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A Sensor Self-aware Distributed Consensus Filter for Simultaneous Localization and Tracking

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Abstract Brain inspired strategies stimulate many insightful means of investigating wireless sensor networks (WSNs). In this paper, we present a sensor self-aware consensus filter for both estimating sensor states distributively and fusing data for target localization and tracking. Specifically, we characterize the sensor world-awareness in terms of the propagation of suitable messages exchanged among neighbouring sensors. Based on the sensor self-awareness, we develop a dynamic graphical model for implementing the information weighted consensus filter (ICF) which locates and tracks a target. Furthermore, the sensor self-awareness is enhanced by a recursive maximum likelihood (RML) scheme, which robustly estimates unknown sensor localization. The overall framework is a generalized distributed adaptive filter with consensus and on-line maximisation. It highly mimics the information exchange mechanism among brain cells for decision making. Simulation results show that the proposed self-aware algorithm is effective for solving the simultaneous localization and tracking (SLAT) problems.

Keywords Information Weighted Consensus Filter · Self-awareness · Recursive Maximum Likelihood · Simultaneous Localization and Tracking

1 Introduction

As an emerging branch from the popular topic of simultaneous localization and mapping (SLAM), simultaneous localization and tracking (SLAT) has

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gained great research interest recently [1]. It is typical to formulate an SLAT problem using a state-augment architecture, where the positions of sensors and targets are treated as one unknown state. One example is the SLAT framework proposed in [2], which is based on Bayesian inference and assumes the sensor positions are unknown and requires moment matching to obtain such information. Similarly, cubature Kalman filters have been developed for non-line-of-sight environments [3], which constructs augmented state vector by concatenating a target state and a sensor location. Besides these centralized methods, a distributed variational filter for SLAT has been proposed [4] to take the messages with both belief propagation and bandwidth consumption into consideration.

In order to exploit the advantages supported by state filtering and parameter estimation, researchers have proposed adaptive structures for solving SLAT problems. One early attempt of such method is the decentralized data fusion method with all-to-all sensor communications proposed in [5], which studies a decentralized version of the recursive maximum likelihood assessment for Hidden Markov Model and introduces a belief propagation message passing algorithm to localize sensors simultaneously with target tracking. Another pioneer work is from [6], which proposes a likelihood consensus scheme with inter-sensor measurements composed of nonparametric belief propagation. These methods, however, rely on specific communication network topologies and are not generally applicable to arbitrarily connected networks. Since they are based on belief propagation in a Bayesian filtering framework, they may have expensive computation costs [7]. Furthermore, these methods heavily rely on distance measurements, which, however, are not always guaranteed in practice due to the limited sensing range of individual sensors[8].

Inspired by how human brain cells interact among neighbouring cells for decision making [9], we propose a distributed consensus algorithm in an adaptive manner to solve practical SLAT problems. The basic assumption is that the sensors of a network are self-aware so that they can cooperate by exchanging messages among neighbours [10]. Specifically, a distributed adaptive consensus estimator is designed for SLAT with maximum likelihood parameter estimation [11]. Specifically, our framework inherits some desirable properties from the information weighted filter(ICF) [12,13]. Since errors in the information held by each sensor become highly correlated with each other during the exchanges, we introduce an analytical expression of the predictive distribution to estimate the sensor localization parameter. By employing a general likelihood function, we are able to characterize the coupling states and parameters for both the target and activated sensor, and then estimate the target state and sensor parameters through adaptive filtering based on ICF and recursive likelihood estimation. Comparing with the belief propagation message passing scheme, our framework has the advantages of low computation cost and complexity because it reduces the unnecessary communication overheads and the additional computation. Furthermore, it can have better performance for localization. Simulation results confirm the advantages of this framework.

The rest of this paper is organized as follows. Section 2 introduces the problem under study; Section 3 proposes the distributed information consensus filter with recursive maximum likelihood; Section 4 examines the proposed framework by simulation and section 5 concludes the paper.

2 Problem Statement

Consider a sensor network (ν, ϵ) where ν denotes the set of N sensors within the network and ϵ denotes the set of edges. Assume that for any pair of sensors $i, j \in \nu$, there is at least one path from i to j. We also assume that communications between sensors are bidirectional. Each sensor maintains a local coordinate system and regards itself as the origin of its coordinate system using the model given by [14], which is introduced below in details.

2.1 Target Dynamic Model

We denote the state vector of a target as $x_t = [p_{x,t}, p_{y,t}, v_{x,t}, v_{y,t}]^T$, where the subscript t indicates the *time* step. Specifically, for a moving target on a 2-D plane, $(p_{x,t}, p_{y,t})$ denote the target position. $(v_{x,t}, v_{y,t})$ denote the target velocities along x-axis and y-axis, respectively. We use a linear Gaussian model for formulating the target state transition with respect to sensor i:

$$x_t^i = A_t x_{t-1}^i + q_{t-1}^i \tag{1}$$

where q_{t-1}^i is zero mean Gaussian additive noise with variance Q_{t-1}^i, A_t is the state transition matrix. This model has been working well in linear conditions, while the general algorithm derived from the ideal linear model can be even further extended to apply in complex nonlinear conditions.

