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Collaborative Maneuvering Target Tracking in Wireless Sensor Network with Quantized Measurements

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***Abstract*—Maneuvering target tracking in wireless sensor network (WSN) with quantized measurements is investigated. The measurement in each local sensor is quantized by uniform quantization scheme and then transmitted to a fusion center (FC). To estimate the state of the target in the FC, the quantized messages are first fused in a weighted average way. Then interactive multiple-model (IMM) scheme using sigma-point Kalman filtering (SPKF) is employed. Focuses are on tradeoff between bandwidth of each sensor and the global tracking accuracy. By performing a change of variable and Lagrange technique, the closed-form solution to the optimization problem for bandwidth scheduling is given, where the mean square error (MSE) incurred by weighted average fusion is minimized subject to a constraint on the total energy consumption. Simulation results reveal that the proposed scheme performs very closely to the clairvoyant IMM-SPKF that based on the analog-amplitude measurements, while obtaining average communication energy saving up to 51.2% and computational burden reduction 31%.**

Keywords—maneuvering target tracking, wireless sensor network, weighted average, nonlinear estimation, quantization

I. INTRODUCTION

Target tracking through wireless sensor network (WSN) is a problem with a large spectrum of applications, such as surveillance, rescue, traffic monitoring, pursuit evasion games, etc [1-3]. The (maneuvering) target tracking problem for traditional sensors or multi-sensor systems has attracted much attention in the last decades for both theoretical and practical reasons (see e.g. [4]-[7], and the references therein).

However, target tracking in WSN needs collaborative communication and computation among multiple sensors since information generated by a single sensor node is usually incomplete or inaccurate (e.g. [8], [9]). Moreover, each sensor node in this circumstance has very limited energy/power source and communication bandwidth. Thus, by using quantized message for storage or transmission in place of the original measurement, considerable savings in storage or transmission bandwidth can be realized, at the expense of some distortion. The fusion center (FC) will combine the quantized messages from local sensors to produce a final estimation of the parameter. The problem of decentralized estimation and tracking based on quantized measurements has been studied in early works such as [10] and [11]. Recently, universal decentralized estimation taking into account local signal-to-noise ratio (SNR) in sensor network is studied [12]. When the noise probabilistic density function (PDF) is unknown, the problem of estimation based on severely quantized data has been also addressed in [13]. A distributed estimation approach based on the sign of innovations (SOI) is developed in [14], where only the transmission of a single bit per measurement is required. Very recently, by optimizing the filter with respect to the quantization levels, a multiple-level quantized innovation Kalman filter (MLQ-KF) for estimation of linear dynamic stochastic systems is proposed in [15]. So far, however, the target tracking problem in WSN is mainly focused on the constant velocity or random-acceleration target tracking. Little work is related to the case of maneuvering target tracking. Since the acceleration cannot be observed directly and the measurements are always quantized to finite bits for power reason, maneuvering target in WSN is usually difficult to attack.

This paper makes three main contributions. First, after receiving the quantized messages from local sensors, the FC fuses the quantized measurements in a weighted average way (under BLUE fusion rule) instead of the augmented scheme. Note that in our approach, the observation vector dimension kept unchanged regardless of the number of the sensors deployed, which has a lower computational load [16]. This is highly desirable in densely deployed WSN since the number of actived sensors will be large, which means the observing space is high dimension. Second, with the focuses on the tradeoff between bandwidth and accuracy of fusion problem of quantized measurements, we give a closed-form solution to the optimization problem for bandwidth scheduling. In the optimal bandwidth scheduling problem, the MSE incurred by weighted average approach is minimized subject to a constraint on the total energy consumption. Third, due to the fact that usually passive sensors are employed in WSNs, nonlinear Gaussian discrete-time model following the intera-ctive multiple-model sigma-point Kalman filtering (IMM-SPKF) principle is investigated for estimate the target state. Some special considerations related to the quantized messages and the weighted average fusion approach is discussed.

