Distributed MHE for Multi-Sensors
Based on Measurements Compensation

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Abstract. In the actual multi-sensor network, the measurements of each sensor can be not enough to achieve the complete state estimation, due to its functional limitation or unexpected environmental factors. For this issue, this paper proposes a distributed moving horizon estimation (DMHE) algorithm based on the measurements compensation strategy. Considering the incomplete observability of each sensor’s measurements, a prediction of complete measurement is utilized by the sensor for compensation. To achieve the estimation consensus of all the sensors in the network, the moving horizon estimation approach is adopted for each sensor, based on its local measurements and its neighbor sensors’ transinformation. Then, a DMHE optimization problem is constructed and the associated implementation algorithm is presented. By implementing the presented DMHE algorithm, all the sensors in the network can give completed and precise state estimations without direct fusion of the state estimations, provided that the collection of all the sensors’ measurements is observable. The result is illustrated by a simulation.

Introduction

Fusion estimation of Multi-sensor [1-5] is the research focus of the target tracking, air traffic control, surveillance and investigation, and has attracted more and more attention in both military and civilian fields. For the multi-sensor, the centralized fusion estimation [6] collects and processes all the information of the sensors by a specified fusion center. With the increase of sensor number, the calculation and communication burdens of the centralized multi-sensor fusion estimation will increased exponentially, even to be intractable. To conquer this problem, the distributed fusion estimation is preferred.

In distributed fusion estimation, the consensus problem is an important concern, and most of algorithms are presented based on Kalman filter [7-11]. By firstly using a consensus filter to achieve the consensus of measurement and inverse-covariance matrices, [7, 8] presented a distributed Kalman filter algorithm for multi-sensor. In [9], only the state estimations are communicated between sensors (which reduces the bandwidth requirements of each sensor), and these estimations are fused in a weighted average way. In [10], the distributed fusion estimation can be partitioned into two stages, i.e., the state estimation stage which adopts a Kalman-like filter and does not require communication, and the estimate fusion stage which uses a weighting matrix to achieve consensus and requires communication. With considering the situation of data missing may induced by the bandwidth and energy constrains, the authors of [11] used the state prediction to compensate the missing data and guaranteed the consensus of the multi-sensor fusion system.

It needs to note that the distributed fusion estimation algorithm based on Kalman filter cannot deal with the target’s a priori information given in the constraint form. In practice, unreasonable state estimation may be calculated if the target’s a priori information is not used in an effectively method. To this end, the moving horizon estimation (MHE) approach [12, 13] which can be used for the
estimation of control system with constraints is adopted to solve this problem. In [14], the global cost function is decentralized by dual decomposition, then dual variables are communicated according to the network topology to guarantee the consensus and stability of the system. Focused on a class of nonlinear systems which are composed of several subsystems and each subsystem interacts with others via their states, [15] designed the distributed estimation algorithm and the local moving horizon estimation scheme for each subsystem.

In fact, the position relationship between sensor and target and/or the other external reasons may cause the unobservability of the target state for a single sensor even for a regional sensor network. However, all of the above algorithms have not considered this situation. In [16], this situation is considered by adopting MHE, and the measurements of each sensor and its neighbor sensors are used to estimate the state. To provide a consensus estimation of state, an appropriate weighting matrix $K$ is select to fuse the state estimation and covariance matrix of filtering error. However, the consensus and the stability of the algorithm are significantly dependent on the selection of the weighting matrix $K$, and the optimal $K$ is difficult to be chosen. Here, we compensate the unobserved part of the state for each sensor by introducing the measurements prediction of its neighbors, then construct the distributed MHE (DMHE) optimization problem and present the associated algorithm. By applying the proposed algorithm, each sensor can achieve a complete and precise estimation of the target state by only solving the constructed DMHE optimization problem, with utilizing the local and its neighbor sensors’ measurements and the compensations. Due to each sensor utilizes the measurements and compensations in an optimal way, and the introduced compensations are based on its neighbors’ measurements prediction, the fusion state and the chosen of an appropriated weighting matrix $K$ can be avoided.

The rest of this paper is organized as follows. Section 2 introduces the distributed estimation problem of multi-sensors, and section 3 details the design approach of the distributed MHE. A simulation example is provided in section 4 to verify the effectiveness of the results. Section 5 summarizes this paper with a conclusion. 0 clarifies the used symbols in the paper.

