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Collaborative target tracking in WSNs using the combination of maximum likelihood estimation and Kalman filtering

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Abstract: Target tracking using wireless sensor networks requires efficient collaboration among sensors to tradeoff between energy consumption and tracking accuracy. This paper presents a collaborative target tracking approach in wireless sensor networks using the combination of maximum likelihood estimation and the Kalman filter. The cluster leader converts the received nonlinear distance measurements into linear observation model and approximates the covariance of the converted measurement noise using maximum likelihood estimation, then applies Kalman filter to recursively update the target state estimate using the converted measurements. Finally, a measure based on the Fisher information matrix of maximum likelihood estimation is used by the leader to select the most informative sensors as a new tracking cluster for further tracking. The advantages of the proposed collaborative tracking approach are demonstrated via simulation results.

Keywords: Target tracking; Wireless sensor network; Maximum likelihood estimation; Kalman filtering; Fisher information matrix; Sensor selection

1 Introduction

Recent advances in microelectromechanical systems (MEMS), wireless communications, and embedded microprocessor technologies have made possible the massive production of inexpensive and low-power sensors which are integrated with sensing, data processing, and communicating components. A wireless sensor network is composed of a large number of such tiny sensors that are randomly and densely deployed in the surveillance area and form a multihop ad-hoc network system through wireless communication [1]. These networked sensors collaboratively sense the event of interest, process the sensed data, and provide resultant information about the monitored events for a large number of potential military and civil applications, ranging from battlefield monitoring and environmental surveillance to health care [2]. In typical wireless sensor network applications, each sensor is usually powered by batteries with limited energy supply. Furthermore, it is impossible and impractical to replace or replenish the batteries on these sensors in many applications. A particular challenging problem in wireless sensor network applications is to develop an energy-efficient information processing approach to prolong the lifetime of the network. The paper is mainly concerned with selection of a subset of sensors for target tracking in wireless sensor networks.

While the tracking result is most accurate when all sensors can communicate their measurements to the leader in a cluster-based target tracking approach, it is usually better to select only a subset of available sensors to track the target in order to conserve the energy consumption for the network. The problem of sensor selection for target tracking in wireless sensor networks have received considerable attentions in the recent literatures [3–8]. In [3], Kaplan presented a global sensor selection approach which is integrated with a decentralized bearing-only extended Kalman filter (EKF)-tracker and minimizes the expected filtered mean squared (MS) position error. Furthermore, Kaplan [4] presented an autonomous node selection (ANS) approach which uses only local knowledge of sensor node localization. Zhao et al. [5–6] proposed a leader-based tracking scheme, in which a sensor that can provide the most information is elected by the previous leader as a new leader to estimate the current location of the target, and different information utility measures, e.g., entropy, Mahalanobis distance, expected posterior distribution, are also given in this paper. Xiao et al. [7–8] proposed adaptive multisensor scheduling scheme combined with the EKF estimator for target tracking in WSNs to reach a balance between tracking accuracy and energy consumption. In these works, the EKFs have been proposed to estimate the target state (which typically consists of the position and velocity of the target), and the corresponding covariance matrix of the state estimate error is further utilized to schedule sensors for energy efficiency.

The EKF algorithms are derived through first linearizing the nonlinear state and measurement equations around the current estimated state and one-step-ahead predicted state,

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respectively, and then applying the standard Kalman filter to the linearized system [9–10]. However, a significant drawback of the EKF algorithms is that the resulting state estimate may seriously diverge from the actual state [11] in many applications. In target tracking applications, target dynamics are usually linearly modeled in the Cartesian coordinates, while the measurements are nonlinear functions in the target state. In these cases, to overcome the drawback of EKF, many measurement conversion methods have been proposed to transform the nonlinear measurement models into linear ones and simultaneously estimate the covariances of the converted measurement noises before applying the standard Kalman filter [9, 12–13]. Significantly improved accuracy and consistency have been achieved using these conversion methods.

In [14], we have presented a target tracking approach based on the combination of maximum likelihood estimation and Kalman filtering. In [15], we further presented a collaborative target tracking algorithm based on this combination. In this paper, we present the collaborative target tracking approach in wireless sensor networks by integrating the maximum likelihood estimation and the Kalman filter with the sensor selection method, and compare our presented collaborative tracking approach with other tracking approaches through simulations.

When a target moves through the monitored region, only one cluster of sensors is triggered to monitor and track the target at every time instant. After receiving all the measurements from the cluster members, the leader performs the following processing procedures. First, the maximum likelihood estimation method is proposed to convert the received nonlinear measurements with the same timestamp into a linear observation model in the target state and approximately evaluate the covariance matrix of the converted measurement noise. This method is based on the triangulation idea, commonly used in global positioning systems (GPS), recently extended to sensor and target localization [16–19] in wireless sensor networks. Then, the converted measurement and the corresponding noise covariance matrix are used in a standard Kalman filter to recursively update the target state estimate. Finally, an information measure based on the expected Fisher information matrix of the above maximum likelihood estimation is used to choose the most informative sensors for the next tracking, which will improve tracking accuracy while maintaining an acceptable energy consumption. We demonstrate via simulation results that the proposed sensor selection approach can achieve significant tracking accuracy compared to two EKF-based collaborative tracking approaches with different sensor selection methods. The main contributions of this paper is a sensor selection measure based on the Fisher information matrix of the maximum likelihood estimation for our previously proposed target tracking approach.