II. PROBLEM STATEMENT

Considering the state estimation problem of the following nonlinear discrete-time system in a sensor network with N sensors deployed

$$x(k+1) = f[x(k),k] + g[\omega(k),k] \tag{1}$$

$$y_i(k) = h_i[x(k),k] + \upsilon_i(k), \quad i = 1,\ 2,\ 3,\cdots,N \tag{2}$$

where $x(k)\in\Re^n$, $y_i(k)\in\Re^m$ are the state of the target and the measurement of ith ($i=1,\ 2,\ 3,\cdots,N$) sensor at the time step k, respectively; $\omega(k)\in\Re^p$ is the noise process caused by disturbances and modeling errors, $\upsilon_i(k)\in\Re^m$ are additive measurement noise vectors of the ith sensor. We assumed the independent noise vectors $\omega(k)$ and $\upsilon_i(k)$ are zero mean and

$$E[\omega(j)\omega^T(k)] = \delta_{jk}Q^2$$
$$E[\upsilon_i(j)\upsilon_i^T(k)] = \delta_{jk}diag\{\sigma_{\upsilon_i}^2\}, \forall j,k$$

The initial state $x(0)$ with mean x_0 and variance P_0 is independent of $\omega(k)$ and $\upsilon_i(k),(i=1,\ 2,\ 3,\cdots,N)$. To ease the analysis, we also assume that all sensors are synchronized and have the same measurement rate.

Due to bandwidth and power limitations, each sensor quantizes its observation into a b_i–bit message, and transmits this locally processed data to a fusion center. Then the FC estimates the state vector of the object according to (1) and the quantized messages. In this paper, the uniform quantization scheme with nearest-rounding [17] is adopted; the quantized measurement at the ith sensor can thus be modelled as

$$m_i(k) = y_i(k) + q_i, \quad i = 1,\ 2,\ 3,\cdots,N \tag{3}$$

where q_i is the quantization error uniformly distributed with zero mean and variance $\sigma_{q_i}^2 = Q_i^2/12$ [17], where $Q_i = W/2^{b_i}$ is the quantization width or the quantizer resolution, and $[-W/2, W/2]$ is the available signal amplitude range common to all sensors, b_i is the bandwidth to be determined later. The adopted quantizer model (3) and the uniform quantization error assumption are widely used in the literature due to analytical tractability. We assume that the channel link between the ith sensor and the fusion center is corrupted by a zero-mean additive nose η_i with variance $\sigma_{\eta_i}^2$.

The problem is to estimate the target state using the noised corrupted quantization messages. The limited bandwidth constraints and weighted average approach will be considered.

III. WEIGHTED AVERAGE APPROACH TO QUANTIZED MEASUREMENT FUSION

Taking the channel link noise η_i into account, the received date from the ith sensor output can be expressed as

$$z_i(k) = y_i(k) + q_i + \eta_i, \quad i = 1,\ 2,\ 3,\cdots,N \tag{4}$$

The existing fusion approach is to merge all the received date into a vector form as

$$\begin{bmatrix} z_1(k) \\ \cdots \\ z_N(k) \end{bmatrix} = \begin{bmatrix} y_1(k) \\ \cdots \\ y_N(k) \end{bmatrix} + \begin{bmatrix} q_1 \\ \cdots \\ q_N \end{bmatrix} + \begin{bmatrix} \eta_1 \\ \cdots \\ \eta_N \end{bmatrix} \tag{5}$$

Then using the BULE scheme to retrieve the original signal (see e.g. [12], [18]), or using the Kalman filtering to get the estimate of the state vector of the system (see e.g. [19]). Our approach will first combine the quantized measurements in a weighted average way, and then the IMM scheme with SPKF technology is employed to estimate the state of the target.

By the assumptions above, the sensor noise υ_i, quantization noise q_i, and the channel link noise $\eta_i,(i=1,\ 2,\ 3,\cdots,N)$ are mutually independent. The relationship between the original signal of ith sensor and the data received by the FC can be reformulated by

$$z_i(k) = h_i[x(k),k] + n_i, \quad i = 1,\ 2,\ 3,\cdots,N \tag{6}$$

where $n_i = \upsilon_i(k) + q_i + \eta_i$ are uncorrelated with each other with zero mean and variance $\sigma_{n_i}^2 = \sigma_{\upsilon_i}^2 + \beta 4^{-b_i} + \sigma_{\eta_i}^2$, where

$$\beta = W^2/12 \tag{7}$$

We approximately consider the noise n_i to be a white noise [18, 19]. The fused measurement can be obtained by weighting quantized measurements using the BLUE scheme

$$z(k) = \left(\sum_{i=1}^{N} 1\big/\sigma_{n_i}^2\right)^{-1} \sum_{i=1}^{N} z_i(k)\big/\sigma_{n_i}^2 \tag{8}$$

$$h(x(k),k) = \left(\sum_{i=1}^{N} 1\big/\sigma_{n_i}^2\right)^{-1} \sum_{i=1}^{N} h_i(x(k),k)\big/\sigma_{n_i}^2 \tag{9}$$

