Estimate the Trajectory of Maneuvering Targets by Sensor Scheduling and Energy Efficient in Dynamic Sensor Networks

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Abstract—**An algorithm by combining sensor scheduling with energy efficient for tracking the maneuvering targets with mobile sensor deployed in WSNs (wireless sensor networks) is proposed and investigated in the article. In order to minimize the estimated error, the sensor sequence and the optimal sensor movement are scheduled previously and determined first. Moreover, due to the targets is varying with time the EKF (extended Kalman filtering) technique is applied to predict MSE (mean square error) of the predicted targets. Finally, simulation by using of the scenario with two maneuvering targets tracking held to validate the accuracy of the proposed algorithm.**

Index Terms—**wireless sensor networks; extended Kalman filtering; mean square error; maneuvering targets.**

I. Introduction

Recently based on several advantages, such as the low cost, the easily establishment, the capacity of self-organizing, and widely deployment, sensor networks become an important role for development or application in the real world. Especially, WSNs (wireless sensor networks) are able to the widely adopted in many directions, such as healthcare, control, military command, communications, and surveillance. Thus, to study issues of each layer about WSNs protocol in becoming gradually a kind of necessity, and those are including power consumption networking topology, signal processing, environment deployment, transmission Media, etc. It is known that in sensor networks the larger number of sensor nodes can provide with the more precise results to the BS (base station). However, in order to reduce the number of parameters for systems performance, to decrease sensor nodes in a good method. Moreover, the mobility of the sensor is also an important point can be applied to solve the problem of coverage hole exists in WSNs [1].

The impact factor of the sensing accuracy, it is with the number of cooperating local sensor nodes for a randomly deployed WSN is investigated in [2]. In [3], authors demonstrate an algorithm, called adaptive multi-sensor scheduling, to improve the tracking reliability and power efficient for collaborative target tracking in WSNs.

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With linear Gaussian dynamics in [4] the EKF (extended Kalman filtering) approach is applied to predict the estimated MSE (mean square error) of the target state by a default defined step ahead.

The particle swarm optimization in [5] is adopted to determine a sub-optimal sensor schedule with three noisy sensors, in order to minimize the measurement error and sensor usage coot. In paper [6] on the basis of a specified detection probability, authors propose a multi-sensor scheduling scheme for collaborative target tracking in WSNs. An IMM (interactive multiple model) filter based on collaborative maneuvering target tracking framework is presented in [7]. The scenario is incorporating a novel energy-efficient sensor scheduling scheme in a distributed WSN using low cost range wireless sensor nodes.

II. Problem Formulation

2.1 system models

The scenario of tracking maneuvering targets with mobile sensors in a 2-dimension Cartesian coordinate system is deployed in this subsection. The position and velocity states of the tracked target are included when the trajectory of targets is assumed going along with a maneuvering path. Additional, in order to manage all of the sensors, the states about the scheduled mobile sensor should be involved in the state space. For the purpose of estimating and predicting the state of both the sensor location and the target, the EKF technical is adopted to estimate the predict MSE (mean square error) of the estimated target states.

The maneuvering target is considered or nearly both constant velocity and constant angular rate within a sensor sampling duration. Then the system model can be established as follows, considering the system states arrangement of combing target state for the i-th sensor, $\mathrm{X}_i[k]$, with sensor states i-th, $S_i[k]$. Thus, the whole system state space model can be expressed as

$$A_g = \tan^{-1}\left[\left(X[k]-S_{X[k]}\right)/\left(Y[k]-S_{Y[k]}\right)\right]$$

$$\mathrm{X}_i[k+1] = \omega_i[k] + G_i[k] + F_i \mathrm{X}_i[k] \qquad (1)$$

where $\omega_i[k]$ is a zero mean Gaussian white noise with variance $Q_i[k]$, where $Q_i[k] = \begin{bmatrix} Q & 0 \\ 0 & M_I \end{bmatrix}$, with the error covariance matrix M_i, movement matrix

$G_i[k] = \left[D_i\left[k\right] \quad 0 \quad 0 \quad 0 \quad 0 \right]$, transition matrix $F_i = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & \Delta T & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$, and $\mathrm{X}_i[k] = \left\{ S_i[k] \cdot \mathrm{X}[k] \right\}^T$,

where

$$\mathrm{X}[k] = W[k] + F \cdot \mathrm{X}[k-1] \tag{2}$$

, and

$$S_i[k] = M_i[k] + A_i[k] + S_i[k-1] \tag{3}$$

A target evolve with linear Gaussian dynamic equation is denoted in (1), and alternates after each time step ΔT, $W[k]$ is considered to be the white Gaussian process noise with covariance matrix Q, that is, $W[k] \sim N(0,Q)$. The well known system state kinematics are characterized by the system matrix and written as $F = \begin{bmatrix} 1 & \Delta T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta T \\ 0 & 0 & 0 & 1 \end{bmatrix}$.

