Estimate to the Trajectory of Maneuvering Targets by Combining Sensor Scheduling with Energy Efficient in WSNs

Joy Iong-Zong Chen, Chih-Chung Yu

***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 to investigate the tracking performance in the article. In order to minimize the estimated error, the sensor sequence and the optimal sensor movement are scheduled previously and determined first. Thus, the sensor scheduling is depending on the results from the evaluation of energy efficient of a sensor node. Moreover, due to the targets is varying with time in the estimation process the EKF (extended Kalman filtering) technique is applied to predict MSE (mean square error) of a predicted target. Finally, simulations by using of the scenario with two and four maneuvering targets tracking are held to validate the accuracy of the proposed algorithm, and the results definitely show the fact that the MSE will decrease when the right way of the sensor scheduling is arranged previously.

***Keywords*—**EKF (extended Kalman filtering), maneuvering targets, MSE (mean square error), WSNs (wireless sensor networks).

I. Introduction

Recently, on the basis of 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. Accordingly, l ot of applications developed based on the WSNs techniques will make much change of the human being life in the future. Thus, to study issues of each layer about WSNs protocol in becoming gradually a kind of necessity, especially in the physical layer of the WSNs [1]. Certainly, the widely research field of the WSNs technologies 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 paved in the application environment can provide with the more precise results to the BS (base station), where can be called as a service center or just a server. However, in order to reduce the number of parameters for systems performance, to decrease sensor nodes in a good method. For the purpose of increasing the performance of a special purpose of a WSNs, there are some of the trade-off should be make decision. Such as the accurate date of the event reported from sensors, when to complete the data fusion between the sensor nodes, how to locate the position of a sensor, and how to prolong the sensor's lifetime and so on [2]. Recently, there are a lot of research papers are published. 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 [3]. In [4], the authors demonstrate an algorithm, called adaptive multi-sensor scheduling, to improve the tracking reliability and power efficient for collaborative target tracking in WSNs. With linear Gaussian dynamics in [5] 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. In [6], there is localization and motion analysis parameter estimation algorithm in mobile WSN by using pseudo-linear-Kalman filtering MLE (maximum likelihood estimator) and EKF technique is proposed. The mobility of the sensor is also an important point can be applied to solve the problem of coverage hole exists in WSNs [7]. The particle swarm optimization in [8] 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 [9] 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 [10], in which the scenario is incorporating a novel energy-efficient sensor scheduling scheme in a distributed WSN using low cost range wireless sensor nodes.

On the basis of the results from aforementioned publications, in which most of them reported the evaluation for a non-mobility target (event), in this paper we propose an algorithm by combining sensor scheduling with energy efficient for tracking the maneuvering targets with mobile sensor deployed in WSNs, that is, (1) targets are considered as varied with time, (2) the mobile sensors are following up a sensor scheduling procedure previously according to the energy stored in a sensor node consumed away in the duration of an event, and (3) the EKF filtering is adopted as an algorithm for the

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surveillance process. The remainder of this report is organized as follows. The system models of a 2-dimension Cartesian coordinate system are described in section 2. Management of mobile sensors selection is shown in section 3. The results from numerical simulation are discusser in section 4 and a brief conclusion stated in section 5.

II. PROBLEM FORMULATION

A. 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, all states about the scheduled mobile sensor should be involved to calculate 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

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

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 $G_i[k] = \begin{bmatrix} D_i[k] & 0 & 0 & 0 & 0 \end{bmatrix}$, 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

$\mathrm{X}_i[k] = \{S_i[k] \cdot \mathrm{X}[k]\}^T$, 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 evolves 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, $M_i[k] \sim N(0, M_i)$; $A_i[k]$ expresses the movement (upward downward, right, and left directions) controlled by commands from central the base station, and $S_i[k-1] = \left[S_i^x[k-1]\ S_i^y[k-1] \right]$ 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

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

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 $h_i(\mathrm{X}[k]) = [P_s\ V_l\ A_g]^T$, 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 $A_g = \tan^{-1}\left[\left(X[k] - S_{X[K]} \right) / \left(Y[k] - S_{Y[k]} \right) \right]$, respectively.

