

## An Energy-Aware Adaptive Probabilistic Tracking Mechanism Based on Quantization for Wireless Sensor Networks

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### Abstract

*Wireless Sensor Networks (WSNs) enable applications where target state estimation is essential. To deal with the energy source and communication bandwidth constraints, an energy-aware adaptive probabilistic tracking mechanism based on quantization was proposed. According to the relationship between the sensing radius and node properties which include stored information and position, a part of redundant nodes were removed under the condition on accuracy. An energy optimization model was established using the quantitative observations and an adaptive sampling interval strategy to reduce traffic for communication between sensor nodes. After that, a probabilistic sensor selection algorithm based on the sensing model of the node is creatively proposed to further reduce energy. In order to show the ascendant functions of the proposed mechanism, numerical simulation results including two scenarios, the single target and multiple Targets, showed that the algorithm can achieve the required tracking accuracy, effectively reduce energy consumption, and distinctly improve the performance of WSNs.*

**Keywords:** *Wireless sensor networks, Optimization quantization, Adaptive sampling interval allocation, Target tracking, Probabilistic sensor selection*

### 1. Introduction

Wireless sensor networks have been utilized in a variety of special applications including monitoring [1] and target tracking [2] in last decades. Due to the limited power supplies of sensor nodes, how to minimize the energy consumption is a key challenge which is faced within the lifetime of the application [3]. In order to realize appointed performance like data collection, WSNs are deployed in the complicated circumstance [4]. Then, one problem how to take advantage of existing network condition to achieve QoS of WSNs rises.

As far as energy conservation, the collected data of sensor nodes are quantized into discrete data channel to determine the optimal quantization value and the transmission power in [5, 6], respectively. In the target tracking process, considering energy resources and bandwidth-constrained channel, [7] exploits a probability quantization strategy to solve the bandwidth scheduling problem and energy consumption at the same time, and also to meet the requirements for tracking accuracy.

To save energy, an optimal sampling interval adaptively using discrete search algorithm based on prediction variance is proposed in [8] taking into account the sampling time intervals impacting on energy consumption. Another method to replace fixed sampling

interval is investigated according to the prediction accuracy and energy costs in [9, 10]. Yilin Mo [11] proposes a multi-step sensor selection strategy to schedule sensors to solve a large class of optimization problems over energy constrained WSNs for an estimate of the process state by means of a Kalman filter.

In this paper, we study the problem of energy conservation by three aspects including adaptive sampling intervals, bandwidth constraint, and sensor selection in the process for target tracking. Under the framework of the extended Kalman filter, an optimization problem is formed with the goal of minimizing an objective function. Furthermore, a subset of one-hop sensors is selected to send their collected data to a fusion center because of channel capacity constraints and limited energy budget.

## 2. Problem Formulation

In this paper, nonlinear discrete dynamic model is utilized to express the following state evolution:

$$X(k+1) = F(\Delta t_k)X(k) + \omega(k, \Delta t_k) \quad (1)$$

where  $X(k)$  is the state variable of target in time  $k$ ,  $\Delta t_k$  is the sampling interval between two adjacent state,  $F(\Delta t_k)$  is a state transition matrix, and  $\omega(k, \Delta t_k)$  stands for the process noise.

In this process, given the observation  $z_i(k)$  of sensor node  $i$  at time  $k$ , the observation model is presented by

$$Z(k) = h(X(k)) + V(k) \quad (2)$$

where  $Z(k) = (z_1(k), z_2(k), \dots, z_N(k))^T$ ,  $h(X(k)) = (h_1(X(k)), h_2(X(k)), \dots, h_N(X(k)))^T$ ,  $V(k) = (v_1(k), v_2(k), \dots, v_N(k))^T$ ,  $h_i(\cdot)$  and  $v_i(k)$  indicate observation equation and observation noise of sensor node  $i$ , respectively. For the sake of convenience, the assumption is essential, that is,  $\omega(k, \Delta t_k)$  and  $v_i(k)$  are of mutual independence, whose covariance matrixes are  $Q(k, \Delta t_k)$  and  $R(k)$ , respectively.