2.2 Sensor Localization Parameter

Define $\theta_*^{i,j}$ to be the *real* position of sensor i in the local coordinate system of sensor j, which means that the state x_t^i relating to the local coordinate system of sensor j can be expressed as follows,

$$x_t^i = x_t^j + \theta_*^{i,j} \tag{2}$$

The sensor *localization* parameters $\theta_*^{i,j}$ remain unchanged since the sensors are not mobile. We note the following straightforward but important relationship: if sensors i and j are connected through intermediate sensors $j_1, j_2, \cdots, j_n$, then

$$\theta_*^{i,j} = \theta_*^{i,j} + \theta_*^{j,j1} + \theta_*^{j1,j2} + \cdots + \theta_*^{j_{n-1},j_n} + \theta_*^{j_n,j} \tag{3}$$

When the state comprises the position and velocity of the target, only the first and second components of $\theta_*^{i,j}$ are meaningful as the other two are redundant with values to $\theta_*^{i,j}(3) = 0$ and $\theta_*^{i,j}(4) = 0$.

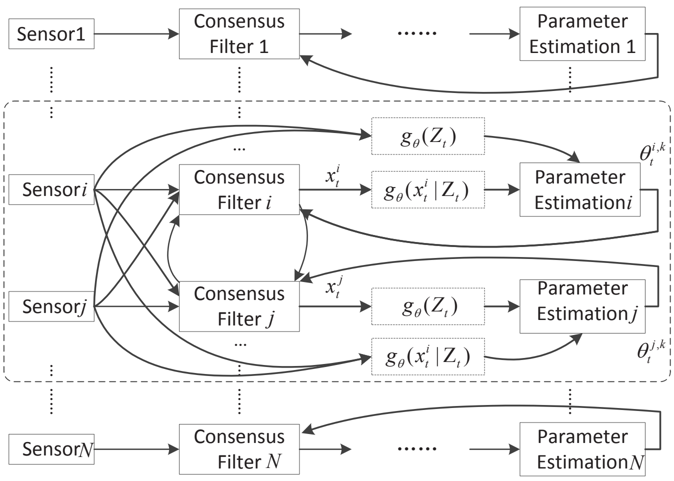

Fig. 1 Structure of the Distributed Adaptive Consensus Filter.

2.3 Measurement Model

The measurement z_t^i made by sensor i is also defined relatively to the local coordinate system at sensor i. For a linear Gaussian observation model, a measurement is generated as follows:

$$z_t^i = C_t^i x_t^i + s_t^i \tag{4}$$

where s_t^i is zero mean Gaussian distribution $\aleph$ with variance S_t^i. Note that the time varying observation model$\{C_t^i, S_t^i\}$ is different for each sensor. We denote $Z_t = \{z_t^1, z_t^2, \cdots, z_t^N\}$ for all the N sensors, and then its joint likelihood function can be written as

$$g_\theta(Z_t) = \sum_{i=1}^{N} \aleph((z_t^i - C_t^i x_t^i), S_t^i) \tag{5}$$

3 Distributed Information Consensus Filter with Recursive Maximum Likelihood

In this section, we present an adaptive distributed filter composed of two stages for target tracking and sensor localization. The first stage is consensus filtering that updates the target state with respect to each sensor. The second stage is recursive parameter estimation that exploits an on-line optimization method for refining the sensor localization. As an integrated framework, each consensus filter is specific to a separate sensor subsystem and gets feedback information from its parameter estimation. Such approach is learned from the information exchange mechanism among brain cells for decision making, and the details can be found in [9,15]. We illustrate the diagram of the mechanism in the context of consensus filter in Fig.1.

3.1 Information Weighted Consensus Filter

To derive the state estimate of both sensor and target using a fully decentralized manner, an information weighted consensus filter is applied to obtain the target state of each sensor. This procedure is referred to as consensus filtering and forms the first stage of our framework.

As shown in Fig.1, a feedback scheme is highlighted in the proposed two-stage framework. The first stage, i.e. consensus filtering, receives feedbacks from the parameter estimation at the second stage that is presented in the next subsection. Therefore, we assume that the sensor localization parameter estimation $\theta_t = \{\theta_t^{i,j}\}_{(i,j)\in\varepsilon}$ has been updated with recursive maximum likelihood at time step t, where $\theta_t^{i,j}$ is known to sensor j only. In practice, every sensor derives an individual state for the target, which is different from the centralised style. All the states for the target is supposed to achieve a consensus subject to certain optimization rules, similar to the exchange of information among brain cells. We assume that there is a reference sensor r, which can broadcast and receive the target state estimation x_t^r referring to its local coordinate system and the sensor localization parameter $\{\theta_t^{r,k}\}_{k\in\nu}$. The sensors are thus self-aware through broadcasting and receiving messages among neighbors.