In (3), where $M_i[k]$ indicates the uncertainty of the mobility for a scheduled sensor, it is assumed that $M_i[k]$ is modeled as Gaussian distribution with zero mean and M_i variance, that is, $M_i[k] \sim N(0, M_i)$; $A[k]$ expresses the movement (upward downward, right, and left directions) controlled by commands from central the base station, and $S_i[k-1] = \left[S_i^x[k] \; S_i^y[k] \right]$ denotes the position of the i-th sensor at the instant step $k-1$. In order to build up the estimation scheme with sensor scheduling, the sensor observation model for the scheduled i-th sensor at the k-th time step can be obtained as

$$Z_i[k] = v_i[k] + h_i(Z[k]) \tag{4}$$

where $v_i[k]$ is the measurement noise for the i-th sensor and it is adopted as independent of the other sensors, $v_i[k]$ is assumed modeled as Gaussian process with zero mean and R_i variance, and $h_i\left(\mathrm{X}[k]\right) = [P_s \; V_l \; A_g]^T$, where $P_S = \sqrt{\left[\left(X[k] - S_{X[k]} \right)^2 + \left(Y[k] - S_{Y[k]} \right)^2 \right]}$, $V_l = \left\{ X[k] \cdot \left(X[k] - S_{X[k]} \right) + Y[k] \cdot (Y[k] - S_{Y[k]}) \right\} / P_S$, and $A_g = \tan^{-1}\left[\left(X[k] - S_{X[k]} \right) / \left(Y[k] - S_{Y[k]} \right) \right]$.

2.2 Tracking with EKF

On the basis of system state space model shown in (1), the signal target tracking problem select one sensor for detection and bringing up measurements at each time step is completed by the EKF algorithm. Firstly, assume that the location of manageable sensors is known a prior and all of them are stationary. The predicted state $\hat{\mathrm{X}}[k+1|k]$ of the target at time $k = 1, ..., \Delta T$ can be determined as

$$\hat{\mathrm{X}}[k+1|k] = F_i[k] \cdot \hat{\mathrm{X}}[k|k] \tag{5}$$

where $F_i[k]$ is shown in (2), and it is given that the estimate $P[k+1|k+1] = P[k+1|k] - K[k+1] \cdot S[k+1] K^T[k+1]$ of $\mathrm{X}[k]$ at the k-th time step with covariance $P[k|k]$. Certainly, the initial state of the system and initial error covariance are given and with $X_i[0]$ and $P[0]$, respectively. Next, the covariance of predicted state becomes as

$$\begin{aligned} P[k+1|k] &= F_i[k] \cdot P[k|k] \cdot F_i^T[k] + Q[k] \\ &= E\left\{ \begin{aligned} &\left(\mathrm{X}_i[k+1] - \hat{\mathrm{X}}_i[k+k|k] \right) \\ &\left(\mathrm{X}_i[k+1] - \hat{\mathrm{X}}_i[k+k|k] \right)^T | Z[k+1|k] \end{aligned} \right\} \end{aligned} \tag{6}$$

, and the predicted measurement of selected sensor is calculated as

$$\hat{Z}[k+1|k] = H(\mathrm{X}[k+1|k]) \tag{7}$$

Hence, the innovation now is given as

$$r[k+1] = Z[k+1] - \hat{Z}[k+1|k] \tag{8}$$

, and with the predicted error covariance of the measurement is denoted as

$$S[k+1] = H[k+1] P[k+1|k] H^T[k+1] \tag{9}$$

where the Jacobian matrix of the measurement function H at time step $t[k+1]$ corresponds to the predicted state is represented as

$$H[k+1] = \frac{\partial}{\partial \mathrm{X}[k]} h\left(\mathrm{X}[k+1|k] \right) \tag{10}$$