According to EKF [10],

1) predictive equation is presented by

$$\hat{X}(k+1/k) = F(\Delta t_k)\hat{X}(k/k) \quad (3)$$

and the corresponding covariance matrix is showed by

$$P(k+1/k) = F(\Delta t_k)P(k/k)F^T(\Delta t_k) + Q(k, \Delta t_k) \quad (4)$$

2) then, the predictive process is expressed by

$$\hat{Z}(k+1/k) = h(\hat{X}(k+1/k)) \quad (5)$$

3) on the basis of the above predictive process, update process is signified by

$$\delta(k+1) = Z(k+1) - \hat{Z}(k+1/k) \quad (6)$$

where the covariance matrix is

$$C(k+1) = H(k+1)P(k+1/k)H^T(k+1) + R(k+1) \quad (7)$$

where,  $H(\cdot)$  and  $h_j(\cdot)$  are Jacobian matrix, therefore, the gain matrix is given by

$$K(k+1) = P(k+1/k)H^T(k+1)C^{-1}(k+1) \quad (8)$$

4) In the end, the estimation process is

$$\hat{X}(k+1/k+1) = \hat{X}(k+1/k) + K(k+1)\delta(k+1) \quad (9)$$

and the covariance matrix is presented by

$$P(k+1/k+1) = P(k+1/k) - K(k+1)C(k+1)K^T(k+1) \quad (10)$$

Especially, for the sake of target tracking in two-dimensional space in this paper, the state variable is signified by

$$X(k) = [x(k) \dot{x}(k) y(k) \dot{y}(k)]^T \quad (11)$$

### 3. Quantization Mechanisms

#### 3.1. Energy Model

Considering indexes of wireless sensor networks, the problem of energy consumption is a very important reference [12].

Given the transmission bandwidth  $b$ -bit of sensor node  $s_i$  who transmits signal and the transmission distance  $d$ , the energy consumption for transmission of sensor node  $s_i$  is presented by

$$E_i(k) = \beta_i(2^{b_i(k)} - 1) \quad (12)$$

where  $\beta_i = \rho d_i^{\alpha_i} \ln(2/P_b)$  indicates energy density.  $\rho$  depends on noise signifies a scaling factor,  $\alpha_i$  is a channel attenuation factor, and  $P_b$  is a bit error rate.

#### 3.2. Quantization based on EKF Update

According to (12), due to the  $b(k)$ , that is, transmission information influence the energy consumption. One way to save energy is to reduce the information between sensor nodes by quantization. The mechanisms of quantization in [13] for sensor node  $s_i$  at time  $k$  is considered by

$$m_{ik} = \begin{cases} 0, & \gamma_{i0} < z_{ib} < \gamma_{i1} \\ 1, & \gamma_{i1} < z_{ib} < \gamma_{i2} \\ \vdots & \vdots \\ L-1, & \gamma_{i(L-1)} < z_{ib} < \gamma_{iL} \end{cases} \quad (13)$$

where  $m_{ik}$  signifies the quantified value of sensor node  $s_i$ , scalars,  $\gamma_{i0}, \dots, \gamma_{iL}$  are quantified thresholds to  $K = \log_2 L$  bits. If the condition  $m_{ik} \in [-M, M]$  is satisfied, then the following equations  $\gamma_{i0} = -M$  and  $\gamma_{iL} = M$  are stood.

According to equation (6),  $\delta(k)$  is quantified as follows.

$$M(k) = \delta(k) + \eta(k) \quad (14)$$

where the vector  $\eta(k) = (\eta_1(k), \eta_2(k), \dots, \eta_N(k))^T$  indicates the quantization error vector, and due to equation  $\eta_i(k) = q_i(k) + v_i(k)$  and quantified noise  $q_i(k)$ , noise variance can be described as  $\sigma_{\eta_i}^2 = \sigma_{v_i}^2 + \sigma_{q_i}^2$ . Seen from [14], the inequality  $\sigma_{q_i}^2 \leq W^2 / (2^{b_i} - 1)^2$  is held.