The collection of all measurements from all sensors can be expressed as

$$\begin{cases} z^1 &= C^1(x^{r,1} + \theta^{r,1}) + s^1 \\ z^2 &= C^2(x^{r,2} + \theta^{r,2}) + s^2 \\ &\vdots \\ z^N &= C^N(x^{r,N} + \theta^{r,N}) + s^N \end{cases} \tag{6}$$

and further expressed in the form of matrices as

$$\zeta = Cx^r + \vartheta + s \tag{7}$$

Where $\zeta = [(z^1)^T, (z^2)^T, \cdots, (z^N)^T]^T \in R^l$, $l = \sum_i l_i$, and ζ includes all measurements from the sensors within the network, and $C = [\left(C^1\right)^T, \left(C^2\right)^T \cdots, \left(C^N\right)^T]^T \in R^{l\times o}$ is the stack of all the observation matrices. For the parameters of target and sensors, $x^r = [(x^{r,1})^T, (x^{r,2})^T, \cdots, (x^{r,1})^T]^T$ and $\vartheta = [(\theta^{r,1})^T, (\theta^{r,2})^T, \cdots, (\theta^{r,N})^T]^T$ denote the augmented state of target and sensor localization recognized by N sensors. For the measurement noise vector, $s = [(s^1)^T, (s^2)^T, \cdots, (s^N)^T]^T$, we denote its covariance as $S \in R^{l\times l}$ and information matrix as $B = S^{-1} \in R^{l\times l}$. We assume the measurement noise to be uncorrelated across sensors. Thus, the measurement covariance matrix is $S = diag\{S^1, S^2, \cdots, S^N\}$ and $B = diag\{B^1, B^2, \cdots, B^N\}$.

In a distributed estimation framework, each sensor i possesses a prior estimate of the state vector that is denoted as $x^i_{t|t-1} \in R^o$. The objective of the network is to use distributed computations across the network such that the posterior state estimate at each sensor converges to the centralized estimate. However, due to resource constraints, this convergence may not be fully achieved at a given time. Therefore, if consensus was performed directly on the priors, the estimate of sensor i can be modeled as follows

$$x^{r,i}_{t|t-1} = x^r_t + \theta^{r,i}_t + q^i_t \tag{8}$$

PROPOSITION 1

Under the assumption that a randomly selected reference sensor r has information about the prior state estimate $x^{r,k}_{t|t-1}, k \in ne(r) \bigcup r$ and information matrix $J^k_{t|t-1}, k \in ne(r) \bigcup r$, where $ne(r)$ denotes the neighbors of sensor r, sensor r could compute a posteriori state and information matrix from $x^{r,k}_{t|t-1}$, $J^k_{t|t-1}$, measurement z^i_t, measurement information matrix B^i_t and measurement model parameter C^i_t as follows

$$x^r_t = \left[\sum_{k=1}^{N} (\frac{J^k_{t|t-1}}{N} + C^T_k B_k C_k)\right]^{-1} \sum_{k=1}^{N} (\frac{J^k_{t|t-1}}{N} x^{r,k}_{t|t-1} + C^T_k B_k (z^k_t - C_k \theta^{r,k}_t)) \tag{9}$$

$$J^r_t = \sum_{k=1}^{N} (\frac{J^k_{t|t-1}}{N} + C^T_k B_k C_k x) \tag{10}$$

PROOF

Denote the collection of all the state priors from all sensors as $\chi_{t|t-1} = [(x^1_{t|t-1})^T, (x^2_{t|t-1})^T, \cdots, (x^N_{t|t-1})^T]^T \in R^{N \times o}$, and the reference sensor's prior estimate as $\chi^r_{t|t-1} = [(x^{r,1}_{t|t-1})^T, (x^{r,2}_{t|t-1})^T, \cdots, (x^{r,N}_{t|t-1})^T]^T$. The relationship between the state, the priors and the prior errors can be summarized as

$$\chi_{t|t-1} {=} C_I x_t + \vartheta_t + q_t \tag{11}$$

where x^r is the true state of the targets referring to sensor r, $q_t = q^1_t, q^2_t, \cdots, q^N_t \in R^{N \times O}$ is the error vector, and $C_I = [\mathbf{I}_o, \mathbf{I}_o, \cdots, \mathbf{I}_o]^T \in R^{o \times o}$.
$\vartheta_t = [(\theta^{r,1}_t)^T, (\theta^{r,2}_t)^T, \cdots, (\theta^{r,n}_t)^T]$.

We define the augment state $\tilde{C} = diag\{C^1, C^2, \cdots, C^N\}$. Combining the measurements with consensus on the priors yields

$$\begin{bmatrix} \chi_{t|t-1} \\ \zeta_t \end{bmatrix} = \begin{bmatrix} C_I \\ \tilde{C} \end{bmatrix} x^r + \begin{bmatrix} \vartheta \\ \tilde{C}\vartheta \end{bmatrix} + \begin{bmatrix} q \\ s \end{bmatrix} \tag{12}$$

$$\begin{bmatrix} \chi^r_{t|t-1} \\ \zeta_t - \tilde{C}\vartheta \end{bmatrix} = \begin{bmatrix} C_I \\ \tilde{C} \end{bmatrix} x^r + \begin{bmatrix} q \\ s \end{bmatrix} \tag{13}$$

Denoting $\mathbf{Z} = \begin{bmatrix} \chi^r_{t|t-1} \\ \zeta_t - \tilde{C}\vartheta \end{bmatrix}$, $\mathbf{C} = \begin{bmatrix} C_I \\ \tilde{C} \end{bmatrix}$, and $\mathbf{D} = \begin{bmatrix} q \\ s \end{bmatrix}$, we have $\mathbf{Z} = \mathbf{C}x^r + \mathbf{D}$, where $D \sim N(0, D')$. The noise term follows Gaussian distribution because it is accumulated through one or more consensus iterations, which are linear operations, performed on Gaussian random variables.

