A MARKET BASED DYNAMIC BIT ALLOCATION SCHEME FOR TARGET TRACKING IN WIRELESS SENSOR NETWORKS

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***Abstract*—In this paper, we propose a market based dynamic bit allocation scheme for target tracking in energy constrained wireless sensor networks using quantized data. We model the dynamic bit allocation problem as a market based policy where the fusion center is the customer and sensors are the producers of the market. The fusion center releases the energy to purchase m-bit measurements from sensors in such a way that the trace of the posterior Cramér-Rao lower bound (PCRLB) on the mean squared error (MSE) is minimized. Sensors then compete to purchase the energy released from the fusion center and produce their m-bit quantized measurements which maximize their profit. Simulation results show that the market based dynamic bit allocation scheme achieves tracking performance close to the case where all the sensors report their most accurate information to the fusion center while the market based dynamic bit allocation scheme releases energy which is significantly less than the energy required to transmit all sensor data to the fusion center.

***Index Terms*—Sensor Management, dynamic bit allocation, resource allocation, auctions, price theory, wireless sensor networks

I. INTRODUCTION

A wireless sensor network (WSN) consists of spatially distributed sensors which are assumed to be tiny devices,with limited on-board energy. A WSN can perform tasks which are useful in a wide range of applications such as battlefield surveillance, environment and health monitoring, and disaster relief operations. Rather than transmitting entire sensor data to the fusion center, sensor management policies activate a subset of sensors to meet the application requirements while minimizing the use of resources. As an example, in sensor selection problems, a decision is made on whether or not a sensor transmits its measurement under the constraint on the total number of selected sensors [1], [2], [3], [4], [5], [6]. In this paper, we study the bit allocation problem which is more general than the sensor selection problem, since in the bit allocation problem, each sensor could represent its measurement using different number of bits. In our previous work [7], we have studied the dynamic bit allocation problem for target tracking which optimizes the tracking performance subject to a constraint on the total number of bits that can be transmitted over the channels between sensors and the fusion center. Since an exhaustive search to find the optimal bit allocation is computationally prohibitive, we have developed computationally efficient sub-optimal algorithms whose tracking performance are close to that of optimal exhaustive search.

Rather than putting a constraint on the total number of bits that can be transmitted from sensors to the fusion center, in this paper, we put a constraint on the total energy which is permitted to be used for transmitting quantized sensor measurements to the fusion center. In order to transmit the quantized measurements to the fusion center without transmission errors, the energy required by each sensor is a function of the number of bits it uses to represent the quantized measurement and its distance to the fusion center [8]. In this paper, similar to the models considered in [9], [10], [11], we consider a mobile fusion center which follows the target by moving to the estimated target location at each time step of tracking based on the gathered sensor measurements.

Market based policies for resource allocation in sensor or communication networks have recently gained significant attention [12], [13], [14], [15]. In [12], the authors propose a market framework for adaptive sensor management where the network resources and the sensor measurements are priced in order to balance the supply and demand. In this market model, sensors purchase resources from the fusion center in order to produce the data, and the fusion center needs to purchase data from the sensors to accomplish its tasks. The work presented in [12], considers a network with multi-modal sensors which transmit analog measurements to the fusion center. The market has $N + 1$ assets where N is the number of sensors in the network and each asset corresponds to the number of measurements that a sensor can provide to the fusion center and the last asset is the resource that the fusion center distributes to the sensors. The fusion center maximizes an information theoretic utility function, where in our previous paper [4] we have shown that the computational complexity of sensor management based on information theoretic metrics increases exponentially as the number of sensors to be managed is increased.

In our market model, rather than using analog sensor measurements, we consider each sensor first quantizes its measurement before transmitting to the fusion center. The quantized measurement of each sensor is represented in m-bits and we let the market determine the value of m for each sensor. In our model, we consider $NM+1$ assets in the market where N is the number of sensors in the network, M is the maximum number of bits that can be transmitted from one sensor to the fusion center, and the last asset is the energy that the fusion center can release to the network for data transmission. The market is said to be clear when the prices of purchasing bits from sensors and the price of unit energy are balanced. In our model, we consider a posterior Cramér-Rao lower bound (PCRLB) based metric for sensor management at the fusion center which has been shown to have similar performance as that with information theoretic metrics when sensor data is transmitted over the channels without error [4]. The computational complexity of PCRLB (or its inverse Fisher Information) based metrics grow linearly with the number of sensors to be managed and they are analytically tractable [4], [7].