#### 4. Optimization Framework

Since sampling time decides the energy consumption, one way to reduce the frequency of information transmission between sensor nodes is to maximize the sampling time for saving energy. According to EKF, the covariance matrix  $P(k+1/k)$  of  $\hat{X}(k/k)$  at time  $k$  is expressed by [10]

$$\Sigma(\Delta t_k) = \begin{bmatrix} \sigma_{11} + 2\Delta t_k \sigma_{12} + \Delta t_k^2 \sigma_{22} & \sigma_{13} + \Delta t_k (\sigma_{14} + \sigma_{23}) + \Delta t_k^2 \sigma_{24} \\ \sigma_{13} + \Delta t_k (\sigma_{14} + \sigma_{23}) + \Delta t_k^2 \sigma_{24} & \sigma_{33} + 2\Delta t_k \sigma_{34} + \Delta t_k^2 \sigma_{44} \end{bmatrix} \quad (15)$$

In order to achieve desired bandwidth and sampling intervals, the optimal model is designed according to energy equation  $E_i(b_i)$  and the sampling interval  $\Delta t_k$  of sensor node  $s_i$ . Given  $B_i^2 = (2^{b_i} - 1)^2$ , the above mentioned optimal model can be expressed by

$$\min \left( \frac{\sum_{i=1}^N \beta_i (2^{b_i(k)} - 1)}{\Delta t_k} \right) \quad (16)$$

s.t.

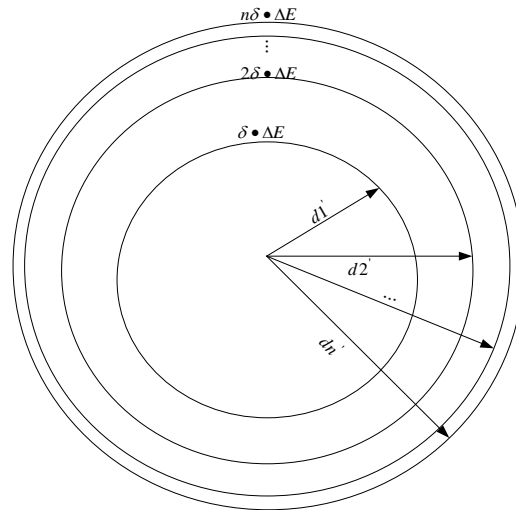
$$\text{trace}(\Sigma(\Delta t_k)) \leq \Phi_0^1$$

$$\sum_{i=1}^N \left( \sigma_{v_i}^2 + \frac{W^2}{(2^{b_i(k)} - 1)^2} \right) \leq \Phi_0^2$$

where,  $\Phi_0^1$  and  $\Phi_0^2$  indicate allocated parameters.

#### 5. Node Selection

At first, the sensor node which is nearest target and owes maximum residual energy is selected as cluster header. According to sensing radius, sensor node selection is chosen from Figure 1.



**Figure 1. Relationships of Energy Increment  $\Delta E$  and the Distance**

Then, the property of every sensor node is allocated by

$$P(N, E_r) = \left(1 - \frac{N}{N_z}\right) \cdot \frac{E_r - E}{E_w} \quad (17)$$

where the number  $N$  signifies the used times of the sensor node over one time step. Number  $N_z$  describes the total used times of all sensor node in current cluster.  $E_r$  represents the current residual energy, and  $E_w$  indicates the total energy.

In order to improve performances of the current cluster, the probability of energy levels is described as follows

$$\Pr(E = E_j) = (d^2 - d_j^2) / (d_{j+1}^2 - d_j^2) \quad (18)$$

$$\Pr(E = E_{j+1}) = 1 - (d^2 - d_j^2) / (d_{j+1}^2 - d_j^2) \quad (19)$$

Therefore, the sensor node marked  $\max(P_i(N, E_r))$  is selected as an activated node between every energy interval  $\Delta E$  controlled by a parameter  $\delta$ .

## 6. Simulations and Results

### 6.1. Signal Target

In these simulations, we assume the number of sensors  $N=100$ , sensor radius  $R = 10m$  and sampling interval  $T_s = 1s$ . They are randomly deployed in a square field  $60*40m^2$ . We also assume that the measurement noise variance of each sensor is 1. At time  $t = 0$ , the initial state  $x_0 = (30, -2, 30, 0)^T$ , and the tracking time last for  $t = 25.7s$ . We set the sampling interval  $[0.1s, 0.5s]$ , and to test optimization framework and sensor selection strategy, we set the target moving along a trajectory in Figure 2.