The EKF Kalman gain is updated with the equation given as

$$K[k+1] = P[k+1|k] \cdot H^T[k+1] \cdot S^{-1}[k+1] \tag{11}$$

Now, by using of the EKF gain obtained in previous equation and the innovation in (8), the state estimation of the target shown in (5) is updated as

$$\hat{\mathrm{X}}[k+1|k+1] = \hat{\mathrm{X}}[k+1|k] + k[k+1] \cdot r[k+1] \tag{12}$$

Therefore the covariance matrix or MSE in (6) can be modified as

$$\begin{aligned} &P[k+1|k+1] = \\ &P[k+1|k] - K[k+1] \cdot S[k+1] K^T[k+1] \end{aligned} \tag{13}$$

For the purpose of discussing the coverage hole problems, which means that the measurement of the target can not be reported from the selected sensor due to the target locates at the ambiguous area. In the case, the MSE of the estimated state is increasing accumulative.

III. MANAGEMENT OF MOBILE SENSORS SELECTION

It should be an important event to address the problem of the expression in Eq. (1) of mobile sensor selection while. Large number of sensor with the mobility to generate high quality outcome is required. An algorithm for the management of mobile sensor selection is proposed in this section. It is assumed that each sensor deployed in this algorithm can make the decided results range and detect the target. The location of the selected sensor is also given determined previously, and the algorithm is able to simply select the sensor modes closest to the predicted target location. Generally, the management of mobile sensor selection includes determination of sensing accuracy, sensor scheduling and sensor movement sequence one of the drawback of the closest sensor node of the sensor scheduling algorithm is that it is only simply to select the scheduled sensor node, however, the contribution of the tracking accuracy is also will be one of the most important quantity candidate for the selected sensor node. An adaptive algorithm of mobile sensor management is proposed under the EFK by externally selecting the next scheduling sensor and determining best accuracy at the same time for mobile sensor tracking system.

Now, according to the state estimation, there are several measurements can be applied to represent the tracking accuracy by mobile sensors, such as the fisher information, the trace and the determinant of the covariance matrix, eigenvalues calculated from the covariance matrix of the state between the desired and the predicted value. On the basis of the Cartesian coordinate system, at time step k the tracking accuracy, $A[k]$, can be defined as the difference between the actual states, $X[k]$, and the estimate states, $\hat{X}[k]$, that is, $A[k]=\left|\hat{X}[k]-X[k]\right|$ where $X[k]$ and $\hat{X}[k]$ are defined in (1) and (5), respectively. The tracking accuracy is considered to cope with the prediction values at the k-th step while $A[k]\le A_{TH}[k]$, where $A_{TH}[k]$ is a pre-defined threshold value of the tracking. Sensor scheduling is an others issue for mobile sensor management. Now, assume that

$$I[k+T]=\left\{\begin{bmatrix} I_1[k+1] \\ I_2[k+1] \\ \vdots \\ I_N[k+1]\end{bmatrix}\cdots\begin{bmatrix} I_1[k+T] \\ I_2[k+T] \\ \vdots \\ I_N[k+T]\end{bmatrix}\right\} \tag{14}$$

, and

$$L[k+T]=\left\{\begin{bmatrix} L_1[k+1] \\ L_2[k+1] \\ \vdots \\ L_N[k+1]\end{bmatrix}\cdots\begin{bmatrix} L_1[k+T] \\ L_2[k+T] \\ \vdots \\ L_N[k+T]\end{bmatrix}\right\} \tag{15}$$

indicates the sensor scheduling sequence and sensor movement sequence at any given time step k by T steps ahead, respectively. The $I[k+t]$ and $L[k+t]$ in (14) and (15) denote the selected sensor and the optimal movement at the $(k+t)$ -th time instant, respectively, $L_i[k]$ is the sensor movement belongs to $F_i[k]$, and $I_i[k]$ in (14) is assigned as the probability value with the expression shown as

$$I_i[k]=\begin{cases}\text{Probability } 0, \text{ if sensor } I \text{ is not scheduled at time step } k \\ \text{Probability } 1, \text{ if sensor } I \text{ is scheduled at time step } k\end{cases}$$