The incurred MSE is thus

$$R = \sigma_n^2 = \left(\sum_{i=1}^{N} 1\big/\sigma_{n_i}^2\right)^{-1} \tag{10}$$

Then, we obtain the weighted measurement in the fusion center in the form

$$z(k) = h(x(k),k) + n \tag{11}$$

Remark 1: Note that in our approach, the observation vector dimension kept unchanged regardless of the number of the sensors deployed, which has a lower computational load [20]. This is especially preferable in densely deployed wireless sensor network since the number of actived sensor in a snapshot will be large, which makes the dimension of observation space high. Furthermore, the cost of calculating inverse matrix, which is involved in computing the gain of the filter, is in proportion to cubic of dimension of system observation space, therefore, the computational burden will increase when using the augmented approach as in (5).

Remark 2: It is easy to see that the accuracy of fused quantized measurement is better if the variance of the quantized noise is smaller. We can make its upper bound small, which means that more bandwidths need to be supplied. However, the sensor power and transmission bandwidth are limited in a wireless sensor network. In the following, we will consider the bandwidth scheduling problem which solves the tradeoff between energy/power constraints and required tracking performance.

IV. BANDWIDTH SCHEDULING

A. Optimization Problem Setup

In this section, we consider the bandwidth scheduling problem in the network. We assume the channel between the *i*th sensor and the FC experiences a pathloss proportional to $a_i = d_i^{\alpha_i}$, where d_i is the transmission distance between the *i*th sensor and the FC. Then the consumed energy of the *i*th sensor at time step *k* is

$$E_i(k) = \omega_i\left(2^{b_i(k)} - 1\right) \tag{12}$$

where $\omega_i = \rho d_i^{\alpha_i} \ln\left(2/P_b\right)$ is the energy density [12], in which ρ is a constant depending on the noise profile, and P_b is the target bit error rate assumed common to all sensor-to-FC links.

Our primary goal is to minimize the overall MSE performance while meeting total power consumption. A secondary goal is to maintain fairness in the bandwidth scheduling among sensors. Thus, we consider the following optimization

$$\begin{aligned} \min\ & \left(\sum_{i=1}^{N} 1/\sigma_{n_i}^2\right)^{-1} = \left(\sum_{i=1}^{N} \frac{1}{\sigma_{\upsilon_i}^2 + \sigma_{\eta_i}^2 + \beta 4^{-b_i}}\right)^{-1} \\ \text{s. t. } & \sum_{i=1}^{N} \omega_i\left(2^{b_i} - 1\right) \le E_T \\ & \text{and} \quad b_i \in Z_0^+,\ 1 \le i \le N \end{aligned} \tag{13}$$

where $E_T > 0$ is a constant constraint on total energy budget.

The problem in (13) can be equivalently rewritten as

$$\begin{aligned} \max\ & \sum_{i=1}^{N} \frac{1}{\sigma_{\upsilon_i}^2 + \sigma_{\eta_i}^2 + \beta 4^{-b_i}} = \sum_{i=1}^{N} \frac{4^{b_i}}{\beta + (\sigma_{\upsilon_i}^2 + \sigma_{\eta_i}^2) 4^{b_i}} \\ \text{s. t. } & \sum_{i=1}^{N} \omega_i\left(2^{b_i} - 1\right) \le E_T \\ & \text{and} \quad b_i \in Z_0^+,\ 1 \le i \le N \end{aligned} \tag{14}$$