Let us denote the augmented state covariance matrix P where its information matrix $F = P^{-1}$ can be expressed as $(o \times o)$ blocks

$$F = \begin{bmatrix} F^{1,1}_{t|t-1} & F^{1,2}_{t|t-1} & \cdots & F^{1,N}_{t|t-1} \\ F^{2,1}_{t|t-1} & F^{2,2}_{t|t-1} & \cdots & F^{2,N}_{t|t-1} \\ \vdots & \vdots & \ddots & \vdots \\ F^{N,1}_{t|t-1} & F^{N,2}_{t|t-1} & \cdots & F^{N,N}_{t|t-1} \end{bmatrix}$$

Let us define the information matrix of the prior of sensor i as

$$J^i_{t|t-1} = (P^{i,i}_{t|t-1})^{-1}$$

Here, $J^i_{t|t-1} \in R^{o\times o}$, and usually $J^i_{t|t-1} \neq F^{i,i}_{t|t-1}$. Assuming that the prior state estimation errors are uncorrelated to noise in the new measurements, we have the block diagonal covariance matrix $D' = diag\{P, R\}$ and its inverse $(D')^{-1} = diag\{F, B\}$.

The centralized maximum a posterior (MAP) estimation of the state x^r_t can be obtained as

$$\begin{aligned} x^r_t &= [\mathbf{C}^T(D')^{-1}\mathbf{C}]^T[\mathbf{C}^T(D')^{-1}\mathbf{Z}] \\ &= [C_I^T F C_I + C^T BC][C_I F \chi^r_{t|t-1} + C^T B(\zeta_t - \tilde{C}\vartheta)] \end{aligned} \tag{14}$$

$$J^r_t = C_I^T F C_I + C^T BC \tag{15}$$

Define

$$F^i_{t|t-1} = \sum_{k=1}^{N} F^{k,i}_{t|t-1},$$

and we have

$$\begin{cases} C_I^T F C_I &= \sum_{k=1}^{N} F^k_{t|t-1} \\ C_I F \chi^r_{t|t-1} &= \sum_{k=1}^{N} F^k_{t|t-1} x^{r,k}_{t|t-1} \end{cases} \tag{16}$$

In order to simplify the expression, we introduce the following two symbols $u_k = C_k^T B_k C_k$ and $U_k = C_k^T B_k(z^k_t - C_k\theta^{r,k}_t)$. By exploiting the block diagonal structure of B, we can have the following neat expressions

$$\begin{cases} C^T BC &= \sum_{k=1}^{N} C_k^T B_k C_k &= \sum_{k=1}^{N} u_k \\ C^T B(\zeta_t - \tilde{C}\phi) &= \sum_{k=1}^{N} C_k^T B_k(z^k_t - C_k\theta^{r,k}_t) &= \sum_{k=1}^{N} U_k \end{cases} \tag{17}$$

Applying the expressions above into (14) and (15), we get

$$x_t^r = \left[\sum_{k=1}^{N} (F_{t|t-1}^k + U^k)\right]^{-1} \sum_{k=1}^{N} (F_{t|t-1}^k x_{t|t-1}^{r,k} + u^k) \tag{18}$$

$$J_t^r = \sum_{k=1}^{N} (F_{t|t-1}^k + U^k) \tag{19}$$

This is the centralized solution that can be computed naturally in a distributed manner based on consensus[13]. In order to implement (17) and (18) distributively, we can introduce $w_t^{r,i} = F_{t|t-1}^i + U^i$ and $W_t^{r,i} = F_{t|t-1}^i x_t^{r,i} + u^i$, so that

$$x_t^r = \left(\sum_{k=1}^{N} \mathrm{W}_t^{r,k}\right)^{-1} \sum_{k=1}^{N} w_t^{r,k} \tag{20}$$

$$J_t^r = \sum_{k=1}^{N} \mathrm{W}_t^{r,k} \tag{21}$$

when the prior errors are uncorrelated across two sensors, by using $F_{t|t-1}^i = J_{t|t-1}^i$ and average consensus, we can compute the centralized MAP estimate and obtain (9) and (10). ■

Summary of the Consensus Filter

Initialization:$J_{t|t-1}^i, x_{t|t-1}^i, H_i, \theta_t$

(1) Obtain measurements z_t^i, B_i

$$u_t^i = \left(C_t^i\right)^T B_i C_t^i \tag{22}$$

$$U_t^i = \left(C_t^i\right)^T B_i (z_t^i - C_t^i \theta_t^{r,i}) \tag{23}$$

(2) Broadcast the message $m_{i\to j} = \{U_t^i, u_t^i, J_{t|t-1}^i, x_{t|t-1}^i\}$, receive the message $m_{j\to i} = \{U_t^j, u_t^j, J_{t|t-1}^j, x_{t|t-1}^j\}$. This step enables the sensor self-awareness through broadcasting and receiving messages among neighbors.