**Notation**

$I_{a,b}$ denotes a set including the integers from $a$ to $b$ (where $a < b$). $\mathbb{R}^n$ denotes the $n$-dimensional Euclidean space. $I_n$ and $0_n$ denote the $n$-dimensional identity matrix and the $n$-dimensional zero matrix. $w \sim N(\mu, Q)$ stands for a Gaussian random scalar/vector variable $w$ with mean value/vector $\mu$ and covariance value/matrix $Q$. The notation $[x; y]^{T}$ stands for $[x^T, y^T]^{T}$. $\| x \|_p$ denotes the 2-norm/P-weight 2-norm of $x$. $x_{\text{det}}$ represents the value of $x$ at the instant $t$, which is estimated at the instant $k$.

**Problem Statement**

The dynamic model of target state can be described as a linear system:

$$ x_{k+1} = Ax_k + Gw_k, \quad k \geq 0 $$

(1)

where $x_k \in \mathbb{R}^n$ and $w_k \in \mathbb{R}^m$ denote the target state and disturbance vectors, respectively, at the instant $k$; $A \in \mathbb{R}^{n \times n}$ and $G \in \mathbb{R}^{n \times m}$ are the transfer matrices corresponding to the state and disturbance.

In practice, usually the state of target is constrained by the physical constraints, which can be expressed in general form as

$$ \psi_i \leq \| \Psi_i x_k \| \leq \varphi_i, \quad i \in I_q $$

(2)

where $\Psi_i \in \mathbb{R}^{n \times m}$ is the parameter of $i$-th constraint, the scalars $\psi_i$ and $\varphi_i$ are the lower and upper bounds, respectively, of $i$-th constraint, the integer $q$ is the number of the constraints, and all of the above constraint parameters are known a priori.
Assume the state are measured by $M$ sensors, according to the following equations (in general different from sensor to sensor)

$$
y_i = C_i x_k + v_i, \quad k \geq 0$$  \hspace{1cm} (3)

where $y_i \in \mathbb{R}^n$ and $v_i \in \mathbb{R}^n$ denote the measurement vector and measurement error, respectively, of sensor $i$ at the instant $k$. $C_i$ is the measurement matrix of sensor $i$. The disturbance $w_k$ and the measurement error $v_i$ are assumed to be zero-mean, Gaussian random variables, i.e., $w_k \sim \mathcal{N}(0, Q)$, $v_i \sim \mathcal{N}(0, R_i)$, where $Q \in \mathbb{R}^{m \times m}$ and $R_i \in \mathbb{R}^{n \times n}$ denote the covariance matrices of $w_k$ and $v_i$, respectively.

The communication network among sensors can be described as an undirected graph $G=(\mathcal{V}, \mathcal{E})$, where the nodes in the vertex set $\mathcal{V} = \{1, 2, \ldots, M\}$ represent the sensors in network, and the relation $(i, j)$ in the edge set $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ means that sensor $i$ can communicate with sensor $j$. If the $G=(\mathcal{V}, \mathcal{E})$ is given, the adjacency matrix $B = [b_{ij}] \in \mathbb{R}^{M \times M}$ can be defined as $b_{ij} = \begin{cases} 1, & (i, j) \in \mathcal{E} \\ 0, & (i, j) \notin \mathcal{E} \end{cases}$.

For the sensor $i$, $\mathcal{V}$ and $M_i$ denote the set and number, respectively, of its neighbor sensors.

To guarantee the complement of state estimation for the entire sensor network, the measurements are generally desired to satisfy the observability condition, i.e., there exists at least a path connecting some sensors in the network that, the target state is observable for their measurement collection. Based on this assumption, this paper intends to design the distributed moving horizon estimator for each sensor to achieve a complete and precise state estimation of each sensor and the estimation consensus of the entire sensor network.

**DMHE Design**

Due to the lack of fusion center in distributed estimation, each sensor has to estimate the target state, and fuses the regional estimated states (i.e., the estimated states of itself and its neighbors). Generally, an appropriate weighting matrix is selected to fuse the estimated states [9, 16]. However, the weighting matrix can be chosen in different ways, and further leads to different estimation and fusion performance. In this paper, we discard the chosen of the weighting matrix, and fuse the regional estimated states in the estimation process. To this end, we firstly introduce the estimated measurements of each sensor as a compensation of its measurements, and then construct the DMHE optimization problem to combine the estimation and fusion.

**The Selection of Compensation Information**

Due to the target state may be not completely measurable for a single sensor even for the regional sensors (i.e., a single sensor and its neighbor sensors), using only the measurements from neighbor sensors is not enough for local estimation. Here, we utilize an estimation of complete measurement to construct a compensation for the actual measurement. By communicating the measurements and its compensation with neighbor sensors, each sensor can achieve complete observability about the target state. See a special example in Tab.1, the target state is not completely observable for each sensor in a chain formed network. By only using the measurements of the regional sensors, all the sensors cannot completely estimate the target state. However, if the measurement compensation (i.e., measurements estimation) is additionally utilized, the complete observability of each sensor can be achieved and every sensor can provide a complete state estimation.