B. 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 $P[k+1|k+1] = P[k+1|k] - K[k+1] \quad \times S[k+1] K^T[k+1]$ 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 with $X_i[0]$ and $P[0]$, respectively. Next, the covariance of predicted state becomes as

$$P[k+1 \mid k] = F_i[k] \cdot P[k \mid k] \cdot F_i^T[k] + Q[k]$$
$$= E\left\{ \begin{array}{l} \left(\mathrm{X}_i[k+1] - \hat{\mathrm{X}}_i[k+k \mid k] \right) \\ \left(\mathrm{X}_i[k+1] - \hat{\mathrm{X}}_i[k+k \mid k] \right)^T \mid Z[k+1 \mid k] \end{array} \right\} \quad (6)$$

where $E[\cdot]$ denotes the mean operator, and the predicted measurement of selected sensor is calculated as

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

Hence, the innovation now is given as

$$r[k+1] = Z[k+1] - \hat{Z}[k+1 \mid k] \quad (8)$$

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

$$S[k+1] = H[k+1] P[k+1 \mid k] H^T[k+1] + R_i \quad (9)$$

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

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

The EKF Kalman gain is updated with the equation given as

$$K[k+1] = P[k+1 \mid k] \cdot H^T[k+1] \cdot S^{-1}[k+1] \quad (11)$$

Now, by means 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

$$\hat{\mathrm{X}}[k+1 \mid k+1] = \hat{\mathrm{X}}[k+1 \mid k] + K[k+1] \cdot r[k+1] \quad (12)$$

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

$$\begin{array}{l} P[k+1 \mid k+1] = \\ P[k+1 \mid k] - K[k+1] \cdot S[k+1] K^T[k+1] \end{array} \quad (13)$$

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 such case, the MSE of the estimated state is going to increase accumulatively.

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 [11]. 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 the other interesting issue for mobile sensor management. Now, assume that

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

, and

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

indicate 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, $L_i[k]$ in (15) 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 [12, 13]

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

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 evaluated as

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

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

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

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 and Discussion

Developing simulation programs (using Matlab[@]) by virtue of the proposed algorithm is implemented in this subsection [14].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 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 and expressed consider 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).Mobile sensor selection 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 mobile sensor is assumed can be controlled by some commands from a control center, then it can move to four directions, those are, upward, downward, right, and left. The conditions of the mobile sensor are set as follows, $A[k] = \begin{bmatrix} 0\ m \\ 150\ m \end{bmatrix}$ is for going to upward direction, $A[k] = \begin{bmatrix} 0\ m \\ -250\ m \end{bmatrix}$ is for going to downward direction, $A[k] = \begin{bmatrix} 150\ m \\ 0\ m \end{bmatrix}$ is for turning to right direction, and $A[k] = \begin{bmatrix} -150\ m \\ 0\ m \end{bmatrix}$ is for turning to left direction.The result from tracking two targets and four targets with the proposed algorithm is illustrated in Fig. 2 and in Fig. 5, respectively. 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 purpose. 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. It is easy to see that the much more match 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 for target_A and target_B are presented in Fig. 4. Since the speed initial value of the X-axis and Y-axis 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. Without loss of the generality, results of tracking path for 4 targets with 4 mobile sensors are shown in Fig. 5, where the distance error of the four targets is revaled. The initial conditions for being adopted to do this simulation are presented in Table II (by taking the initial values of target_A to target_D). The case for all of the tracking paths tightly parallel the true path marked with circle symbols can be captured and illustrated same as that shown in Fig. 2. It is reasonable to see that the much faster initial speed of target_B is set up, the much steep path of it is. By the way, accumulated distance errors for tracking to four targets and position errors calculated with MSE are plotted in Fig. 6, and Fig. 7, respectively. In Fig. 6 the steps number versus accumulate distance error is shown for the estimated four targets with four mobile sensors. Wherein the accumulate distance error is growing for the target_B after the 44th step, this is due to the initial value of the speed for target_B is much larger then the other three. By following up the same way, the distance error, the accumulate distance error and the MSE values for the tracking of five targets are illustrated in Fig. 8, Fig. 9 and Fig. 10, respectively, and the initial conditions of the five targets are presented at Table III. Moreover, results from tracking to the case with larger number of targets, that is, for tracking seven targets are shown in Fig. 11 and the initial conditions is described in Table IV. This is just for making sure that the algorithm proposed in this paper able to be approved by tracking large number of targets too. It is obviously to understand that there are few differences exist between the results from tracking to four targets and that of to five targets. Furthermore, it is easily to state that the larger position error is mainly generated by the reason which is due to the quickly variation of the target. On the other hand, under the same usage of mobile sensors, the much maneuverability of the target is caused much more estimate error. However, since the sensor scheduling is proposed to joint into this algorithm, the accurate estimate of the targets can be hold closely.

