begin{pmatrix}
0.9996 & -0.03 \\
0.03 & 0.9996
\end{pmatrix}
\]

and \( w(k) \in \mathbb{R}^2 \) is a white, Gaussian noise, with covariance matrix \( Q = 0.15I_2 \). Each sensor has a sensing model of the form:

\[ y_i(k) = C_i x_i(k) + v_i \]

where the observation matrices \( C_i \) are chosen at random to be \([0,1]\) or \([1,0]\) with the same probability. The measurement noise \( v_i(k) \in \mathbb{R} \) is assumed white and Gaussian with variance \( R_i = \sigma_v^2 I \) and \( \sigma_v = 30 \).