To compensate the measurement with measurement estimation, each sensor collects its actual measurement and its measurement estimation at every instant $t$, and defines the collection as reconstructed measurement, which is formulated as

$$\bar{y}_i = [y_i; \hat{y}_{[i]}], \quad t = t - N + 1, \ldots, k$$  \hspace{1cm} (4)
where \( \hat{y}_{ik-1}^i = C \hat{x}_{ik-1}^i \) is estimated at the instant \( k-1 \) by sensor \( i \), and \( C \) is a complete measurement matrix for the target state. According to (3), the relation between the reconstructed measurement and the target state can be derived as

\[
\bar{y}_{ik}^i = \bar{C}_i x_i + \bar{v}_{ik}^i
\]  

(5)

where \( \bar{C}_i = [C_i; C] \) is the reconstructed measurement matrix of sensor \( i \) and \( \bar{v}_{ik}^i = [v_i^j; C(\hat{x}_{ik}^i - x_i)] \) denotes the reconstructed measurement error.

Let \( \hat{R}_{ik-1} = C \Pi_{ik-1} C^T \) denote the covariance matrix of the measurement estimation error \( \hat{y}_{ik}^i = y_i^j - \hat{y}_{ik}^i \), and \( \Pi_{ik-1}^i \) denote the covariance matrix of the state estimation error \( \hat{x}_{ik-1}^i = x_i - \hat{x}_{ik-1}^i \) which is generally updated according to Kalman filter (see (12)). However, due to the target state may be incompletely observable with the individual (even regional) measurement, the covariance matrix \( \Pi_{ik-1} \) updated according to Kalman filter cannot precisely describe the accuracy of the state estimation \( \hat{x}_{ik-1} \). Hence, the covariance matrix \( \hat{R}_{ik-1} \) depending on \( \Pi_{ik-1} \) cannot precisely reflect the accuracy of the measurement estimation \( \hat{y}_{ik} \). Here we simply multiply it with a confidence factor \( d_i \), which is pre-specified with respect to the observability of sensor \( i \).

Now, the covariance matrix of the error \( \bar{v}_{ik} \) can be easily calculated as \( \bar{R}_{ik} = \text{diag}(R_i, \hat{R}_{ik-1}^i) \). By adopting the MHE approach, the measurement estimation sequence of each sensor is updated at every instant \( k \), i.e., \( \hat{y}_{ik}^i = \hat{y}_{ik} \) does not hold. For this reason, each sensor prefers to utilize the latest reconstructed measurements and the corresponding covariance matrices, which requires the communication of the following information

\[
z_i = \{ (y_i^j, R_i), (\hat{y}_{i-Nk-1}^i, \hat{R}_{i-Nk-1}^i), \ldots, (\hat{y}_{ik-1}^i, d_i \hat{R}_{ik-1}^i) \}
\]  

(6)

Table 1. Observability comparison, where each sensor node communicates only with its adjacent neighbors.

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DMHE Optimization Problem

By adopting the MHE approach, sensor \( i \) can collect at the instant \( k \) its measurements and received information as

\[
\{ y_{i-Nk}^j, \ldots, y_{ik}^j \}, \{ \bar{y}_{i-Nk}^j, \ldots, \bar{y}_{ik}^j \}, \quad j \in V_i
\]  

(7)

and estimate the target state by minimizing the following objective function

\[
\Phi_k = \| x_{i-Nk} - \hat{x}_{i-Nk} \|_2 + \sum_{t=1}^{k-1} \| w_{it} \|_2 + \sum_{t=1}^{k} \| \bar{v}_{it} \|_2 + \sum_{t=1}^{k} \| \bar{R}_{ik} \|_2 + \sum_{t=1}^{k} \| \hat{R}_{ik} \|_2
\]  

(8)
where $\hat{x}_{k-Nk-1}^i$ is the state estimation obtained at the last instant $k-1$, with the covariance matrix $\mathbf{P}_{k-Nk-1}^i$ smoothly updated according to (13) and (14). $N$ denotes the estimation horizon. The estimation $x_{k-Nk}^i$ and the estimated disturbance $w_n^i$ are the decision variables to be determined. Based on these decision variables, the subsequent state estimation can be expressed as

$$x_{t+1k}^i = Ax_{tk}^i + Gw_{tk}^i$$  \hspace{1cm} (9)

The estimations for the measurement error of sensor $i$ and the reconstructed measurement error of sensor $j$ ($(j\in \mathcal{V}_i)$) can be expressed, respectively, as $\hat{v}_{tk}^i = y_{tk}^i - C_{tk}^i x_{tk}^i$ and $\hat{v}_{tk}^j = y_{tk}^j - C_{tk}^j x_{tk}^j$.