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. This tracking technique has been investigated for its advantages in choosing an optimal correlation between mobile sensor measurements and existing target tracks. Moreover, an adaptive procedure for tracking maneuvering targets is also employed in this algorithm. On the basis of the simulation results obtained in this study, it can be claimed that this algorithm is capable of obtaining the optimal correlations between true targets and mobile sensor measurements in WSN scenarios. Finally, the approach developed in this research has demonstrated not only stable performance for tracking procedures but definitely also excellent efficiency when tracking both constant velocity and maneuvering targets.

The proposed algorithm might have a hardware complexity (number of neurons) in direct linear proportion to the number of tracked targets and the deployed mobile sensors in WSNs. Moreover, tracking for targets with mobile sensors by using the proposed algorithm in WSNs is constrained by the requirement for training the mobile sensor nodes. However, it can be thoroughly implemented in analog VLSI technology with currently existing methods. Therefore, the authors believe that, overall, since it is based in multi-mobile sensor tracking environments, one may expect to see many such applications in WSN constructions in the near future. Furthermore, although in this type of environment the size of the optimization problem requiring much attention is considerably larger, the proposed algorithm performs quite well, as in the simulation illustration. This is probably due to a sparse assumption of fewer tracked targets. However, the scale would be required for the implementation of a practical mobile sensor might become a problem when the number of sensors and the measurements become very large. A current issue for development is reduction of the scale of the quadratic optimization problem that must solve, so that available analog IC (integrated circuit) implementation can be used to build practical mobile sensors. Besides, the trends for implementing the WSN in large scale network are generally to distribute the fused-data in some small area networks separately. Finally, since the amount of energy consumed by a mobile sensor during the processing is large, such consumption is another important issue. Recently, several methods have been proposed for investigating energy-awareness problems in the mobile sensors in WSNs [15]. The authors are currently working on developing a method for decreasing energy consumption by a mobile sensor so that the lifetime of sensors in WSNs can be increased.

REFERENCES

[1] G. J. Pottie, “Wireless Sensor Networks,” IEEE Transactions on Information Theory, pp. 139-140, June 1998.

[2] A. –P. Ruth, et al. “Multisensor Data Fusion Schemes for Wireless Sensor Networks”, IEEE International Conf. on Application-Specific Systems, Architectures and Processors (ASAP) 2007, pp.136-141.

[3] X. Wang, D. Wang, Y. Wang, D. P. Agrawal, and A. Mishra, "On Data Fusion and Lifetime Constraints in Wireless Sensor Networks," IEEE International Conference on Communications, ICC' 07, 24-28 June 2007, pp.3942-3947.

[4] J. Lin, F. Lewis, W. Xiao, and L. Xie, "Accuracy Based Adaptive Sampling and Multi-Sensor Scheduling for Collaborative Target Tracking," The 9th International Conference on Control, Automation, Robotics and Vision, ICARCV '06, Dec. 2006, pp. 1-6.

[5] S. Maheswararajah, S. Halgamuge, "Mobile Sensor Management for Target Tracking," The 2nd International Symposium on Wireless Pervasive Computing, (ISWPC '07), Feb. 2007, pp. 506-510.

[6] S. Li, D. Zhang, Z. Yang, N. Chang, “A Novel Algorithm for Node Localization and Motion Analysis in Wireless Sensor Networks,” Proceeding of the 2006 IEEE International Conf. on Automation Science and Engineering, Shanghai, China, Oct. 7-10, 2006, pp. 574-579.

[7] W. Xiao, L. Xie, J. Lin, J. Li, "Multi-Sensor Scheduling for Reliable Target Tracking in Wireless Sensor Networks," ITS Telecommunications Proceedings, 2006 6th International Conference on, June 2006, pp. 996-1000.

[8] S. Maheswararajah, S. Halgamuge, "Sensor Scheduling for Target Tracking Using Particle Swarm Optimization," The 63rd IEEE Vehicular Technology Conference, VTC 2006-Spring, vol. 2, pp. 573-577.