B. Alternative Formulation

To facilitate analysis, we first observe that, since $b_i \in Z_0^+$, it follows $\sum_{i=1}^{N} \omega_i\left(2^{b_i} - 1\right) \le \sum_{i=1}^{N} \omega_i\left(4^{b_i} - 1\right)$: this implies we can replace the total energy constraint in (14) by the following one without violating the overall energy budget requirement:

$$\sum_{i=1}^{N} \omega_i\left(4^{b_i} - 1\right) \le E_T \tag{15}$$

With the aid of (15) and by performing a change of variable with $B_i = 4^{b_i} - 1$, the optimization problem becomes

$$\begin{aligned} \max\ & \sum_{i=1}^{N} \frac{B_i + 1}{(\beta + \sigma_{\upsilon_i}^2 + \sigma_{\eta_i}^2) + (\sigma_{\upsilon_i}^2 + \sigma_{\eta_i}^2) B_i} \\ \text{s. t. } & \sum_{i=1}^{N} \omega_i B_i \le E_T \\ & \text{and} \quad B_i \ge 0,\ 1 \le i \le N \end{aligned} \tag{16}$$

Furthermore, we relax the integer B_i to be a real positive number so as to render the problem tractable, and drop the last constraint on B_i as they become inactive at the optimum point. The major advantage of the alternative problem formulation (16) is that it admits the form of convex optimization and can moreover lead to a closed-form solution as shown next.

C. Optimal Solution

By leveraging the standard Lagrange technique, the optimal solution to (16) can be obtained as follows. Without loss of generality, we first assume that $\omega_1 \ge \omega_2 \ge \cdots \ge \omega_N$, and define

$$f(K) := \frac{E_T\left(1 + \dfrac{\beta}{\sigma_{\upsilon_i}^2 + \sigma_{\eta_i}^2}\right)^{-1} + \sum_{j=K}^{N} \omega_j}{\sqrt{\omega_K} \sum_{j=K}^{N} \sqrt{\omega_j}} \quad \text{for } 1 \le K \le N \tag{17}$$

Let $1 \le K_1 \le N$ be the unique integer such that $f(K_1 - 1) < 1$ and $f(K_1) \ge 1$; if $f(K) \ge 1$ for all $1 \le K \le N$, then simply set $K_1 = 1$. Then simple manipulations of (16) lead to the optimal solution given by

$$\lambda^* = \left(\frac{\sqrt{\beta}}{\sigma_{\upsilon_i}^2 + \sigma_{\eta_i}^2}\left(\sum_{j=K_1}^{N} \sqrt{\omega_j}\right)\left(E_T + (1 + \frac{\beta}{\sigma_{\upsilon_i}^2 + \sigma_{\eta_i}^2}) \sum_{j=K_1}^{N} \omega_j\right)^{-1}\right)^2 \tag{18}$$

and

$$B_i^* = \begin{cases} 0 & \text{for } 1 \le i < K_1 - 1 \\ \dfrac{1}{\sigma_{\upsilon_i}^2 + \sigma_{\eta_i}^2} \sqrt{\dfrac{\beta}{\lambda^* \omega_i}} - \left(1 + \dfrac{\beta}{\sigma_{\upsilon_i}^2 + \sigma_{\eta_i}^2}\right) & \text{for } K_1 \le i \le N \end{cases} \tag{19}$$

Once the optimal real-value $B_i^* = 4^{b_i} - 1$ is computed, the associated bit loads can be readily obtained through upper integer rounding, as in [12], [18], and [19].

Remark 3: Recall from (12) that the energy consumption of each sensor is proportional to the path loss gain $d_i^{\alpha_i}$. Hence, large value of the energy consumption corresponds to sensor deployed far away from the FC, usually with poor background channel gain. In light of this point, the optimal solution (19) is intuitively attractive: for those active nodes, the assigned bandwidth is inversely proportional to the energy consumption of this node [18]. This is intuitively reasonable since sensors with better link conditions should be allocated with more bits to improve the measurement fusion accuracy.

V. IMM-SPKF-BASED MANEUVERING TARGET TRACKING

Once the optimal bandwidth values b_i^{opt} are obtained, the measurement in each sensor will be quantized according to b_i^{opt} and then be transmitted to the FC. Using the dynamic equation (1) and the weighted measurement (11), the state of the target can be estimated through IMM scheme with some nonlinear filtering technique such as extended Kalman filtering and sigma-point Kalman filtering. Here we briefly overview single-scan of the recursive IMM algorithm as follows.