Additionally with respect to the *a priori* knowledge formulated by constraint (2), the state estimation $x_{tk}^i$ should satisfy

$$\psi_j \leq \|x_{tk}^i\| \leq \psi_j, \quad j\in\{1,2,\ldots,q\}$$  \hspace{1cm} (10)

for any $t \in \{k-N,\ldots,k\}$.

By incorporating the objective function (8) and the constraints (9) and (10), the MHE optimization problem of sensor $i$ can be directly given as

$$\min_{x_{tk},w_{tk}^i} \Phi_i^f$$

s. t. (9), (10)  \hspace{1cm} (11)

In the common framework of MHE, the covariance matrix of the state estimation error is usually updated according to the Kalman filter covariance update formula

$$\mathbf{P}_{tk}^i = GQG^T + A\mathbf{P}_{tk}^i A^T - A\mathbf{P}_{tk}^i (H_i)^T \left( r_{tk}^i + H_i \mathbf{P}_{tk}^i (H_i)^T \right)^{-1} H_i \mathbf{P}_{tk}^i A^T$$  \hspace{1cm} (12)

where $r_{tk}^i$=diag($R_{n+1}, \ldots, R_{jn}^j$), $H_i$=[$C_{j_1}, \ldots, C_{j_M}$] , $j_1, \ldots, j_M \in \mathcal{V}_i$.

Because the state estimation sequence $\{\hat{x}_{k-Nk}^i, \ldots, \hat{x}_{k-1k}^i\}$ utilized for the compensation calculation is updated at every instant $k$ , here we adopt the following smooth update formula [12]

$$\mathbf{P}_{tk}^i = \mathbf{P}_{tk}^i - \mathbf{P}_{tk}^i H_i^T \left( r_{tk}^j + H_i \mathbf{P}_{tk}^i (H_i)^T \right)^{-1} H_i \mathbf{P}_{tk}^i$$  \hspace{1cm} (13)

$$\mathbf{P}_{tk}^i = \mathbf{P}_{tk}^i + \mathbf{P}_{tk}^i A^T (\mathbf{P}_{tk}^i A)^{-1} (\mathbf{P}_{tk}^i - \mathbf{P}_{tk}^i A^T \mathbf{P}_{tk}^i A^{-1} A^T) \mathbf{P}_{tk}^i, \quad t = k-N,\ldots,k-1$$  \hspace{1cm} (14)

with $\mathbf{P}_{tk}^i$ to provide a better description for the accuracy of state estimation sequence.

**DMHE Algorithm**

Now, we can directly sketch the DMHE algorithm as follows.

**Off-line Stage.** 1) For each sensor $i$, choose an initial state estimation $\hat{x}_0^i$ and an associated covariance matrix $\mathbf{P}_{0k}^i$, set $\hat{x}_{0k-1}^i = \hat{x}_0^i$ and $\mathbf{P}_{0k-1}^i = \mathbf{P}_{0k}^i$.

2) Determine a proper moving horizon size $T \geq 1$ and the confidence factor $d_i > 0$ for each sensor $i$.

**On-line Stage.** If $0 \leq k < T$, set $N = k$, else set $N = T$. Each sensor $i$ performs the following procedures.

1) Sends the $z_k^i$ (see (6)) to its neighbor sensors $j \in \mathcal{V}_i$.
2) Receives $z_i^j$ from its neighbor sensors $j \in V_i$, and collects the individual measurements $\{y_{k-N+1}, \ldots, y_{ik}\}$, the reconstructed measurements $\{\tilde{y}_{k-N+1}, \ldots, \tilde{y}_{ik}\}$ and the covariance matrices $\{R_{k-N+1}, \ldots, R_{ik}\}$.

3) Solves the optimization problem (11) to obtain the optimal solution $\hat{x}_{k-N}^i$ and $\hat{\delta}_{ik}$ and calculates the current state estimation $\hat{x}_{ik}^t$ according to (9).

4) Updates the covariance matrix sequence $\{\Pi_{k-N}^i, \ldots, \Pi_{ik}\}$ according to (12), (13) and (14).