The remainder of the paper is organized as follows. The target motion model, sensor measurement model and problem formulation are given in Section 2. The proposed collaborative target tracking method is detailed in Section 3. Simulation results are reported in Section 4. Conclusions are reached in Section 5.

2 System models and problem formulation

For simplicity, we only consider the problem of tracking a single target moving in a two-dimensional field monitored by a wireless sensor network in this paper. We first give a widely adopted nearly-constant-velocity (CV) target motion model, and then present a sensor measurement model with additive Gaussian noise. Finally, we present problem formulation for target tracking in wireless sensor networks.

2.1 Target motion model

When a target moves across a two-dimensional field covered by a wireless sensor network, the state of the target is usually described by its position and velocity in the X-Y plane,

$$x_k = [x(k)\ \ y(k)\ \ v_x(k)\ \ v_y(k)]^{\mathrm{T}},$$

where $x(k)$ and $y(k)$ are the position coordinates of the target along X- and Y-axes at time instant t_k, respectively, and $v_x(k)$ and $v_y(k)$ are the velocities of the target along X- and Y-directions at time instant t_k, respectively. The following CV model [9] is adopted to represent the motion of the target:

$$x_{k+1} = F_k x_k + G_k w_k, \tag{1}$$

where

$$F_k = \begin{bmatrix} 1 & 0 & \Delta t_k & 0 \\ 0 & 1 & 0 & \Delta t_k \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},\ G_k = \begin{bmatrix} \Delta t_k^2/2 & 0 \\ 0 & \Delta t_k^2/2 \\ \Delta t_k & 0 \\ 0 & \Delta t_k \end{bmatrix}.$$

In the above equations, $\Delta t_k = t_{k+1} - t_k$ is the sampling time interval between two successive measurement time instants t_{k+1} and t_k, $w_k = [w_x\ w_y]^{\mathrm{T}}$ is a white Gaussian noise sequence with zero mean and covariance matrix Q_w, and w_x and w_y correspond to noisy accelerations along the X- and Y-axes, respectively.

2.2 Measurement model

We assume that all sensors in the network are of the same type and have different noisy statistics for their different distances to the target. Denote by $z_i(k)$ the distance measurement to the target obtained by sensor i at time t_k. To simplify our notation, the dependence on time t_k is suppressed in the sequel, e.g., $z_i(k)$ is simplified to be z_i.

Let r_i be the true distance between sensor i and the target, then r_i is described as the following equation:

$$r_i = \sqrt{(x - x_i)^2 + (y - y_i)^2},$$

where (x_i, y_i) is the known location of sensor i, and (x, y) is the unknown position of the moving target at time instant t_k. The measurement model is represented in the following form of additive noise:

$$z_i = r_i + n_i,\ \ i = 1, \dots, N, \tag{2}$$

where n_i is the additive Gaussian noise of sensor i with zero-mean and variance σ_i^2, and N is the number of sensors tasked at time instant t_k.

According to equation (2), the conditional probability density function of the measurement z_i, given (x, y), is written as follows:

$$p(z_i|x, y) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\Big\{ -\frac{(z_i - r_i)^2}{2\sigma_i^2} \Big\}. \tag{3}$$

2.3 Problem formulation

We assume that there are N_k ($N_k \geqslant 3$) sensors that have been selected to detect the target at time t_k, and all the measurements (with the corresponding timestamps) are transmitted to the leader. Let Z_k denote the measurements gathered from all the N_k sensors, that is, $Z_k = \{z_1(k), \dots, z_{N_k}(k)\}$. The collaborative target tracking problem is for the leader to recursively estimate the target state x_k, denoted by $\hat{x}_{k|k}$, given the current measurements $\{Z_k\}$ and the past target trajectory history, and then select the most informative set from all available sensors for the next time target tracking to achieve the tradeoff between energy consumption and tracking performance.

3 Collaborative target tracking algorithm

In this section, we discuss our proposed collaborative target tracking algorithm in detail. When a target moves through the surveillance region monitored by a wireless sensor network, multiple activated sensors which can sense the target form a temporary tracking cluster, and one of them is designated as the leader which serves as the center of signal and information processing. All the activated sensors simultaneously detect the target, evaluate their distance from the target, and transmit their measurements to the leader. After receiving all the measurements, the leader will perform the following steps to fulfill the tracking task.

Step 1 (Measurement conversion) The leader utilizes the maximum likelihood estimation method to convert the received nonlinear measurements to a good linear estimate of the target position in the Cartesian coordinates and evaluate the approximate covariance matrix of the converted measurement noise.

Step 2 (Target trajectory updating) The converted measurement and the corresponding noise covariance matrix are used by a standard Kalman filter to recursively update the target state estimate and the corresponding estimate error covariance matrix.

Step 3 (Sensor selection) The leader selects the most informative sensors as a new tracking cluster for the next time tracking according to a given criterion. And one of them is designated as the leader of the new cluster.

Step 4 (Data transmissions) The current leader wakes up the selected cluster and transmits the current estimate (including the corresponding covariance matrix) to the new selected leader. The current cluster sensors are going to sleep for energy efficiency.

The above processing steps continue until the the target disappears or leaves the monitored region.

In the remainders of this section, we first lay out the prelocalization algorithm using maximum likelihood estimation method. The solution to the maximum likelihood estimation-based prelocalization is solved by a Newton iterative method. This will be followed by a standard linear Kalman filter for recursive estimation of the target state. Then, the Cramer-Rao lower bound is analyzed for target tracking in wireless sensor networks. Finally, we introduce a sensor selecting approach using a Fisher information matrix-based measure to choose an optimal subset of available sensors to balance the tracking performance with the energy consumption.