Seen from Figure 2 and Figure 3, the effect with quantization is a little lower than the one without quantization under the condition on tracking threshold. However, the reason is to reduce energy through sacrificing accuracy.

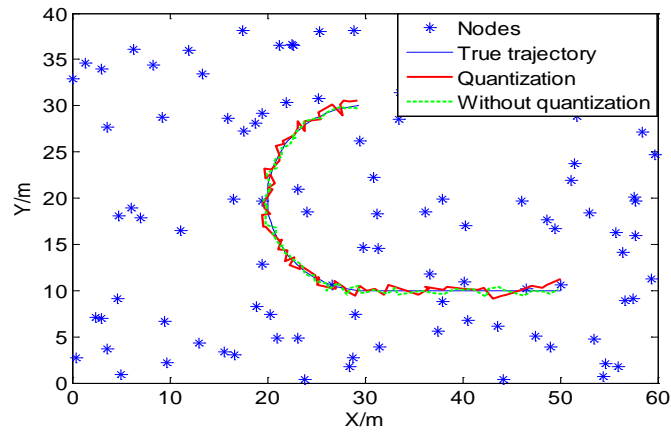


Figure 2. Target Tracking Trajectories

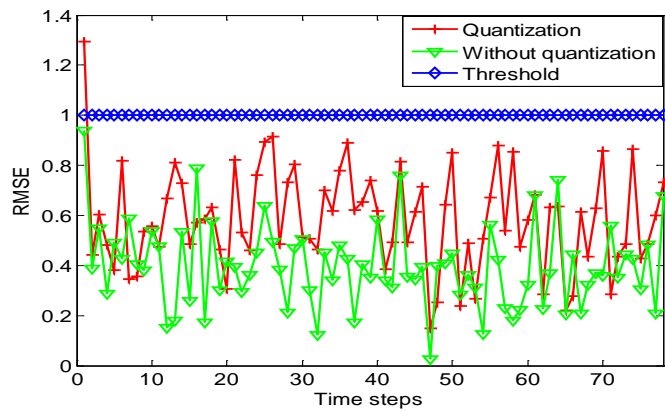


Figure 3. Root mean Square Errors

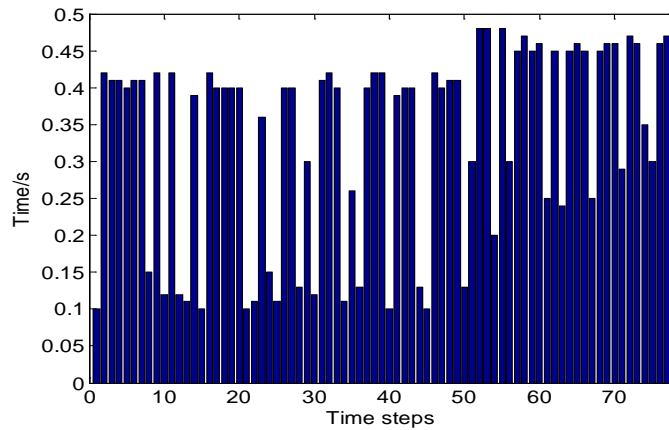
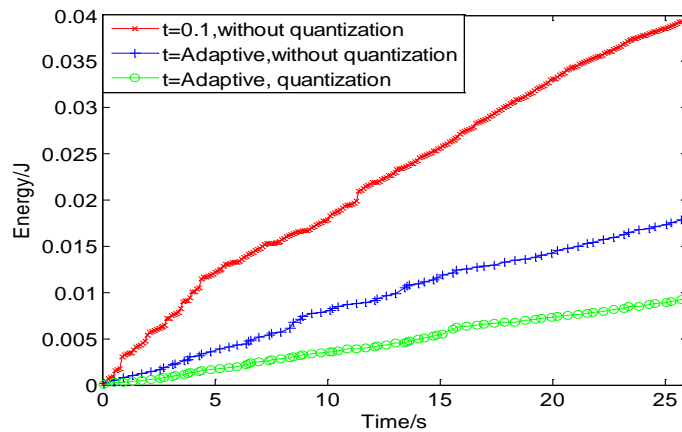