Once, the arrangement of sensor scheduling and sensor movement is accomplished. The calculation of the cost function is followed up and it is determined by the energy consumption. The total energy consumed by current selected sensor u with selecting sensor v as the scheduled for the next tracking tack is able to be obtained as

$$E_T[u,v]=\sum_{t=1}^{T}(e_{t,t}+e_{r,t}/r_{uv}^{\alpha})\cdot b_t \tag{16}$$

where b_t is the number of bits for transmission, α denotes the time-invariant channel model of the transmission, r_{uv} indicates the distance between the u-th and the v-th sensor, and $e_{t,t}$ and $e_{r,t}$ denote the required energy specified by the transmitter and the receiver of the scheduled sensor, respectively. Hence, the energy consumed in sensing and/or processing data with b_t bits by sensor u is $E_{sen,\,t}(u)=b\cdot e_{sen,\,t}$, and the energy consumed in the receiving data is $E_{r,\,t}(u)=b\cdot e_{r,\,t}$. Thus, the total energy consumed during T time steps is constrained as

$$E_T=E_T[u,v]+\sum_{t=1}^{T}[E_{r,t}(u)+E_{sen,t}+E_{M,T}(u)] \tag{17}$$

where $E_{M,T}(u)$ expresses the consumed energy for the sensor movement in each $K+T$ time step. The total amount of energy available for T time step is assumed by a threshold value E^{Th}.

IV. Simulation Results

Developing simulation programs (using Matlab @) by virtue of the proposed algorithm is implemented in this subsection. The developed algorithm associating with sensor scheduling combining with energy efficient is first validated in an environment wherein two maneuvering targets are tracked in WSN deployments, which is shown in Fig. 1. The initial conditions for simulating the tracking of two targets are listed in Table I, mentioned here mainly for demonstrating the accuracy and efficiency of the proposed algorithms.

The transition matrix $F(k)$ has been considered in subsection 2.1, and the noise gain matrix , which is defined as $G(k)=\begin{bmatrix} T^2/2 & 0 \\ T & 0 \\ 0 & T^2/2 \\ 0 & T\end{bmatrix}$, corresponds to the target is assumed in the simulation to be two seconds. The initial value of the state error covariance is assumed to default as $P(0\,|\,0)=\begin{bmatrix} 10000 & 100 & 0 & 0 \\ 0 & 100 & 100 & 0 \\ 0 & 0 & 10000 & 100 \\ 0 & 0 & 100 & 100\end{bmatrix}$.

After the assignment of initial conditions is completed, the procedure of the simulation is following steps illustrated below:.

1. *Initial conditions assignment,* $F(k)$, $G(k)$, $P(0\,|\,0)$ *and step numbers.*
2. *Make true target system and measurement model.*
3. *CHNN calculation for each target according to the process shown in section III.*
4. *Estimation procedures (with the EKF and sensor*

scheduling algorithm).

5. *The average error determination, i.e.. the difference between the estimation and the measurement.*
6. *End of the procedure.*

The result from tracking two targets with the proposed algorithm is illustrated in Fig. 2. In these simulations fifty steps Monte Carlo are implemented; moreover, with the different symbol estimated tracking (measurements) with energy efficient calculation are sampled for reciprocal comparison for accuracy. It is easy to see that the many more matching situations occur in Fig. 2. I.e., all of the tracking paths tightly parallel the true path marked with circle symbols. It should be emphasized that a little difference does exist the paths of the true targets and the results presented in Fig. 2, since the tracking is generated with a random function of the software program. Usage of random-number generators for the measurement of noise and clutter points is illustrated in the simulation. Furthermore, a EKF is utilized to recursively estimate the state vector $\hat{X}(k|k)$. On the basis of each hypothesis formulated from the measurement data received, the corresponding correlations can be promptly calculated. Hence, the accumulate position errors caused by the use of this proposed algorithm are plotted in Fig. 3. It is reasonable to state that the larger position error occurs in the case of tracking for target_ B, it is because of the much more variety induced by the setting of that target. On the other hand, the accumulate speed error is presented in Fig. 4. Since the speed initial value of the X-axis and Y-Ax setting for target_B is much faster than that for target_A, it is significantly to see the accumulated speed error of target_B is much more than that of target_A after about eighteenth step.

V. Conclusion

In this paper an algorithm of combining the sensor scheduling with energy efficient for the mobile sensor to track maneuvering targets is proposed. By taking the Monte Carlo simulation to verify the accuracy of the proposed algorithm, there are two maneuvering targets considered tracked by adopting the method proposed in this paper. The mobile sensors are randomly distributed in the scenario of the simulation. Thus, the EKF can be applied to estimate the predicted MSE of the estimated target state. On the other hand, the decision of optimal sensor path and the determination of the schedule of sensor sequence could minimize the predicted estimation error caused by tracking the maneuvering targets.