[9] S. Zhang, W. Xiao, M. H. Ang, and C. K. Tham, "IMM Filter Based Sensor Scheduling for Maneuvering Target Tracking in Wireless Sensor

Networks," Intelligent Sensors, Sensor Networks and Information, 2007, 3rd International Conference on, ISSNIP 2007, pp. 287-292.
[10] X. Shan., and J. Tan, "Mobile Sensor Deployment for a Dynamic Cluster-based Target Tracking Sensor Network". IEEE/RSJ International Conference on Intelligent Robots and Systems, 2005. (IROS 2005), pp. 1452-1457.
[11] F. Zhao, L. J. Guibas, Wireless Sensor Networks, an Information processing Approach, Elsevier (Singapore) Pte Ltd, 2004.
[12] Y. He, and Edwin. K. P. Chong, "Sensor Scheduling for Target Tracking in Sensor Networks," 43th Ed. IEEE conference on Decision and Control, Atlanties, Dec. 2004, pp. 743-748.
[13] J. Evans, V. Krishnamurthy, "Optimal Sensor Scheduling for Hidden Markov Models," Acoustics, Speech and Signal Processing, 1998. Proceedings of the 1998 IEEE International Conference on, vol. 4, May 1998, pp. 2161-2164.
[14] Grewal M.S., and Andrew A. P.: 'Kalman Filtering, Theory and Practice-Using MATLAB, 2nd ed.', John Wiley & Sons, Inc., New York 2001.
[15] Wang X., Wang D., Wang Y., Agrawal, D.P., and Mishra, A.: 'On data fusion and lifetime constrains in wireless sensor networks', Proc. IEEE Int. Commun. Conf., Glasgow, Scotland, vol. 9, June 2007, pp. 3942-3947.

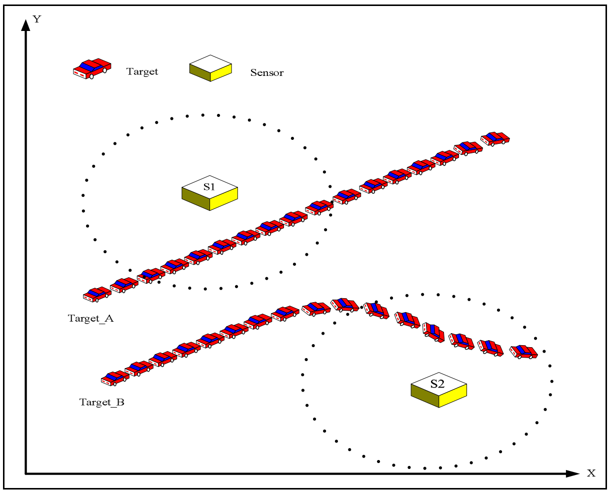

Fig. 1 Deployment with two targets and two mobile sensor nodes with sensing areas covered in circles.

Table I. Initial conditions of two tracked targets

	X_axis (*m*)	*Y_axis* (*m*)	$\dot{X}$_axis (m/s)	$\dot{Y}$_axis (m/s)
Target_A	1005	1019	230	111
Target_B	4523	4677	214	120

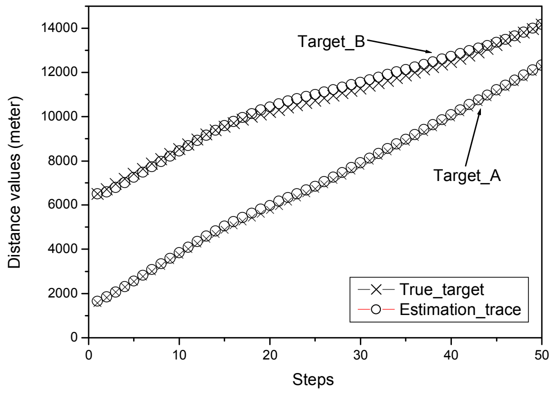

Fig. 2 Results with two mobile sensors for tracking two maneuvering targets

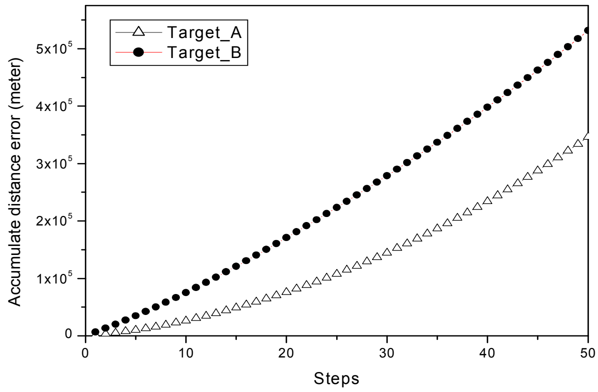

Fig. 3 Accumulate position error of the distance with two mobile sensors for tracking two maneuvering targets