The rest of the paper is organized as follows. In Section II, we introduce the problem set-up for target tracking in WSNs. In Section III, we explain the details of the market based dynamic bit allocation scheme. Section IV presents a numerical example and Section V concludes our work.

II. System Model

In this paper, we assume N sensors that are grid deployed in a square surveillance area of size b^2 as shown in Fig. 1. Note that target tracking based on sensor readings can be performed for an arbitrary network layout if sensor placements are known in advance. All the sensors report to a mobile fusion center which physically tracks the target according to the estimated the target state, i.e., the position and the velocity of the target. We assume that the target (e.g., an acoustic or an electromagnetic source) emits a signal from the location (x_t, y_t) at time t.

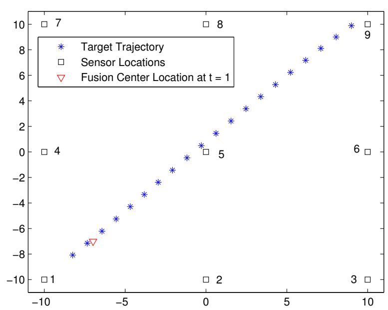

Fig. 1: A WSN with $N = 9$ sensors, an example target trajectory with $q = 2.5 \times 10^{-3}$ and the location of the fusion center at $t = 1$.

In this paper, we use exactly the same WSN model we had used in our previous work [7]. We consider a single target moving in a two-dimensional Cartesian coordinate plane. At time t, the target dynamics are defined by the 4-dimensional state vector $\mathbf{x}_t = [x_t \quad y_t \quad \dot{x}_t \quad \dot{y}_t]^T$ where $\dot{x}_t$ and $\dot{y}_t$ are the target velocities in the horizontal and the vertical directions. The superscript T denotes the transpose operation. Target motion is defined by the following white noise acceleration model:

$$\mathbf{x}_{t+1} = \mathbf{F}\mathbf{x}_t + \upsilon_t \tag{1}$$

where $\mathbf{F}$ models the state dynamics and υ_t is the process noise which is assumed to be white, zero-mean and Gaussian with the covariance matrix $\mathbf{Q}$ [7]. Note that $\mathbf{Q}$ is defined by Δ and q which denote the time interval between adjacent sensor measurements and the process noise parameter, respectively.

The target is assumed to be an acoustic or an electromagnetic source that follows the power attenuation model. Let P_0 denote the target signal power, $d_{i,t} \triangleq \sqrt{(x_i - x_t)^2 + (y_i - y_t)^2}$ is the distance between the target and the i^{th} sensor, and (x_i, y_i) are the coordinates of sensor i sensor. At time t, the received signal at sensor i is given by

$$z_{i,t} = \sqrt{\frac{P_0}{1 + d_{i,t}^2}} + n_{i,t} \tag{2}$$

where $n_{i,t}$ is the noise term modeled as additive white Gaussian noise (AWGN), i.e., $n_{i,t} \sim \mathcal{N}(0, \sigma_n^2)$, which represents the cumulative effects of sensor background noise and the modeling error of signal parameters. A sensor measurement $z_{i,t}$ at sensor i is locally quantized before being sent to the fusion center using $R_{i,t}$ bits for $R_{i,t} = m, m \in \{0, 1, \ldots, M\}$. M is the maximum number of bits that a sensor can use to transmit to the fusion center and $M = 0$ means that the sensor does not transmit its measurement to the fusion center. The quantization thresholds are assumed to be identical at each sensor for simplicity. In order to find the decision thresholds at each quantization rate, we use the Fisher information based heuristic quantization method which has been described in [16]. The fusion center receives the data vector $\mathbf{D}_t = [D_{1,t}, \ldots, D_{N,t}]$ from N sensors with a corresponding quantization rate vector $\mathbf{R}_t = [R_{1,t}, \ldots, R_{N,t}]$. The details of the quantization process and the likelihood function of the sensor data $\mathbf{D}_t$ given the target location $\mathbf{x}_t$ and rate vector $\mathbf{R}_t$ have been given in our previous work [7].