Figure 4. Sampling Intervals



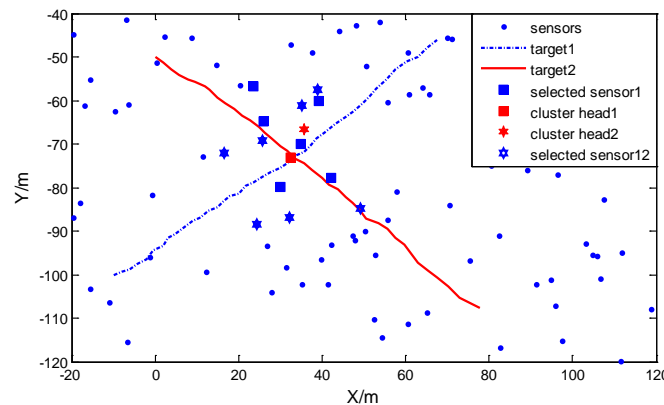
**Figure 5. Energy Consumption**

Figure 4 is the tracking sampling intervals based on quantization. At the beginning of initialization, the minimum sampling interval is set as 0.1s, then, it is adjusted to 0.42s according to the tracking accuracy. Seen from Figure 4, the average sampling interval for nonlinear trajectory is lower than linear trajectory, 0.3040 and 0.401, respectively. The reason is that the error of nonlinear trajectory is larger than the linear one.

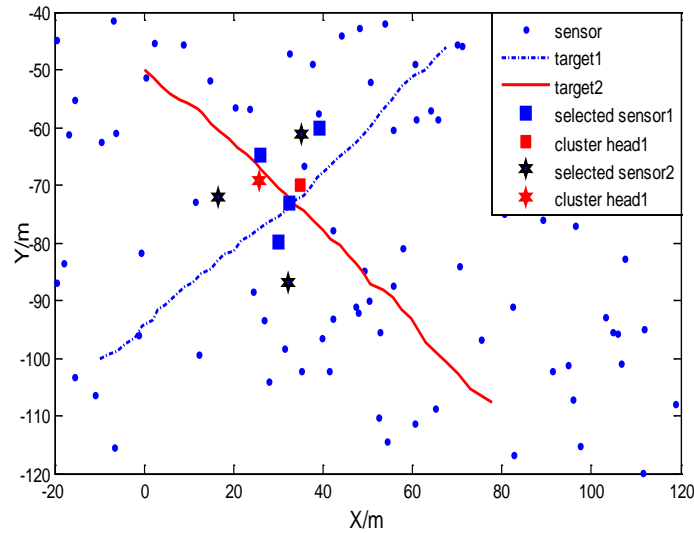
In Figure 5, due to short sampling interval and no quantization, energy consumption for single sensor node exceeds the way of multiple sensor node collaboration. With the strategy of adaptive sampling, energy consumption with quantization is cut down by 48.6%.

## 6.2. Multiple Targets

For further analysis, we consider the scenario of two targets. For the scenario of more targets, we can obtain the similar results. Conveniently, we consider sensor selection for the multi-target tracking case under the assumption that sensors exactly know the tags of targets in tracking [6] and all the simulation parameters are the same as the scenario of single target except for the initial state and the trajectory. The initial state of target indicated in blue dotted line in the figure 6 is  $x_0 = [0 \ -100 \ 2 \ 1]^T$ , and the initial state of target signed in red solid line curve in the figure 7 is equivalent to  $x_0 = [0 \ -50 \ 2 \ 1]^T$ .