3.1 Prelocalization using maximum likelihood estimation

In this section, we discuss how to convert the nonlinear distance measurements into a linear model with respect to the position of the target in the Cartesian coordinates using the maximum likelihood estimation method. We assume that every sensor has the knowledge of the positions of their neighborhoods and themselves. Also we assume that the geometrical relation of the sensors is such that, if measurement noises are not present, the position of the target can be uniquely determined. Note that with three or more sensors, this is not a problem unless all the sensors are in a line, a case which can be easily discounted by a careful selection of sensors. We further assume that there are no delays and losses when sensors transmit their measurements to the processing center. We will call this measurement conversion process prelocalization.

Our method for prelocalization is based on maximum likelihood estimation. Assume that there are N_k ($N_k \geqslant 3$) sensors which have been selected to detect the moving target at time instant t_k (which we will suppress in the following section for simplicity) and that the measurement noises of different sensors are mutually independent. Define $Z = \{z_i, i = 1, \dots, N_k\}$. Denote by $p(Z|x, y)$ the jointly conditional probability density function of Z, given the location of the target, (x, y).

The maximum likelihood estimation-based prelocalization is to seek for the unknown target positions (x, y) such that $p(Z|x, y)$ is maximized. Since the noises of individual sensors are mutually independent, the jointly conditional probability density function is represented as

$$p(Z|x, y) = \prod_{i=1}^{N_k} p(z_i|x, y), \tag{4}$$

where $p(z_i|x, y)$ is given by (3). Under the assumption of Gaussian measurement noise, the maximum likelihood estimate of (x, y) is given by

$$(\bar{x}, \bar{y}) = \arg\max_{x,y} p(Z|x, y) = \arg\min_{x,y} f(x, y), \tag{5}$$

where

$$f(x, y) = \sum_{i=1}^{N_k} \frac{(r_i - z_i)^2}{2\sigma_i^2}. \tag{6}$$

It is obvious that the maximum likelihood estimation-based prelocalization is reduced to a nonlinear weighted least squared problem.

The minimization of (5) is numerically difficult because $f(x, y)$ is a nonlinear function in the unknown parameters (x, y). The Newton-Raphson iterative method [20] has been widely used to solve this nonlinear optimization problem. Let $p = [x\ \ y]^{\mathrm{T}}$, the iterative solution is given by

$$\hat{p}^{(j+1)} = \hat{p}^{(j)} - H^{-1}(\hat{p}^{(j)}) \cdot \nabla f^{\mathrm{T}}(\hat{p}^{(j)}),$$

where $\nabla f^{\mathrm{T}}(\hat{p}^{(j)})$ and $H(\hat{p}^{(j)})$ are the first and second derivatives of $f(p)$ evaluated at $p = \hat{p}^{(j)}$. The initial values is given as follows:

$$\hat{p}^{(0)} = \begin{bmatrix} \hat{x}^1_{k|k-1} \\ \hat{x}^2_{k|k-1} \end{bmatrix},$$

where $\hat{x}^1_{k|k-1}$ and $\hat{x}^2_{k|k-1}$ are the first and second elements of the one-step-ahead predicted state $\hat{x}_{k|k-1}$ of the Kalman filtering algorithm presented in the next section.

Although it is theoretically possible for the Newton iterative method not to converge to a global minimum unless we initialize the MLE to a value close to the correct solution for $f(p)$ is a noncovex function, simulation results show that this is not a problem in our target tracking applications. Typically, only a few iterations are sufficient to guarantee the iterative process to converge to the global minimum. The nice convergence is partly due to the fact that the initial estimate of the iterative process coming from the Kalman predictor is typically good and near the true target position, provided that the sampling time interval is not too long.

3.2 Kalman filtering

Once the above prelocalization is completed, we only need to consider the new converted measurement $\bar{z}_k = [\bar{x}(k)\ \bar{y}(k)]^{\mathrm{T}}$, which has the following linear representation in the target state:

$$\bar{z}_k = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} x_k + v_k = Cx_k + v_k, \quad (7)$$

where v_k is the converted measurement noise. The statistics for noise v_k must be given before the converted measurement $\bar{z}_k$ can be used in Kalman filtering. The computation method for the converted measurement noise is summarized in the following lemma.

Lemma 1 Assuming that the prior probability density function for the position of the target, $p_{\mathrm{a}}(x(k), y(k))$, is uniform (i.e., we have no knowledge of the target position). The converted measurement equation after prelocalization, $\bar{z}_k$, can be approximated by (7) and the associated converted noise v_k is Gaussian white with zero mean and covariance matrix R_k approximately given in (8),

$$R_k = H^{-1}(\bar{x}(k), \bar{y}(k)), \quad (8)$$

where $H(\bar{x}, \bar{y})$ is the Hessian matrix given by

$$H(x,y) = \begin{bmatrix} \dfrac{\partial^2 f(x,y)}{\partial x^2} & \dfrac{\partial^2 f(x,y)}{\partial x \partial y} \\ \dfrac{\partial^2 f(x,y)}{\partial y \partial x} & \dfrac{\partial^2 f(x,y)}{\partial y^2} \end{bmatrix} \quad (9)$$

evaluated at $(\bar{x}, \bar{y})$.