(3) Prepare data

$$y_t^i = \sum_{j\in N_i} u_t^j \tag{24}$$

$$Y_t^i = \sum_{j\in N_i} U_t^j \tag{25}$$

$$x_{t|t-1}^{r,i} = x_{t|t-1}^i - \theta_t^{r,i} \tag{26}$$

$$J_{t|t-1}^{r,i} = J_{t|t-1}^i \tag{27}$$

(4) Compute consensus

$$\begin{aligned} w_t^{r,i} &= \tfrac{1}{N} J_{t|t-1}^{r,i} x_{t|t-1}^{r,i} + u_t^i + \varepsilon \sum_{j \in N_i} \left(\tfrac{1}{N} J_{t|t-1}^{r,i} x_{t|t-1}^{r,i} + u_t^i - \left(\tfrac{1}{N} J_{t|t-1}^{r,j} x_{t|t1}^{r,j} + u_t^i \right) \right) \\ &= \tfrac{1}{N} J_{t|t-1}^{r,i} x_{t|t-1}^{r,i} + u_t^i + \varepsilon \tfrac{1}{N} \sum_{j \in N_i} \left(J_{t|t-1}^{r,i} x_{t|t-1}^{r,i} - J_{t|t-1}^{r,j} x_{t|t-1}^{r,j} \right) + \varepsilon \left(N' u_t^i - y_t^i \right) \end{aligned} \tag{28}$$

$$\begin{aligned} W_t^{r,i} &= \tfrac{1}{N} J_{t|t-1}^{r,i} + U_t^i + \varepsilon \sum_{j \in N_i} \left(\tfrac{1}{N} J_{t|t-1}^{r,i} + U_t^i - \left(\tfrac{1}{N} J_{t|t-1}^{r,j} + U_t^i \right) \right) \\ &= \tfrac{1}{N} J_{t|t-1}^{r,i} + U_t^i + \varepsilon \tfrac{1}{N} \sum_{j \in N_i} \left(J_{t|t-1}^{r,i} - J_{t|t-1}^{r,j} \right) + \varepsilon \left(N' U_t^i - Y_t^i \right) \end{aligned} \tag{29}$$

(5) Compute a posterior state

$$x_t^{r,i} = \left(W_t^{r,i} \right)^{-1} w_t^{r,i} \tag{30}$$

$$J_t^{r,i} = N W_t^{r,i} \tag{31}$$

$$x_t^i = x_t^{r,i} + \theta_t^{r,i} \tag{32}$$

$$J_t^i = J_t^{r,i} \tag{33}$$

(6) Predict

$$x_{t+1|t}^i = A x_t^i \tag{34}$$

$$J_{t+1|t}^i = [A (J_t^i)^{-1} A^T + Q]^{-1} \tag{35}$$

3.2 Recursive Maximum Likelihood Estimation for Sensor Self-awareness

Our aim is to solve SLAT recursively for sensor i using its sequence of observations. By using the analytic expression of predictive distribution, it is only necessary to propagate the mean and covariance of these densities. Recursive Maximum Likelihood estimation identifies the static parameter $\theta_*^{i,k}$ by using a stochastic gradient algorithm. At time t, the estimated parameter $\theta_t^{i,k}$ is given by

$$\begin{aligned} \theta_t^{i,k} &= \theta_{t-1}^{i,k} + \gamma_t \nabla \log(P(Z_t | Z_{1:t-1}^t)) \\ &= \theta_{t-1}^{i,k} + \gamma_t \nabla \log(\textstyle\int g_\theta(Z_t | x_t^i) g_\theta(x_t^i | Z_{1:t-1}) dx_t^i) \end{aligned} \tag{36}$$

Consider a network with N sensors. At each sensor i, the target being tracked obeys the dynamics specified by (2) and yields an observation given by (4).Thanks to the linear and Gaussian assumptions, at time t, we have

$$g_t^i(x^i) = \aleph(x_t^i, (J_t^i)^{-1}) \tag{37}$$

$$g^i_{t+1|t}(x^i) = \aleph(x^i_{t+1|t}, (J^i_{t+1|t})^{-1}) \tag{38}$$

whose parameters can be computed using a distributed consensus Kalman filter mentioned above, for Eq.(37), parameters associated with the normal probability could be obtained from Eq.(32) to Eq.(33), and for Eq.(38), parameters could be obtained from Eq.(34) to Eq.(35).