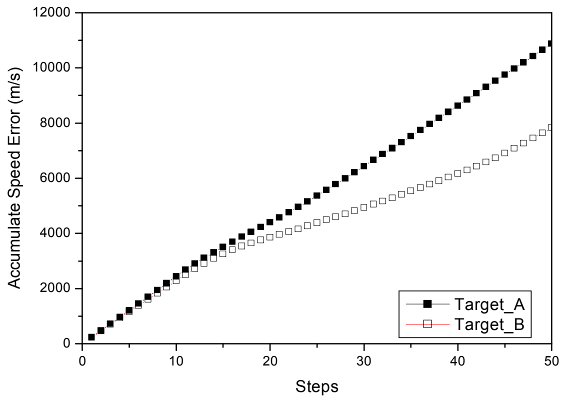

Fig. 4 Accumulate speed error of two mobile sensors for tracking two maneuvering targets

Table II. Initial conditions of four tracked targets

	X_axis (m)	Y_axis (m)	$\dot{X}$_axis(m/s)	$\dot{Y}$_axis(m/s)
Target_A	1500	1500	50	110
Target_B	2500	2500	500	100
Target_C	4000	4050	100	140
Target_D	6000	6005	290	150

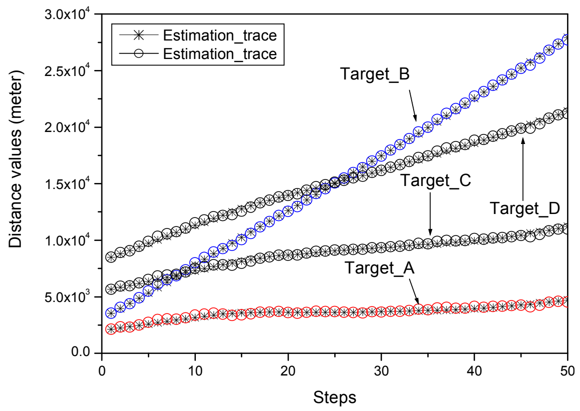

Fig. 5 Results with four mobile sensors for tracking four maneuvering targets

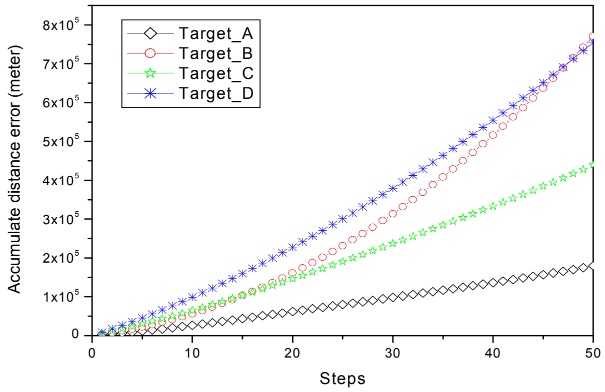

Fig. 6 Accumulate distance error of the distance with four mobile sensors for tracking four maneuvering targets

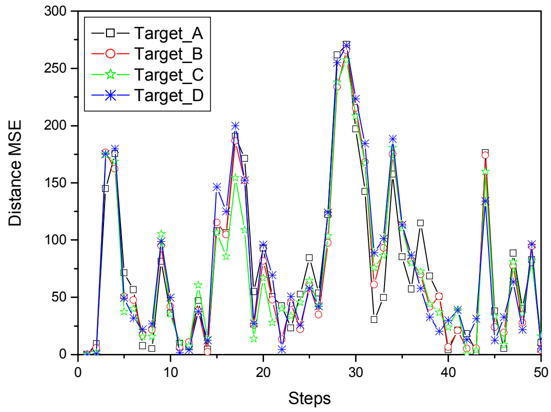

Fig. 7 MES of the distance with four mobile sensors for tracking four maneuvering targets