(I) **Model-matching reinitialization**: the posterior density at $k-1$ for model j is represented by $N\left(\hat{x}_{k-1}^j; \hat{x}_{k-1|k-1}^{(j)}, P_{k-1|k-1}^{(j)}\right)$,

$$\hat{x}_{k-1|k-1}^{(j)} = \sum_{i=1}^{s} \mu_{k-1}^{i|j} \hat{x}_{k-1|k-1}^{i} \tag{20}$$

$$P_{k-1|k-1}^{(j)} = \sum_{i=1}^{s} \mu_{k-1}^{i|j} \left[P_{k-1|k-1}^{i} + (\hat{x}_{k-1|k-1}^{i} - \hat{x}_{k-1|k-1}^{(j)})(\hat{x}_{k-1|k-1}^{i} - \hat{x}_{k-1|k-1}^{(j)})^T\right] \tag{21}$$

The weights in (20) and (21), however, are the mixing probabilities $\mu_{k-1}^{i|j}$, defined as

$$\mu_{k-1}^{i|j} = \frac{\pi_{ij}\omega_{k-1}^{i}}{\sum_{i=1}^{s} \pi_{ij}\omega_{k-1}^{i}} \tag{22}$$

where π_{ij} are transitional probabilities and ω_{k-1}^{i} are the model probabilities of ith model.

(II) **Model-matched filtering**: In this step, nonlinear estimation techniques can be used according to the target dynamic model (1) and the fusion measurement equation (11). The celebrated extended Kalman filtering (EKF) linearizes (1) and (11) around a single point ($\hat{x}(k-1 \mid k-1)$ for the prediction and $\hat{x}(k \mid k-1)$ for the observation update). This solution does not account for the spread of the random variables and uses only the first-order Taylor expansion of the nonlinear functions. Therefore, it often leads to the divergence of the filter. To avoid the flaws of the EKF, SPKF is employed as the model-matched filter in this paper (see e.g. [21], [22]).

Remark 4: Note that calculating the inverse matrix of $P_{zz}(k) + R(k)$ is required to obtain the gain of SPKF, where $P_{zz}(k)$ is the weighted covariance of innovation. However, the dimension of innovations is determined by the quantized measurements from local sensors. Augmented scheme, in which all observation vectors are merged into a vector in the form of (5), requires calculation of $mN \times mN$ inverse matrix. While in our approach as (11) only calculation of $m \times m$ inverse matrix is required. It is the shortcoming of augmented scheme especially in the case of a large number of sensors are deployed since the cost of calculating inverse matrix is in proportion to cubic of dimension of system observation space.

(III) **Model probability update**: Suppose the posterior density of mode j at k is represented by $N\left(\hat{x}_k^j; \hat{x}_{k|k}^{(j)}, P_{k|k}^{(j)}\right)$. Using the Bayes rule, the model probabilities are updated as follows

$$\omega_k^j = \frac{\Lambda_k^j \sum_{i=1}^{s} \pi_{ij}\omega_{k-1}^{i}}{\sum_{i=1}^{s} \Lambda_k^j \sum_{i=1}^{s} \pi_{ij}\omega_{k-1}^{i}} \tag{23}$$

where $\Lambda_k^j = N\left(\upsilon_k^j; 0, S_k^j\right)$ is the model conditioned likelihood function, υ_k^j and S_k^j are the innovation and its covariance from the model-matched filter j, respectively.

Remark 5: In the case the dynamic or the measurement equation corresponding to model i is nonlinear or non-Gaussian, the likelihood function Λ_k^j is not Gaussian anymore. Nevertheless, even then, we can approximately consider the noises n in (11) to be white Gaussian noise and using the Quasi- maximum likelihood estimation (QMLE) to obtain likelihood function, and in turn, the model probabilities. In any case, this approach is expected to outperform the IMM-EKF because the spread of the target state is taken into account in the model-matched filtering step (II).