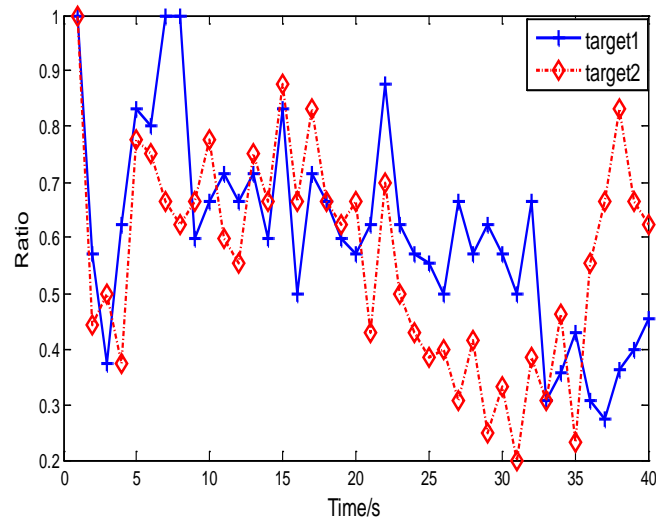


**Figure 6. Sensor Selections for all Sensor Nodes at the Crossing of Two Targets**



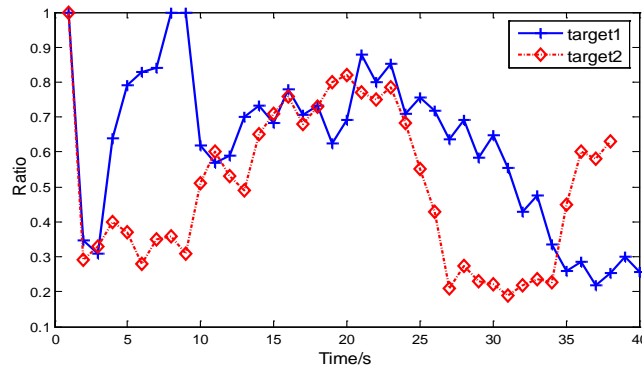
**Figure 7. Sensor Selections for Strategies in Section 5 at the Crossing of Two Targets**

Figure 6 and Figure 7 present the case of sensor selection for cluster head and tasking sensors. For Figure 6, the two nearest sensors close to the predicted position of two targets at crossing are selected cluster heads respectively, and all sensors with the tags of targets collect tracking information as tasking sensors. However, for Figure 7, cluster heads are selected according to the schemes discussed in Section 5, and tasking sensors are selected by property (17) with (18) and (19). Seen from two figures, cluster heads are obviously different by considering the residual energy and a suboptimal sensor set is selected to satisfy the tracking performances in Figure 7.



**Figure 8. Sensor Ratios of Strategies in Section 5 Compared with all Sensor Nodes**





**Figure 9. Energy Consumption Ratios of Strategies in Section 5 Compared with all Sensor Nodes**

Figure 8 demonstrates the number of sensors in Section 5 compared with all nodes in a cluster for two targets over the tracking intervals. From the figure, the ratios are 1 at the beginning of the initial phase to guarantee the detection for two targets. Owing to the sparse sensors, more sensors are utilized to track for target 1 in the initial time step. The ratio is equivalent to 1 at seventh and eighth time steps, when the tasking sensors are 4 and 3 respectively. They are all selected within the framework of Section 5. Ratios for target 2 are similar. With the tendency which two targets close to each other, the relative density for each target become less, that is, more and more sensors appear in the intersection of the sensing region such that sensors are divided into two parts according to the tags of targets. Especially, two targets encounter at the crossing point. After the crossing point, the scenario is on the contrary. When sensors in WSNs are dense, the ratios become descended. For the red dotted line, it tends to increase because of sparse sensors in sensing regions.

Energy consumption is proportional to the number of tracking sensors, and the ratios of two targets are generally consistent with Figure 9. However, the energy consumption of every sensor is confined by the position to the cluster head and the role at every time step. Therefore, the chart presents local difference as far as total energy consumption in the respective cluster. Another influence factor also comes from the local density of WSNs as the ratios in Figure 9.

## 6. Conclusions

To deal with the energy source and communication bandwidth constraints, an adaptive tracking optimization mechanism based on quantization of collected data and sensor selection strategy was proposed. According to the relationship between the incremental energy consumption and the sensing radius of one node with the addition of the node properties, which include stored information and position, a part of redundant nodes were removed to reduce the redundancy information. The energy optimization objective function is established using quantitative observation mechanisms and adaptive sampling strategy to reduce traffic between nodes, and adjust tracking sampling time adaptively. In the future, we will focus on data-intensive energy consumption and the problem of how to choose sensor nodes for transmitting data to save energy in wireless sensor networks.

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