We propose an iterative implementation of the RML estimation method for computing all the coordinate transformations as follows

$$\begin{aligned} &\log p^i_\theta(Z_t|Z^i_{1:t-1}) \\ &= -\tfrac{1}{2}\sum_{j\in\nu}(z^j_t - C^j_t\theta^{i,j}_t)^T B_j^{-1}(z^j_t - C^j_t\theta^{i,j}_t) \\ &-\tfrac{1}{2}(x^i_{t|t-1})^T J^i_{t|t-1}x^i_{t|t-1} + \tfrac{1}{2}(x^i_t)^T J^i_t x^i_t \end{aligned} \tag{39}$$

where Z_t denotes all the measurements at time t, $Z_t = \{z^i_t\}_{i\in\nu}$, and we also introduce $Z_{1:t}$ to represent sequence $(Z_1, \cdots, Z_t)$. Calculating the differentiation of this expression w.r.t. $\theta^{i,k}$ yields

$$\begin{aligned} &\nabla \log p_\theta(Z_t|Z_{1:t-1}) \\ &= -\nabla_{\theta^{i,k}}\left(x^i_{t|t-1}\right)^T J^i_{t|t-1}x^i_{t|t-1} \\ &\quad + \nabla_{\theta^{i,k}}\left(x^i_t\right)^T J^i_{t|t}x^i_t \\ &\quad + \sum_{j\in\nu'}\nabla_{\theta^{i,k}}\left(\theta^{i,j}_t\right)^T\left(C^j_t\right)^T B_j^{-1}\left(z^j_t - C^j_t\theta^{i,j}_t\right) \end{aligned} \tag{40}$$

As shown in the above equation, the derivatives can be calculated using the terms of the right-hand side as follows

$$\nabla_{\theta^{i,k}}\left(x^i_t\right)^T = \dot{x}^i_t = \dot{x}^{r,i}_t + \nabla_{\theta^{i,k}}\theta^{r,i}_t = \dot{x}^{r,i}_t + I_p \tag{41}$$

$$\dot{x}^{r,i}_t = \left(V^{r,i}_t\right)^{-1}\dot{v}^{r,i}_t \tag{42}$$

$$\dot{w}^{r,i}_t = \frac{1}{N}J^{r,i}_{t|t-1}\dot{x}^{r,i}_{t|t-1} + \varepsilon\frac{1}{N}\sum_{j\in N_i}\left(J^{r,i}_{t|t-1}\dot{x}^{r,i}_{t|t-1} - J^{r,j}_{t|t-1}\dot{x}^{r,j}_{t|t-1}\right) \tag{43}$$

$$\dot{x}^{r,j}_{t|t-1} = \dot{x}^i_{t|t-1} - \nabla_{\theta^{i,k}}\theta^{r,i}_t = \dot{x}^i_{t|t-1} - I_p \tag{44}$$

$$\nabla_{\theta^{i,k}}\left(x^i_{t|t-1}\right)^T = \dot{x}^i_{t|t-1} = A\dot{x}^i_{t-1} \tag{45}$$

The last term of $\nabla \log p_\theta(Z_t|Z_{1:t-1})$ can be computed as follows

$$\sum_{j\in\nu'}\nabla_{\theta^{i,k}}\left(\theta^{i,j}_t\right)^T\left(C^j_t\right)^T B_j^{-1}\left(z^j_t - C^j_t\theta^{i,j}_t\right) = U^i_t + Y^i_t \tag{46}$$

$$\begin{aligned} &\nabla \log P_\theta(z_t|z_{1:t-1}) \\ &= -\dot{x}^i_{t|t-1}J^i_{t|t-1}x^i_{t|t-1} + \dot{x}^{r,i}_t J^i_{t|t}x^i_t + U^i_t + Y^i_t \end{aligned} \tag{47}$$

$$\theta_t^{i,k} = \theta_{t-1}^{i,k} + \gamma_t[-\dot{x}_{t|t-1}^i J_{t|t-1}^i x_{t|t-1}^i + \dot{x}_t^{r,i} J_{t|t}^i x_t^i + U_t^i + Y_t^i] \quad (48)$$

The recursive maximum likelihood (RML) scheme provides a robust and accurate estimate for unknown sensor locations[5]. It thus enhances the performance of sensor self-awareness in the ICF. We summarize the proposed ICF-RML SLAT algorithm in Algorithm 1.

Algorithm 1: Information Consensus Filter with Recursive Maximum Likelihood for SLAT.

Input: Generate measurements according to (4), Initialize $\{J_{t|t-1}^i, x_{t|t-1}^i, H_i, \theta_t\}$ and messages $\{m_{i\to j}\}$
Output: $x_t^i, \theta_t^{i,j}$
for $t = 1, 2, \cdots,$ **do**
  for $i = 1, 2, \cdots,$ **do**
    while *sensor is active* **do**
      Distributed filtering:
      Broadcast message $m_{i\to j}$ and receive message $m_{j\to i}$;
      Prepare data according to (24) - (27);
      Compute information weighted consensus following (28) and (29);
      Compute a posterior state according to (32) and (33);
      Get the prediction based on (34) and (35);
      Parameters Update:
      Each sensor i of the network will update its values according to (41) - (47);
      Update the parameters of sensor localization using (48).
return x_t^i, $\theta_t^{i,j}$

4 Simulation

In this section, we evaluate the performance of the proposed ICF-RML algorithm using simulations, and compare it with the belief propagation filter and recursive maximum likelihood approach [14], denoted as BPF-RML. We simulate a wireless sensor network comprising a moving target and $N = 11$ sensors, which are uniformly deployed. Its topology follows a tree graph shown in Fig.2, and remains unchanged in the experiments.