This step is to utilize the Kalman filtering algorithm to update the target state using the converted measurements and associated noises. Its expression is standard [10] and given below:

Phase 1 (Prediction phase) Predict the next state and the corresponding state prediction covariance matrix as follows:

$$\hat{x}_{k+1|k} = F_k \hat{x}_{k|k}, \quad (10)$$

$$P_{k+1|k} = F_k P_{k|k} F_K^{\mathrm{T}} + G_k Q_w G_k^{\mathrm{T}}, \quad (11)$$

where $\hat{x}_{k+1|k}$ is one-step-ahead predicted state of x_{k+1} based on measurements $\{\bar{z}_i, i = 0, \dots, k\}$, $P_{k+1|k}$ is the corresponding predicted error covariance matrix.

Phase 2 (Correction phase) Use the converted observation $\bar{z}_{k+1}$ to correct the predicted state and the corresponding error covariance matrix as follows:

$$S_{k+1} = CP_{k+1|k}C^{\mathrm{T}} + R_{k+1}, \quad (12)$$

$$K_{k+1} = P_{k+1|k} C^{\mathrm{T}} S_{k+1}^{-1}, \quad (13)$$

$$\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1}(\bar{z}_{k+1} - C\hat{x}_{k+1|k}), \quad (14)$$

$$P_{k+1|k+1} = P_{k+1|k} - K_{k+1} S_{k+1} K_{k+1}^{\mathrm{T}}. \quad (15)$$

$\hat{x}_{k+1|k+1}$ is the state estimate of x_{k+1} based on the measurements $\{\bar{z}_i, i = 0, \dots, k+1\}$, $P_{k+1|k+1}$ is the estimated error covariance matrix, K_{k+1} is the Kalman gain and S_{k+1} is the covariance of the innovation.

The initial estimates are given as $\hat{x}_{0|0} = \hat{x}_0$ and $P_{0|0} = P_0$ for some large positive definite P_0.

3.3 Cramer Rao lower bound for target tracking

The lower bound on the minimum achievable covariance in state estimation is given by the (posterior) Cramer-Rao lower bound (CRLB) for random parameters [21–23]. Under the above Gaussian noises and linear measurements and target models case, the covariance of the Kalman filter $\hat{x}_{k|k}$ given by the solution $P_{k|k}$ to the Riccati equations (11) and (15) achieves the CRLB, which can be rewritten as the inverse of the Fisher information matrix (FIM)

$$J_{f,k} = J_{p,k} + J_{z,k}, \quad (16)$$

where $J_{f,k} = P_{k|k}^{-1}$, $J_{p,k} = P_{k|k-1}^{-1}$, and $J_{z,k} = C^{\mathrm{T}} R_k^{-1} C$ represent the posterior, prior and measurement Fisher information matrices, respectively.

From equation (16), it is easy to show that $J_{f,k}$ is related to the covariance R_k of the converted measurement noises $\bar{z}_k$. Furthermore, the covariance R_k is also lower bounded by the CRLB which can also be represented as the inverse of the FIM,

$$J_k = -E \begin{bmatrix} \dfrac{\partial^2 \ln p(Z|x,y)}{\partial x^2} & \dfrac{\partial^2 \ln p(Z|x,y)}{\partial x \partial y} \\ \dfrac{\partial^2 \ln p(Z|x,y)}{\partial x \partial y} & \dfrac{\partial^2 \ln p(Z|x,y)}{\partial x^2} \end{bmatrix}$$
$$= \sum_{i=1}^{N} \frac{1}{\sigma_i^2} \begin{bmatrix} \dfrac{(x-x_i)^2}{r_i^2} & \dfrac{(x-x_i)(y-y_i)}{r_i^2} \\ \dfrac{(x-x_i)(y-y_i)}{r_i^2} & \dfrac{(y-y_i)^2}{r_i^2} \end{bmatrix} \quad (17)$$

evaluated at the true target position or an estimate of it. The FIM of the estimator $\bar{z}_k = [\bar{x}(k)\ \bar{y}(k)]^{\mathrm{T}}$ is related not only to the geometry of the target and the sensors, but also to the measurement statistics of the sensor noises, $\sigma_i^2\ (i = 1, \dots, N)$.

The variances of the target position estimate $\bar{x}(k)$ and $\bar{y}(k)$, obtained from the prelocalization procedure are lower bounded by the diagonal elements of the inverse matrix of the FIM, respectively, i.e.,

$$\mathrm{var}(\bar{x}(k)) \geqslant [J_k^{-1}]_{1,1}, \ \ \mathrm{var}(\bar{y}(k)) \geqslant [J_k^{-1}]_{2,2}, \quad (18)$$

where $[J_k^{-1}(x,y)]_{1,1}$ and $[J_k^{-1}]_{2,2}$ are the first and second diagonal elements of $J_k^{-1}(x,y)$. Then, we have the following result:

$$\mathrm{var}(\bar{x}(k)) + \mathrm{var}(\bar{y}(k)) \geqslant [J_k^{-1}]_{1,1} + [J_k^{-1}]_{2,2}$$
$$= \frac{\mathrm{tr}\{J_k\}}{\det\{J_k\}} = \frac{\sum\limits_{i=1}^{N} \dfrac{1}{\sigma_i^2}}{\det\{J_k\}}. \quad (19)$$

The trace of the FIM is only related the statistics of the sensors. If all sensors have the same variances, i.e., $\sigma_i^2 = \sigma^2$, then (19) is reduced to the following equation:

$$\mathrm{var}(\bar{x}(k)) + \mathrm{var}(\bar{y}(k)) \geqslant \frac{\sum_{i=1}^{N} \frac{1}{\sigma^2}}{\det\{J_k\}} = \frac{N}{\sigma^2 \det\{J_k\}}. \quad (20)$$

In this case, the accuracy of prelocalization is only related to the geometry of the target and the sensors.