**Simulation**

Consider an estimation problem for a moving target (in 3D dimension space) by a multi-sensor network of $M = 5$ sensors. The target state is evolved according to the dynamics (1) with the following parameters $A = \begin{bmatrix} I_3 & \delta I_3 & \frac{1}{2} \delta^2 I_3 \\ 0_3 & I_3 & \delta I_3 \\ 0_3 & 0_3 & I_3 \end{bmatrix}$, $G = \begin{bmatrix} \frac{1}{2} \delta^2 I_3 \\ \delta I_3 \\ I_3 \end{bmatrix}$, $Q = 5I_3$.

the sampling period $\delta = 0.5$ s, and the initial state $x_0 = [200, 90, 0, 200, 20, 0, 200, 40, 0]^T$.

There exists the lower and upper bounds for velocity, which can be depicted as $v_{\text{min}} \leq \|\Psi x_k\| \leq v_{\text{max}}$, the parameters $\Psi = \begin{bmatrix} 0_3 & I_3 & 0_3 \end{bmatrix}$, $v_{\text{min}} = 100$ m/s, $v_{\text{max}} = 280$ m/s.

The communication topology of the multi-sensor network is shown in Fig.1, which leads to the adjacency matrix $B = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}$.

The measurement matrices of the sensors are given as $C_1 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$, $C_2 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$, $C_3 = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$, $C_4 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$, $C_5 = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$, and the measurement error covariance matrices are set as $R_i = 100$, $i = 1, 2, 3, 4, 5$. It is obvious that all the sensors cannot estimate the completely target state individually.

![Figure 1. Communication topology of multi-sensor network.](image)

According to the communication topology and the measurement matrices, we can classify the sensors in the network into three categories. Sensors 3 and 4 belong to the first category, which can provide regionally complete measurements. The second category is composed of sensors 2 and 5, which cannot provide regionally complete measurements but can directly communicate with sensors in the first category. Sensor 1 belongs to the third category because it can neither provide regionally complete measurement nor communicate directly with sensors in the first category.

To provide a benchmark for comparison, we choose a sensor with complete measurement, i.e., the measurement matrix $C = [I_3, 0_3, 0_3]$ and the measurement error covariance matrix $R_i = 100$. 
In the simulation, we choose the initial state estimation \( \hat{x}_0 = [0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0 \ 0]^T \) and the corresponding covariance matrix \( \Pi_0 = 10^{10} I_9 \) for each sensor. The disturbance covariance matrices \( Q = 5I \), the size of the moving horizon is set as \( T = 10 \) and the confidence factors \( d_1 = d_2 = d_5 = 10 \), \( d_3 = d_4 = 1 \). All the simulation results are provided as follows.
Fig. 2, Fig. 3 and Fig. 4 show the estimations of all sensors for, respectively, the position, velocity and acceleration of the target in three coordinates. It can be easily seen that all the state estimations of the multi-sensors can converge to the actual ones and achieve consensus, although there is no sensor can provide complete measurement. This verifies the effectiveness of the proposed DMHE algorithm.

The 2-norms of the target velocity and its different estimations are plotted in Fig. 5, in which the satisfaction of the velocity constraint is directly shown. The utilization of the constraint formed knowledge known a priori is inherited from the MHE approach, which can improve the estimation performance.

The root mean square error (RMSE) with 500 Monte-Carlo runs is provided in Fig. 6. It is clearly shown that (see the subplot in Fig. 6), the estimation performances of sensors 2, 3 and 4 are comparable with that of benchmark, while the performances of sensors 1 and 5 are worse but acceptable. The comparable performances of the sensors in the first category are contributed by their regionally complete measurements, where the proposed DMHE algorithm mainly plays its fusion role. The comparable, worse but acceptable performances of the sensors in the second and third categories are contributed by the measurement compensations received from the sensors in the first category, where the proposed DMHE algorithm mainly plays its consensus role. This additionally verifies the advantage of the proposed DMHE algorithm.
Summary

In this paper, we investigate the distributed estimation problem of the multi-sensors network with incomplete measurements, and propose a distributed moving horizon estimation algorithm. By reconstructing the measurements with utilizing an estimation of complete measurement as compensation, the regional measurements can be completed artificially. Because each sensor constructs its complete measurement estimation based on the currently estimated state, and sends it to its neighbor sensors for their next state estimation, the estimation consensus of the multi-sensors network can be achieved without the direct fusion of the estimated state. Additionally, due to each sensor estimates the target state by on-line solving an optimal estimation problem, the consensus results are provided in an optimal sense, and the selection of an appropriate weighting matrix for consensus can be avoided.

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