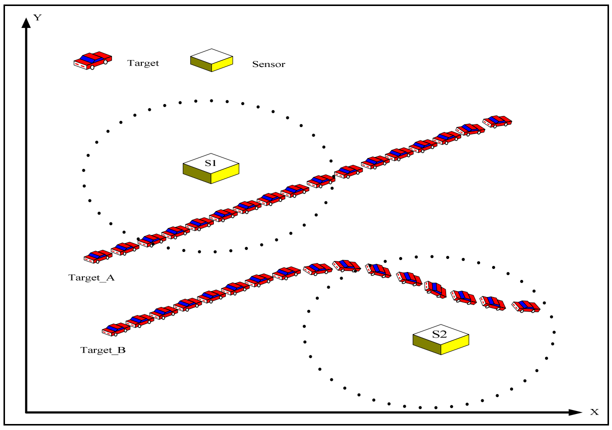

Fig. 1 Deployment with two targets and two mobile sensor nodes with sensing areas covered in circles

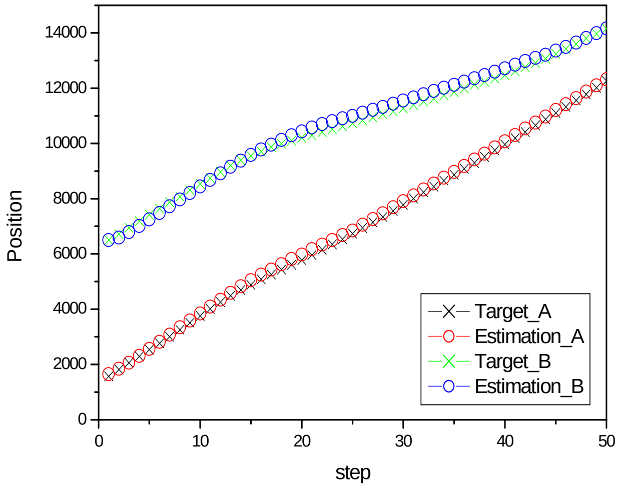

Fig. 2 Results with two mobile sensors for tracking two maneuvering targets

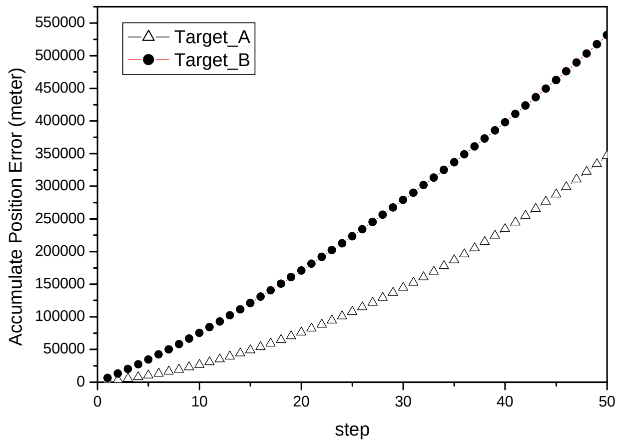

Fig. 3 Accumulate position error of the distance with two mobile sensors for tracking two maneuvering targets

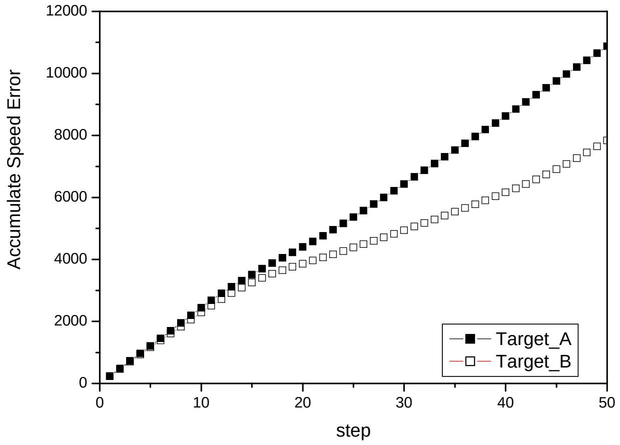

Fig.4 Accumulate speed error of two mobile with two mobile sensors for tracking two maneuvering targets

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