(IV) **Estimation fusion**: The output of the IMM is computed as follows

$$\hat{x}_{k|k} = \sum_{i=1}^{s} \omega_k^i \hat{x}_{k|k}^i \tag{24}$$

$$P_{k|k} = \sum_{i=1}^{s} \omega_k^i \left[P_{k|k}^i + (\hat{x}_{k|k}^i - \hat{x}_{k|k})(\hat{x}_{k|k}^i - \hat{x}_{k|k})^T\right] \tag{25}$$

VI. SIMULATION EXAMPLE

Consider K=225 sensors randomly deployed in the query area, which is 50m $\times$ 50m with the coordinate from (-25, -25) to (25, 25). The layout of the network is illustrated in Fig. 1, where a '*' stands for the location of a sensor. The proposed weighted quantized measurements scheme using IMM and

SPKF (*Quan-Weig-IMM-SPKF*) is applied to track a maneuvering target moving along constant turn model with angle velocity [5, 6]

$$\omega_T = \begin{cases} 0.1, & 0 < k \le 200 \\ 0.15, & \text{otherwise} \end{cases}$$

and step-size $T = 0.25$. In Fig. 1, the thick real line is the track of the target traveling start from (10, -22), while the dashed line represents the estimate of the target state using the proposed scheme. The measurement model of the *i*th sensor is [14]

$$y_i(k) = a / \left\| \left(x(k), y(k)\right) - \left(x_s(i), y_s(i)\right) \right\| + \upsilon_i(k)$$

where $a = 40$ is the assumed known amplitude of the sound source (the target), $\left\| \left(x(k), y(k)\right) - \left(x_s(i), y_s(i)\right) \right\|$ denotes the distance between the target and the *i*th sensor, and $\upsilon_i(k)$ the measurement noise with distribution $p(\upsilon_i(k)) = N(\upsilon_i(k);0, \sigma^2_{\upsilon_i})$. The sensor positions are assumed to be known in the FC.

The nearest-neighbors multi-sensor scheduling scheme is used to perform the tracking task. In each time step, the sensors lies within the sensing radius are selected to form a temporary tasking group with one of them being the leader. All the member sensors in the group are assumed to perform the sensing task simultaneously. The measurements from those sensors who successfully detect the target are quantized and transmitted to the leader, who functions as a local FC, in addition to its basic sensing function. We assume that the sensor messages are perfectly received by the FC, and that all of the sensors deployed into an area have the same characteristics, i.e. the same sensing radius $\gamma_s = 8$ m, the measurement noise covariance $\sigma^2_{\upsilon_i} = 1$, and the measuring amplitude range $[0, W]$ with $W = 20$. The simulation is running for 100 Monte Carlo runs each with 350 time steps.

The initial estimate of the sound source is assumed to be $[8, 2, 0, -20, 1, 0]^T$ with covariance matrix I_6. In the FC, the bandwidth scheduling is implemented with optimization problem (13) where $E_T = 0.1$, then the IMM-SPKF is used to estimate the state of the target according to (1) and (11). For IMM algorithm, we use one constant velocity (CV) model and two constant acceleration (CA) models with different maneuvering accelerations. The initial model probability and the model transitional probability are set to be, respectively, $\omega_0 = [0.4, 0.3, 0.3]^T$ and

$$\pi = \begin{bmatrix} 0.92 & 0.05 & 0.03 \\ 0.04 & 0.92 & 0.04 \\ 0.1 & 0.2 & 0.7 \end{bmatrix}$$

For comparison, the following four schemes are also applied:

1) *Quan-Augm-IMM-SPKF*: the quantized measurements are merged into a vector as in (5); then IMM algorithm using SPKF technology is employed to estimate the target state.

2) *Clair-Augm-IMM-SPKF*: clairvoyant IMM-SPKF using augmented *unquantized* messages.

3) *Clair-Weig-IMM-SPKF*: clairvoyant IMM-SPKF using weighted *unquantized* messages.

4) *Quan-Augm-CV-SPKF*: single model (constant velocity model) with SPKF is used to estimate the augmented quantized measurements.