A key problem in target tracking in wireless sensor networks is to improve tracking accuracy under the energy constraint. However, tracking accuracy is not only associated with the motion model of the target, but also the converted measurement using prelocalization. In this paper, we consider selecting an optimal sensor set along the target trajectory at every time instant to provide the best information for target localization, and to further improve the performance of target tracking, with the fixed number of tasked sensors.

3.4 Sensor selection using Fisher information matrix

The objective of target tracking is to estimate the state of the target as accurately as possible under energy and communication constraints. The best target state estimate is obtained by employing all sensors in the network to sense the target and transmit their measurements to the processing center. However, transmitting all the information to the center will incur huge energy consumption on communication. It is critical to select an optimal subset of sensors and incorporate their measurements into target tracking. This process is called sensor selection, or sensor scheduling. Different measures have been presented for sensor selection according to the adopted sensor measurement models and the required estimation accurate and processing time; see a survey paper [5]. In this paper, we consider selecting a set of M sensors from available sensors at every time which minimize the target localization variance of the prelocalization.

From the previous section, we know that the variance of the target prelocalization is lower bounded by (19) or (20). In this section, we propose to use this lower bound as a measure to select the optimal subset of sensors for our proposed tracking approach. This measure can be computed using the predicted state of the Kalman filter. Therefore, the current leader sensor does not require the transmission of measurements from the available sensors when it selects sensors and hence avoids communicating useless information. Assume that there are N_{k+1} ($N_{k+1} \geqslant 3$) sensors available for target tracking at next time instant t_{k+1}, i.e., the target will move into the detecting ranges of these N_{k+1} sensors according to one-step-ahead predicted state of the Kalman filter, $\hat{x}_{k+1|k}$. Define S_{k+1} to be the set of all the available sensors, $S_{k+1} = \{1, \dots, N_{k+1}\}$. In this paper, we choose a subset consisting of $M (M \geqslant 3)$ sensors from the total N_{k+1} candidates for target tracking at t_{k+1}. Since we are usually more concerned with the target position, an information measure based on the Fisher information matrix J_{k+1} for prelocalization is given as follows [5–6]:

$$C_{k+1}(S) = \frac{\mathrm{tr}\{J_{k+1}\}}{\det\{J_{k+1}\}}, \quad (21)$$

where S is a sensor set, J_{k+1} is the Fisher information matrix obtained from the sensor set S, and evaluated at one-step-ahead predict of the target position ($x = \hat{x}^1_{k+1|k}, y = \hat{x}^2_{k+1|k}$). $\hat{x}^1_{k+1|k}$ and $\hat{x}^2_{k+1|k}$ denote the first and second elements of $\hat{x}_{k+1|k}$, respectively. Then, a subset of M sensors is selected from S_{k+1} to minimize the information measure,

$$L^*_{k+1} = \arg \min_{L_{k+1} \subset S_{k+1}} C_{k+1}(L_{k+1}), \quad (22)$$

where L_{k+1} denote the set of M selected sensors and $C_{k+1}(L_{k+1})$ is the information measure that the sensors of L_{k+1} can achieve. If all sensors have the same measurement statistics, i.e., $\sigma_i^2 = \sigma^2$, the information measure can be given as follows:

$$C'_{k+1}(S) = \det\{J_{k+1}\}. \quad (23)$$

A subset of M sensors is selected to maximize C',

$$L^*_{k+1} = \arg \max_{L_{k+1} \subset S_{k+1}} C'_{k+1}(L_{k+1}). \quad (24)$$

In this paper, we use the optimal enumerative search method to determine the M sensors. To arrive at the optimal M sensors all possible combinations of M sensors have to be considered. If N_{k+1} sensors are available for target tracking at time t_{k+1}, there are $C^M_{N_{k+1}}$ sensor combinations to be considered. To reduce the computation complexity of the above FIM-based sensor selection, the 'add one sensor node at a time' method can be used to select one sensor at a time by maximizing the determinant of the FIM [3].

4 Simulation results

We run Monte Carlo simulations to compare the performance of the proposed collaborative target tracking approach with FIM-based sensor selection, with two EKF-based tracking approaches with different sensor selection methods: 1) FIM-based sensor selection method calculated by EKF [23]; and 2) prediction nearest neighbor (PNN)-based sensor selection method in which the first M sensors nearest to the prediction of the target position, $(\hat{x}^1_{k+1|k}, \hat{x}^2_{k+1|k})$, are taken as the selected sensor. That is, the best set L of M sensors are selected according to the following iterative procedure: L is set to be an empty set first, i.e., $L = \varnothing$, then for $i = 1 : M$,

$$j_i^* = \arg \min_{j \in S_{k+1}} \sqrt{(x_j - \hat{x}^1_{k+1|k})^2 + (y_j - \hat{x}^2_{k+1|k})^2},$$
$$L = L \cup j_i^*,$$
$$S_{k+1} = S_{k+1} - \{j_i^*\},$$

where (x_j, y_j) is the coordinate of sensor j and S_{k+1} is the available sensor subset excluding the selected sensors.