The first experiment evaluates the performance of the proposed method in terms of localization accuracy. We choose sensors $3, 4, 6, 9$ as root sensors and update their adjacent edges at each iteration. For the sake of implementation, we choose to use a constant step size $\gamma_t = 3 \times 10^{-4}$. We also initialise $\theta^{i,j} = 0$ for all $(i, j) \in \epsilon$. In Fig. 3 and Fig. 4, the results demonstrate that the location information $\theta^{i,j}$ can be obtained precisely.

Fig.3 and Fig.4 illustrate the sensor localization estimation by using the distributed ICF-RML and BPF-RML algorithms, respectively. The parameter that varies in the experiment is the iteration index k. It is easy to see that

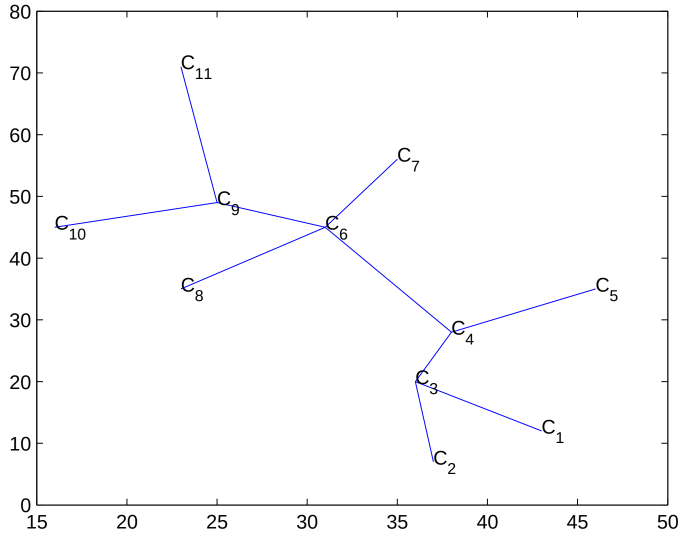

Fig. 2 Topology of a sensor network.

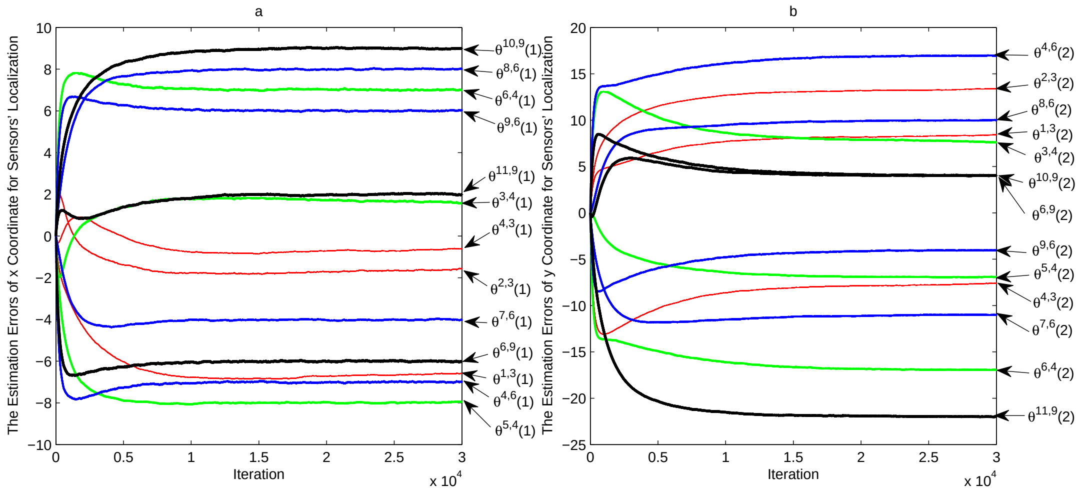

Fig. 3 The convergence behaviors of ICF-RML

both of them require similar amount of time to converge, with the converging rate depending on the network and simulation parameters. The tracking task is performed on an object that traverses the field of view of the sensors. Information is shared between sensors in a way that allows self-localization. In such conditions, the algorithms would need longer time and achieve more accurate results.

In both Fig.5 and Fig.6, we plot the errors $\theta_t^{i,j} - \theta_*^{i,j}$ against iteration. The objective of this experiment is to compare the performance of these two different estimation algorithms directly. For the distributed ICF-RML case and