Based on the received data $\mathbf{D}_t$ quantized with rate vector $\mathbf{R}_t$, and the prior probability density function of $\mathbf{x}_t$, $p(\mathbf{x}_t)$, the PCRLB on the mean squared estimation error has the form,

$$E\left\{[\hat{\mathbf{x}}_t - \mathbf{x}_t][\hat{\mathbf{x}}_t - \mathbf{x}_t]^T | \mathbf{R}_t\right\} \geq \mathbf{J_t^{-1}}(\mathbf{R_t}) \tag{3}$$

where $\mathbf{J}_t(\mathbf{R}_t)$ is the 4×4 Fisher information matrix (FIM) and can be decomposed into two parts as,

$$\mathbf{J}_t(\mathbf{R}_t) = \mathbf{J}_t^D(\mathbf{R}_t) + \mathbf{J}_t^P \tag{4}$$

where $\mathbf{J}_t^D(\mathbf{R}_t)$ represents the Fisher information matrix obtained from the sensor data and can be written as the summation of Fisher information matrices of individual sensors [7]. Finally $\mathbf{J}_t^P$ is the a *priori* Fisher information. We employ a particle filter to solve the Bayesian sequential estimation problem for the system given in (1) and (2). Particle filters are sequential Monte Carlo methods based on particle representations of probability density function $p(\mathbf{x}_t)$ which are useful to compute the data part and the *a priori* part of the Fisher information matrices [17] as well as the minimum mean squared error (MMSE) estimate of the target location. Due to space limitations, we omit the details of derivation of the Fisher information for the system model considered in this work and the computation of Fisher information by using the particle filter approximation. A detailed discussion can be found in our previous work [7].

In our model, we consider a mobile fusion center which moves to the estimated target location at each time step of tracking. Let $(x_{0,t}, y_{0,t})$ be the location of the fusion center at time step t. Let the distance between sensor i and fusion center be denoted by $h_{i,t} = \sqrt{(x_i - x_{0,t})^2 + (y_i - y_{0,t})^2}$. Then, in order to transmit m bits successfully to the fusion center, each sensor should transmit its measurement with energy [8],

$$e_i(m) \propto m h_{i,t}^2 \tag{5}$$

III. Market Based Dynamic Bit Allocation Scheme

Price theory explains the trade of assets between consumers and producers. Consumers in the market buy and sell different assets and producers are able to transform assets of one kind into assets of a different kind. In our problem, the fusion center is the sole customer who buys information from the sensors. The sensors are the producers who compete for the energy released from the fusion center to produce the bits that represent their measurement. In our proposed market there are $NM+1$ assets where NM assets represent the purchase of m-bit measurements $m \in \{1, \ldots, M\}$, from sensor i, $i \in \{1, \ldots, N\}$. The last asset is the energy released from the fusion center or the total energy purchased by the sensors to transmit their quantized measurements successfully to the fusion center.

For the fusion center, the demand preference is represented by the demand vector of size $NM+1 \times 1$, $\boldsymbol{\phi}_d \triangleq [\phi_{d,1}, \ldots, \phi_{d,j}, \ldots, \phi_{d,NM+1}]^T = [q_{1,1}, \ldots, q_{i,m}, \ldots, q_{N,M}, q_e]^T$ where $q_{i,m} \in \{0,1\}$ is the demand requesting m bits from sensor i. If sensor i transmits its measurement in m bits, $q_{i,m} = 1$, otherwise $q_{i,m} = 0$. q_e is then the total energy released from the fusion center. In the demand vector, $\boldsymbol{\phi}_d$, the assets $q_{i,m} > 0$, since the fusion center buys the assets and $q_e < 0$, since the fusion center sells the asset. Then $\mathbf{p} \triangleq [p_{1,1}, \ldots, p_{i,m}, \ldots, p_{N,M}, p_e]^T$ is the price vector where $p_{i,m}$ is the price paid to purchase m bits from sensor i and p_e is the price of unit energy. Given the price vector, $\mathbf{p}$, the fusion center minimizes the error in estimation by minimizing the trace of the PCRLB matrix subject to the constraints,

$$\begin{aligned} \min_{\phi_{d,1},\ldots,\phi_{d,NM}} \quad & \operatorname{trace}\left(\sum_{i=1}^{N} \sum_{m=1}^{M} q_{i,m} \mathbf{J}_{i,t}^{D}(R_{i,t} = m) + \mathbf{J}_t^P \right)^{-1} \\ \text{s.t.} \quad & \sum_{m=1}^{M} q_{i,m} \leq 1 \quad i \in \{1, 2, \ldots, N\} \\ & \sum_{i=1}^{N} \sum_{m=1}^{M} q_{i,m} p_{i,m} \leq p_e E_0 \ ; \ q_{i,m} \in \{0,1\} \end{aligned} \tag{6}$$