The MSE of *x*-direction over 100 Monte Carlo runs is shown in Fig. 2. It is noted that the proposed algorithm performs very closely to the *Quan-Augm-IMM-SPKF* (PAIR 1) while the *Clair-Weig-IMM-SPKF* also performs very closely to the *Clair-Augm-IMM-SPKF* (PAIR 2). Both pairs of the fusion strategy have the similar performance, the difference is that the latter ones in both pairs merge the quantized (or *unquantized*) measurements into a large vector, which will bring large computational burden in the fusion center. Furthermore, it is worth mentioned that PAIR1 performances very closely to PAIR 2, although the latter are based on analog-amplitude measurements. The MSE in *y*-direction performs similarly, therefore, is omitted here for space limitation, as well as for *Quan-Augm-CV-SPKF* since it is divergent. Beside, we compare the proposed power scheduling scheme (19) to the uniform quantization allocation scheme, in which each sensor quantizes the observation into the minimal same number of bits to achieve the target MSE distortion [12]. Fig. 3 shows the percentage of communication energy saving versus time steps. The average percentage of communication energy saving is up to 51.2%. On the other hand, computation complexity of the four convergent schemes is compared in Tab. 1, which shows that both the proposed scheme and the *Clair-Weig-IMM-SPKF* that based on weighted measurement have less computational burden than both the *Quan-Augm-IMM-SPKF* and *Clair-Augm-IMM-SPKF*. Comparing to the augmented approach, our approach save more than 31% computational energy in the fusion center, this will prolong the lifetime of the whole network abundantly.

VII. CONCLUSIONS

The maneuvering target tracking in WSN with quantized measurements has been investigated. To estimate the state of the target in the FC, the quantized messages from local sensors are first combined in a weighted average way in stead of merging all the measurements into a large vector. Then IMM scheme with SPKF technology is employed. Focuses have been on tradeoff between bandwidth of each sensor and the global tracking accuracy. By Lagrange technique, the closed-form solution to the optimization problem for bandwidth scheduling has been given, where the MSE incurred by weighted average fusion is minimized subject to a constraint on the total energy consumption.

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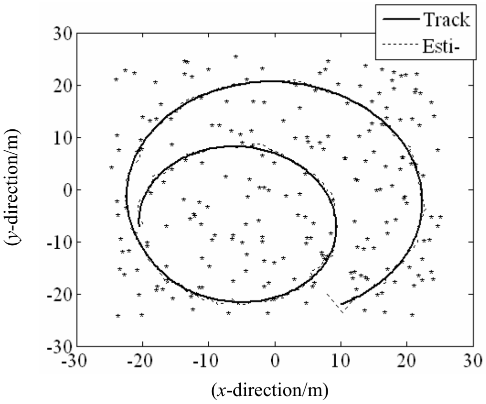

Figure 1. The layout of the network with uniform distributed sensors.

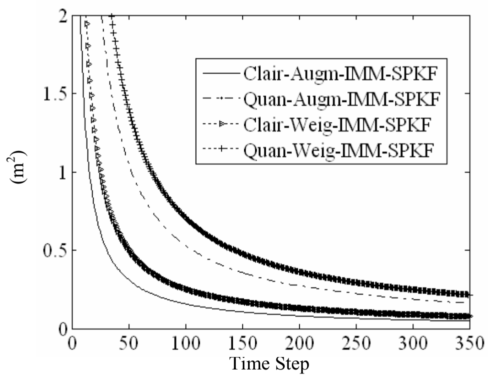

Figure 2. Comparison of MSE of position in x-direction.

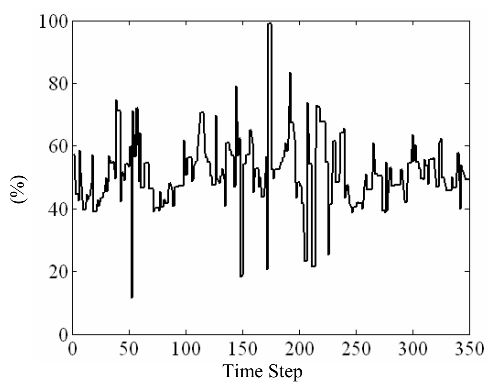

Figure 3. Percentage of communication energy saving.

TABLE I. COMPARISON OF COMPUTATION COMPLEXITY

Algorithms	Quan-Augm-IMM-SPKF	Clair-Augm-IMM-SPKF	Clair-Weig-IMM-SPKF	Quan-Weig-IMM-SPKF
Time (ms)	501.6	471.9	352.7	344.8
Ratio	1.0	0.94	0.70	0.69

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