As shown in Fig. 1, there are 100 sensors, denoted by circles, randomly and densely deployed in a $20\,\mathrm{m} \times 20\,\mathrm{m}$ region. We assume that all sensors in the network have the same sensing radius $r_s = 4\,\mathrm{m}$, and constant variance $\sigma^2 = 0.01$ for all sensory observations. A target moves through the surveillance region with a constant speed of $v = 1.2\,\mathrm{m/s}$ along a programmed trajectory from $(1.0, 1.0)$, as shown by the solid line in Fig. 1. The process noise w_k corresponds to the variable acceleration of the target at time instant t_k and is approximated by a white Gaussian sequence with zero mean and covariance matrix of $Q = \mathrm{diag}\{0.25, 0.25\}$. In the simulations the initial state estimate and the corresponding estimation error covariance matrix for all collaborative target tracking approaches are given as follows:

$$\hat{x}_{0|0} = [1.1 \;\; 0.7 \;\; 0.9 \;\; 0.3]^{\mathrm{T}}; \;\; P_{0|0} = 0.01 \cdot I_4,$$

where I_n is an $n \times n$ identity matrix. And we set $M = 4$, that is, 4 sensors are chosen from available sensors at every time instant.

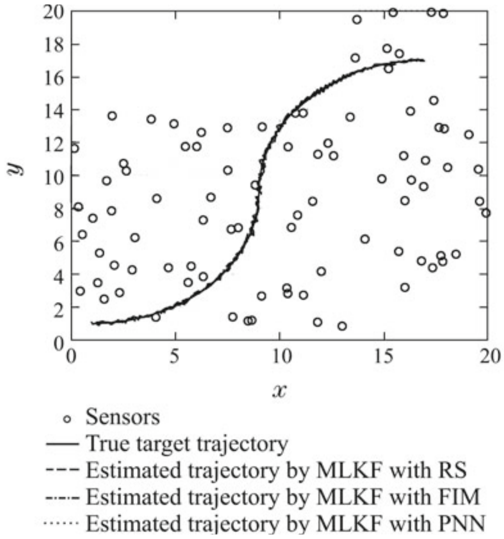

Fig. 1 True and estimated target trajectories using different tracking approaches with the different sensor selection methods.

The performance of the proposed tracking approach with FIM-based sensor selection is compared with the other two EKF-based target tracking with different sensor selection methods, in terms of the MSEs of the target state estimate. Fig. 1 shows a successful tracking process of our proposed collaborative target tracking approach with FIM-based sensor selection and the other two tracking ones. The solid line is the actual trajectory; the dashed line is the estimated trajectory using the tracking approach based on the EKF with FIM-based sensor selection, and the dashdot line is the estimated trajectory using our tracking approach with FIM-based sensor selection, the dotted line is the estimated trajectory using the EKF with PNN-based sensor selection. It demonstrates that our proposed tracking approach achieves more accurate tracking results than the other tracking approaches.

Figs. 2 and 3 show the mean square errors (MSEs) of the target position in x and y coordinates, respectively. They show that our proposed tracking approach with FIM-based sensor selection offers a significant error reduction for most of the tracking time compared to the other two tracking approaches based on the EKF with FIM-based sensor selection and PNN-based sensor selection, respectively. The MSE of the position estimate improves approximately by 10.97% using the proposed method compared to the EKF method with FIM-based sensor selection, and 70.71% compared to the EKF with PNN-based selection on X-coordinate, and 11.35% and 73.85% on Y-coordinate, respectively.

Moreover, we also compare the computation times of the three sensor selection methods. Our proposed sensor selection consumes about 0.307 microseconds, the EKF-based tracking approach with FIM-based sensor selection consumes about 0.562 microseconds, and the EKF-based tracking approach with PNN-based sensor selection consumes about 0.042 microseconds. Although the PNN-based sensor selection is faster than the other two selection methods, it has the poorest tracking performance. And our proposed sensor selection method is faster than the EKF-based tracking approach with FIM-based sensor selection, and also has higher tracking accuracy than the other two sensor selection methods.

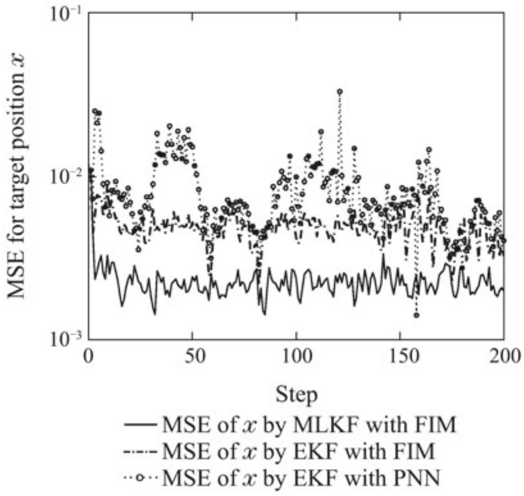

Fig. 2 Comparison of MSEs for the x coordinate of target position calculated using different tracking approaches with different sensor selection methods.