Then, the solution of the above optimization problem determines the released energy to the network as,

$$\phi_{d,NM+1} = q_e = -\frac{\sum_{i=1}^{N} \sum_{m=1}^{M} q_{i,m} p_{i,m}}{p_e} \tag{7}$$

In (6), the first N constraints ensure that each sensor can only use one of M levels to quantize its measurement or can stay silent. In the next constraint, E_0 is the fusion centers endowment of energy that is the maximum energy that can be released for the use of sensors. This constraint implies that the total wealth that can be spent to minimize the trace of the PCRLB, should be less than the wealth that can be generated by selling all the energy.

Sensors in the network act as producers who buy energy from the fusion center in order to produce their m-bit measurements. In the production model of sensor i, $q_{i,m} > 0$ is the output and $E_i < 0$ is the input (raw product) of the production. We assume that sensor i has an initial wealth, represented by W_i. Then, the amount of energy that a sensor can afford to buy from the fusion center is $E_i = -W_i/p_e$. . The production vector of sensor i is represented by $\boldsymbol{\chi}_i \triangleq [q_{i,1}, \ldots, q_{i,M}, E_i]^T$. If $e_i(m) \leq -E_i$, sensor i has sufficient energy to transmit its measurement in m-bits. Given the price vector $\mathbf{p}$, sensor i quantizes its information in m-bits which maximizes the profit,

$$\begin{aligned} \max_{\boldsymbol{\chi}_i} \quad & \sum_{m=1}^{M} p_{i,m} q_{i,m} + p_e E_i \\ \text{s.t.} \quad & e_i(m) \leq -E_i \end{aligned} \tag{8}$$

where we find the optimal m for sensor i among the feasible m's. Having solved (8) for all $i \in \{1, 2, \ldots, N\}$, we define $\boldsymbol{\chi}_p$ as the WSN's production vector of size $NM+1 \times 1$ and $\boldsymbol{\chi}_p \triangleq [\chi_{p,1}, \ldots, \chi_{p,j}, \ldots, \chi_{p,NM+1}]^T = [q_{1,1}, \ldots, q_{i,m}, \ldots, q_{N,M}, q_p]^T$ where $q_p = \sum_{i=1}^{N} E_i$.

$\boldsymbol{\phi}_d$ and $\boldsymbol{\chi}_p$ are the solutions of the two separate optimization problems given in (6) and (8) given the price vector $\mathbf{p}$. Let the j^{th} asset of demand vector $\boldsymbol{\phi}_d$ and production plan vector $\boldsymbol{\chi}_p$ be $\phi_d(j)$ and $\chi_p(j)$ respectively for all $j \in \{1, 2, \ldots, NM+1\}$. The market equilibrium is reached by updating the price vector, $\mathbf{p}$, as a function of the demand $\boldsymbol{\phi}_d$, and the production $\boldsymbol{\chi}_p$, of each asset in this market. The market is said to be clear at price $\mathbf{p}$ if $\phi_d(j) = \chi_p(j)$ for all $j \in \{1, 2, \ldots, (NM)+1\}$. In this paper, we use the iterative auction algorithm given in Algorithm 1 to find the market equilibrium [12]. We assume that the fusion center knows the locations of each sensor and carries out all the steps of Algorithm 1. The fusion center then requests the quantized measurements from sensors as determined by the bit allocation scheme.