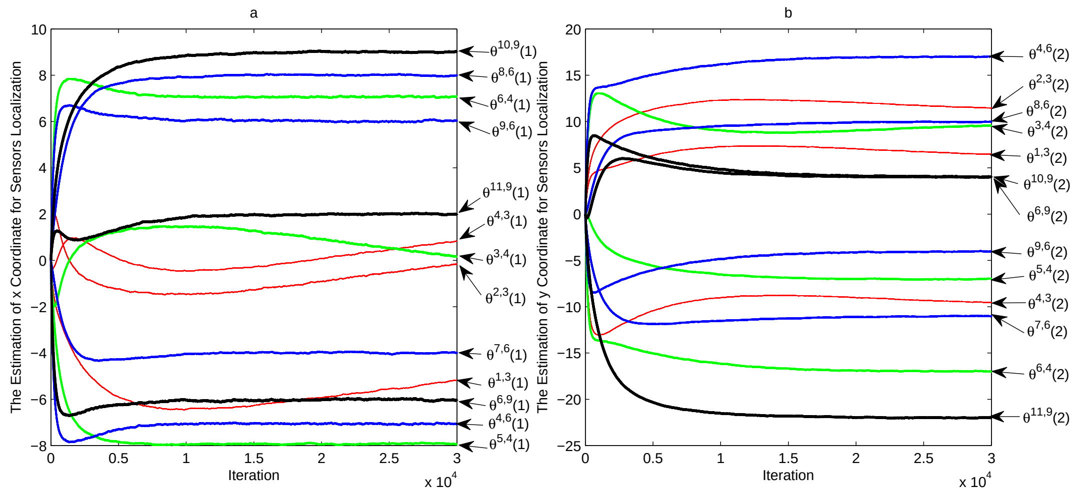

Fig. 4 The convergence behaviors of BPF-RML

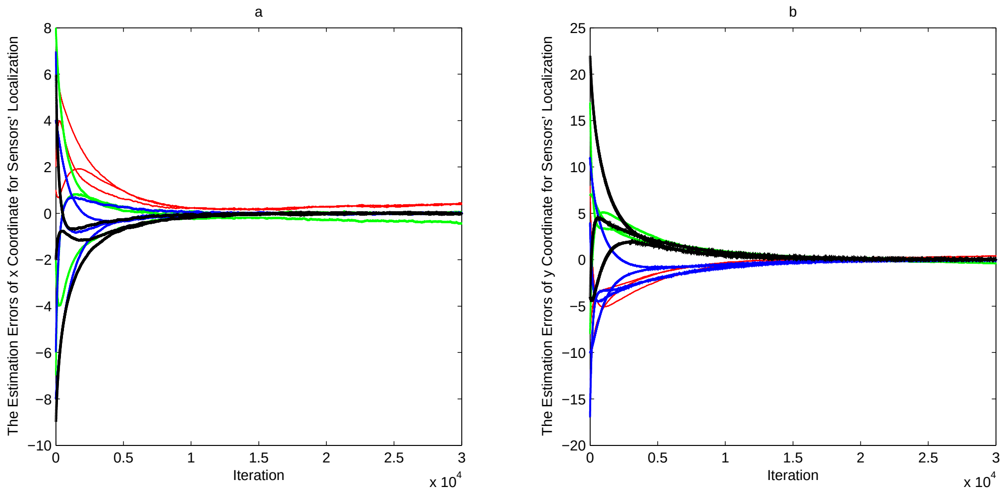

Fig. 5 Error at each iteration in ICF-RML case

distributed BPF-RML case, we can find that the errors converge to zero in ICF-RML case, while there are residual errors in BPF-RML case. The performance comparison with respect to RMSE in position is shown in Fig.5 and Fig.6, and the simulation results suggest that the proposed ICF-RML performs better than the BPF-RML. This is expected since the distributed estimation with sufficient communication mechanism often achieves higher accuracy than that of the sub-sufficient case. In addition, the performance of the ICF-RML is comparable with that of the BPF-RML even if the latter assumes known prior communication topology.

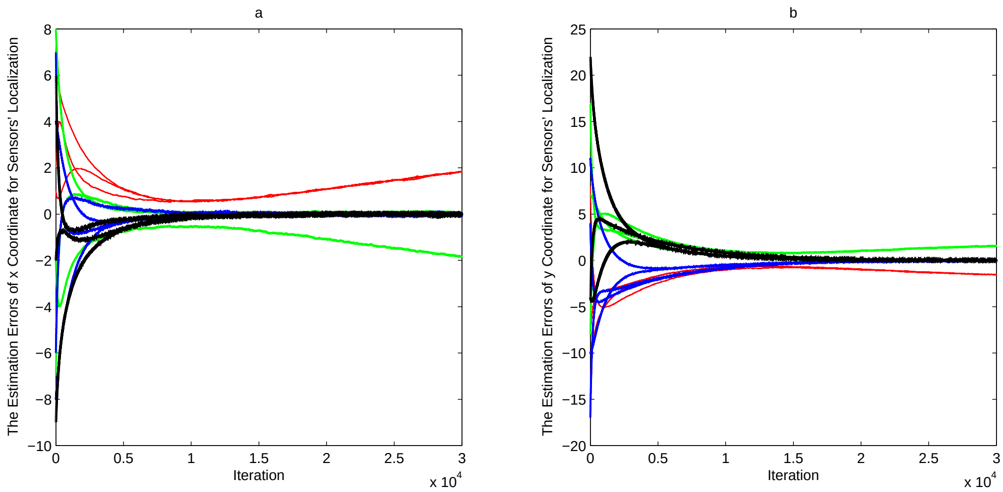

Fig. 6 Error at each iteration in BPF-RML case

5 Conclusion

In this paper, we present a fully decentralized and sensor self-aware algorithm based on adaptive filtering for estimating target states of sensor networks expressed by dynamic models. We apply this approach to formulate the simultaneous localization and tracking problem and propose an effective solution, summarized in the paper. For small-size sensor networks with Gaussian graphs, our algorithm can be implemented through a distributed version of Kalman filter and a consensus protocol. Comparing the existing method, our solution has higher accuracy in estimation and lower complexity.

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