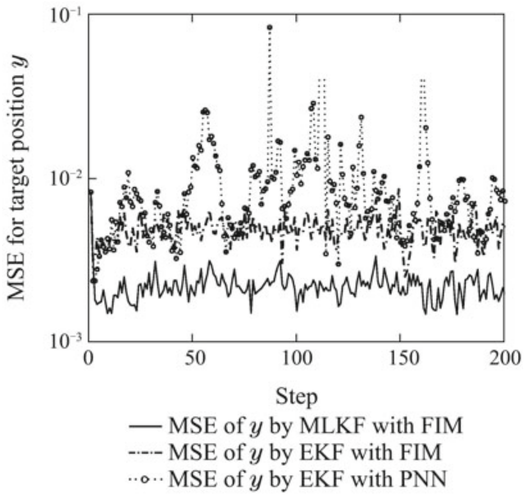

Fig. 3 Comparison of MSEs for the y coordinate of target position calculated using different tracking approaches with different sensor selection methods.

We further compare our proposed collaborative target tracking approach with FIM-based sensor selection to the target tracking approach without sensor selection in terms of the MSEs of the target position estimate. In our proposed tracking approach, only $4\,(M = 4)$ sensors (including the leader) are activated to sense, communicate and track the target, while in the optimal tracking approach without sensor selection, all available sensors along the target trajectory are utilized to track the target at each time instant. Figs. 4 and 5 show that the performance of the proposed collaborative tracking approach are less than that of the optimal tracking approach without sensor selection, while Fig. 6 shows that it uses less sensors than the optimal approach without sensor selection. Although the proposed collaborative tracking approach has larger MSE than the optimal tracking approach without sensor selection, it wake ups less sensors to track the target at every time instant, which will consumes less energy (In this paper, we assume that all sensors have the same energy consumption on sensing, data processing and communicating, thus, the tracking energy consumption is only related to the number of the activated sensors).

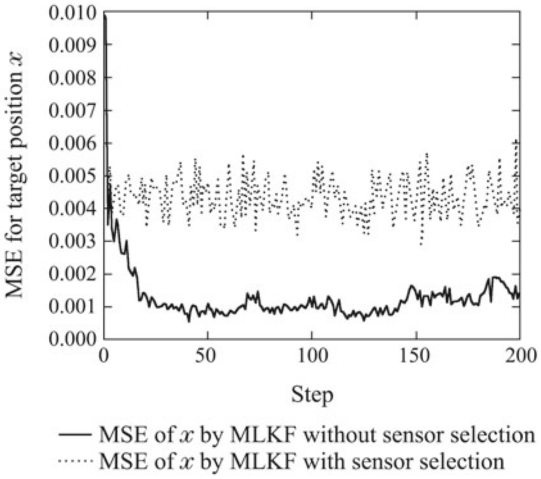

Fig. 4 Comparison of MSEs for the x coordinate of target position.

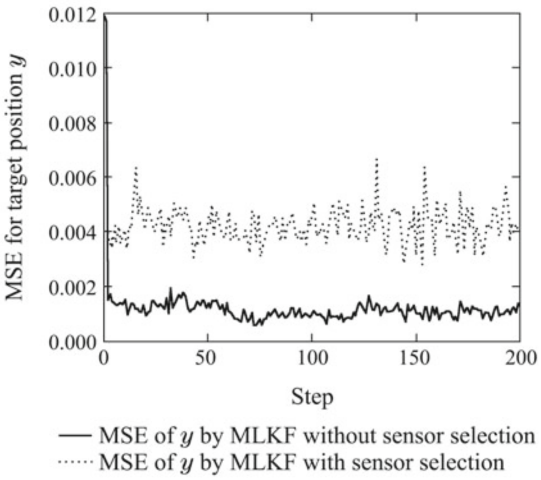

Fig. 5 Comparison of MSEs for the y coordinate of target position calculated.

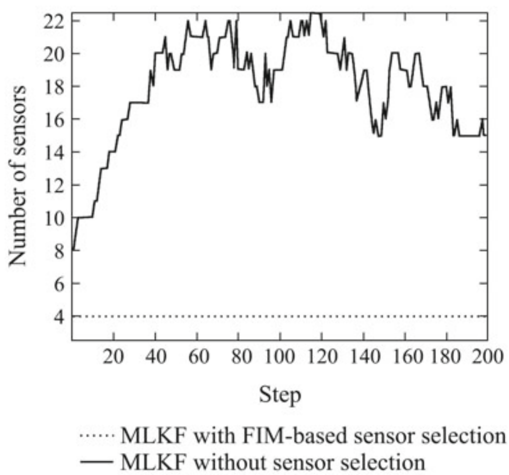

Fig. 6 Comparison of the number of activated sensors.

Fig. 7 illustrates the behavior of the proposed approach in MSE improves whenever M increases. As M increases, more sensors are selected to track the target, which will provide more information about the target state. In order to improve the tracking performance, more sensors along the trajectory can be selected to track the target, but will incur more energy consumption. Therefore, a tradeoff can be made between the tracking performance and the energy consumption of the network.

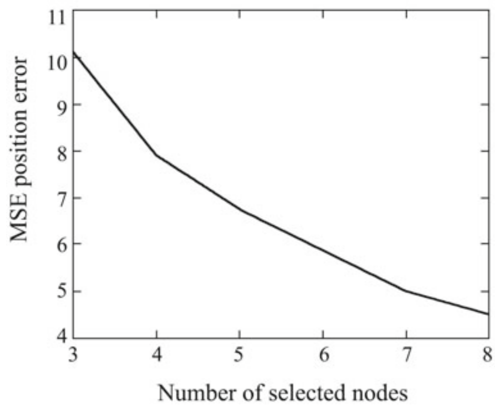

Fig. 7 Tracking performance comparison with respect to the number of selected sensors.