Table III. Initial conditions of five tracked targets

	X_axis (m)	Y_axis (m)	$\dot{X}$_axis (m/s)	$\dot{Y}$_axis (m/s)
Target_A	100	100	20	100
Target_B	1500	1500	50	110
Target_C	2500	2500	500	100
Target_D	4000	4050	100	140
Target_E	6000	6005	290	150

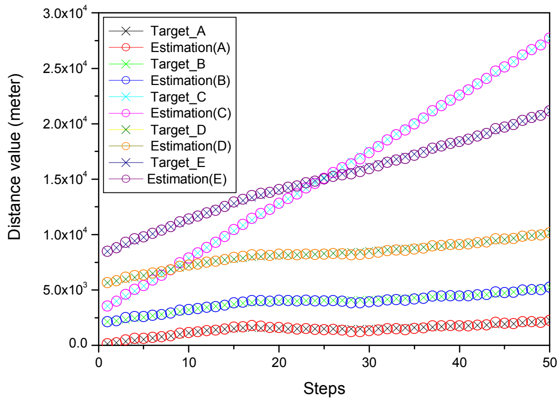

Fig.8 Results with four mobile sensors for tracking five maneuvering targets

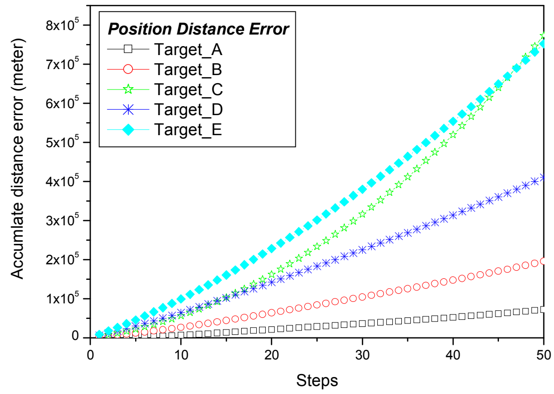

Fig. 9 Accumulate distance error of the distance with four mobile sensors for tracking five maneuvering targets

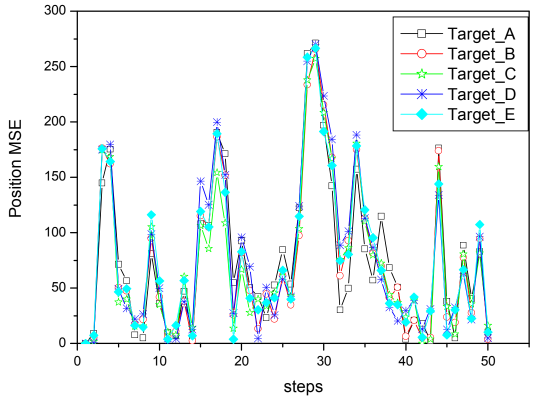

Fig. 10 MES of the distance with four mobile sensors for tracking four maneuvering targets

Table IV. Initial conditions of seven tracked targets

	X_axis (*m*)	*Y_axis* (*m*)	$\dot{X}$*_axis* (*m/s*)	$\dot{Y}$*_axis* (*m/s*)
Target_A	1000	1000	100	110
Target_B	2500	2500	122	120
Target_C	3500	3500	230	230
Target_D	5000	5000	300	340
Target_E	6000	6005	-65	60
Target_F	8000	8005	486	480
Target_G	15000	-200	15000	-220

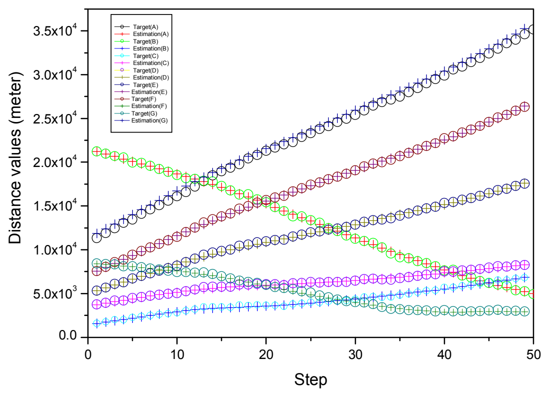

Fig. 11 Results with four mobile sensors for tracking seven maneuvering targets