5 Conclusions

In this paper, we have presented a new collaborative target tracking approach in a wireless sensor network based on the combination maximum likelihood estimation and Kalman filtering, and Fisher information matrix-based sensor selection. The maximum likelihood estimator is used for prelocalization of the target and measurement conversion to remove the measurement nonlinearity. The converted measurement and its associated noise statistics are then used in a standard Kalman filter for recursive update of the target state. Finally, the sensors which collectively minimize the measure function established on the Fisher information matrix, are activated while other sensors are still in the idle state to conserve energy. The proposed approach is very simple and yet effective. Simulation results have shown that the proposed approach improve the tracking accuracy at the energy consumption constraints.

References

[1] I. Akyildiz, W. Su, Y. Sankarasubramaniam, et al. Wireless sensor networks: a survey. *Computer Networks*, 2002, 38(4): 393 – 422.

[2] C. Otto, A. Milenkovic, C. Sanders, et al. System architecture of a wireless body area sensor network for ubiquitous health monitoring. *Journal of Mobile Multimedia*, 2005, 1(4): 307 – 326.

[3] L. M. Kaplan. Global node selection for localization in a distributed sensor network. *IEEE Transanctions on Aerospace and Electronic Systems*, 2006, 42(1): 113 – 135.

[4] L. M. Kaplan. Local node selection for localization in a distributed sensor network. *IEEE Transanctions on Aerospace and Electronic Systems*, 2005, 42(1): 136 – 146.

[5] F. Zhao, J. Shin, J. Reich. Information-driven dynamic sensor collaboration for tracking applications. *IEEE Signal Processing Magazine*, 2002, 19(2): 61 – 72.

[6] M. Chu, H. Haussecker, F. Zhao. Scalable information-driven sensor querying and routing for ad hoc heterogeneous sensor networks. *The International Journal of High Performance Computing Applications*, 2002, 16(3): 293 – 313.

[7] W. Xiao, L. Xie, J. Chen, et al. Multi-step adaptive sensor scheduling for target tracking in wireless sensor networks. *Proceedings of International Conference on Acoustics, Speech, and Signal Processing*. New York: IEEE, 2006: 705 – 708.

[8] J. Lin, W. Xiao, F. Lewis, et al. Energy efficient distributed adaptive multi-sensor scheduling for target tracking in wireless sensor networks. *IEEE Transactions on Instrumentation and Measurement*, 2009, 58(6): 1886 – 1896.

[9] Y. Bar-Shalom, X. Li, T. Kirubarajan. *Estimation with Application to Tracking and Navigation*. New York: John Wiley & Sons, 2001.

[10] B. D. O. Anderson, J. B. Moore. *Optimal Filtering*. Englewood Cliffs: Prentice-Hall, 1979.

[11] S. J. Julier, J. Uhlmann. Unscented filtering and nonlinear estimation. *Proceedings of the IEEE*, 2004, 92(3): 401 – 422.

[12] X. Li, V. P. Jilkov. A survey of maneuvering target tracking – Part III: measurement models. *Proceedings of the SPIE Conference on Signal and Data Processing of Small Targets*. Bellingham: SPIE-International Society For Optical Engineering, 2001: 423 – 446.

[13] Z. Zhao, X. Li, V. P. Jilkov. Best linear unbiased filtering with nonlinear measurements for target tracking. *IEEE Transactions on Aerospace and Electronic Systems*, 2004, 40(4): 1324 – 1336.

[14] X. Wang, M. Fu, H. Zhang. Target tracking in wireless sensor networks based on the combination of KF and MLE using distance measurements. *IEEE Transactions on Mobile Computing*, 2012, 11(4): 567 – 576.

[15] X. Wang, H. Zhang, J. Xiang. Collaborative target tracking in WSNs based on maximum likelihood estimation and Kalman filter. *The 30th Chinese Control Conference*. Piscataway: IEEE, 2011: 4946 – 4951.

[16] X. Sheng, Y. Hu. Maximum likelihood multiple-source localization using acoustic energy measurements with wireless sensor networks. *IEEE Transactions on Signal Processing*, 2005, 53(1): 44 – 53.

[17] R. L. Moses, D. Krishnamurthy, R. Patterson. A self-localization method for wireless sensor networks. *EURASIP Journal on Applied Signal Processing*, 2003, 4: 348 – 353.

[18] T. Zhao, A. Nehorai. Information-driven distributed maximum likelihood estimation based on Gauss-Newton method in wireless sensor networks. *IEEE Transactions on Signal Processing*, 2007, 55(9): 4669 – 4682.

[19] N. Patwari, J. Ash, S. Kyperountas, et al. Locating the nodes: cooperative localization in wireless sensor networks. *IEEE Signal Processing Magazine*, 2005, 22(4): 54 – 69.

[20] G. E. Forsythe, M. A. Malcolm, C. B. Moler. *Computer Methods for Mathematical Computations*. Englewood Cliffs: Prentice-Hall, 1977.

[21] P. Tichavsky, C. H. Muravchik, A. Nehorai. Posterior Cramer-Rao bounds for discrete-time nonlinear filtering. *IEEE Transactions on Signal Processing* 1998, 46(5): 1386 – 1396.

[22] S. M. Kay. *Fundamentals of Statistical Signal Processing: Estimation Theory*. Englewood Cliffs: Prentice-Hall, 1993.

[23] L. Zuo, R. Niu, P. K. Varshney. Posterior CRLB based sensor selection for target tracking in sensor networks. *Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing*. Piscataway: IEEE, 2008: 1041 – 1044.

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