Algorithm 1 Iterative Auction algorithm to find the market equilibrium

(1) Set $v = 0$, and price vector $\mathbf{p} = \mathbf{p}^0$.
(2) Given $\mathbf{p}^v$, solve (6) to find the demand vector $\boldsymbol{\phi}_d$.
(3) Given $\mathbf{p}^v$, solve (8) to find the production plan vector $\boldsymbol{\chi}_p$.
(4) Set $C(j) = 0$ for all $j \in \{1, 2, \ldots, NM+1\}$,
IF $\boldsymbol{\phi}_d(j) \approx \boldsymbol{\chi}_d(j)$, $C(j) = 1$ ENDIF
IF $\sum C(j) = NM+1$, terminate the auction algorithm, ELSE go to Step (5) ENDIF.
(5) Given $\boldsymbol{\phi}_d$ and $\boldsymbol{\chi}_p$ update prices. For all $j \in \{1, 2, \ldots, NM+1\}$, do
IF $\boldsymbol{\phi}_d(j) > \boldsymbol{\chi}_p(j)$, $p_j^{v+1} = p_j^v[1 + \delta p_j^v(\boldsymbol{\phi}_d(j) - \boldsymbol{\chi}_p(j))]$ // Demand is greater than supply, increase the price.
ELSE IF $\boldsymbol{\phi}_d(j) < \boldsymbol{\chi}_p(j)$, $p_j^{v+1} = p_j^v/[1 + \delta p_j^v(\boldsymbol{\chi}_d(j) - \boldsymbol{\phi}_p(j))]$ // Demand is less than supply, decrease the price.
ELSE $p_j^{v+1} = p_j^v$ ENDIF. Set $v = v+1$ and go to Step (2).

IV. Numerical Example

In this section, we provide a numerical example to illustrate the effectiveness of the proposed bit allocation scheme. We assume that each sensor can quantize its measurement in up to $M = 5$ bits. Furthermore, the initial wealth of sensors is assumed to be identical and selected as $W_i = 1$. The δ parameter of Algorithm 1 is selected as $\delta = 0.2$. Note that smaller values of δ result in slower convergence and for larger values of δ, the market prices do not clear. We first relax the problem given in (6) by replacing the Boolean variables with their continuous counterparts, i.e., $0 \leq q_{i,m} \leq 1$. Then, we use KNITRO solver [18] to solve the relaxed problem by using its active-set algorithm. Algorithm 1 is initialized with $\mathbf{p}^0$ as the all one vector. Price, demand and production vectors obtained at the end of each iteration are used as initial points for the next iteration of the auction algorithm. Table I presents the first NM elements of the demand vector at $t = 1$ and when $E_0 = 1000$ units of energy is available. As shown in Fig. 1, sensor 1 is relatively close to the fusion center and the fusion center can buy $M = 5$ bit information from sensor 1 at a cheap price and the energy released for sensor 1 to transmit 5 bit information is $p_{1,5}/p_e \approx 213.6$. Fusion center also buys 1-bit measurement from sensors 2,4 and 5 and the total energy consumption is around 300 units. After relaxing problem (6), the solution vector includes $q_{4,5} = 0.0897$ and the fusion center allocates around $p_{4,5}/p_e \approx 700$ units of energy for transmitting $q_{4,5}$ which is actually not used during the data transmission.

TABLE I: Fusion center demand $q_{i,m}$ at the price equilibrium at $t = 1$. For all $i \in \{3, 6, 7, 8, 9\}$, $q_{i,m} = 0$

	$m = 1$	$m = 2$	$m = 3$	$m = 4$	$m = 5$
$i = 1$	0	0	0	~ 0	1 (213.6)
$i = 2$	1 (20.1)	0	0	0	0
$i = 4$	0.9103 (18.2)	0	0	0	0.0897 (720.4)
$i = 5$	1 (27.72)	0	0	0	0

Fig. 2-(a) shows the total energy required to transmit sensor data to the mobile fusion center and Fig. 2-(b) shows the MSE performance of tracking. For $E_0 = 1000$, total energy consumption is around 300, because of the reasons described previously. We compare the performance of the market based bit allocation scheme, with the bit allocation scheme with the total number of bits constraint [7] where we remove the total energy consumption constraint and limit the total number of bits that can be transmitted from sensors to the fusion center. In other words, the fusion center now distributes 5 bits among $N = 9$ sensors. The bit allocation scheme with the total number of bits constraint allocates all the bits to sensor 5 around $t \in [6, 11]$. For $t \in \{[2, 5] \bigcup [12, 16]\}$, the average energy consumption of market based bit allocation scheme with $E_0 = 1000$ and the bit allocation scheme with the total number of bits constraint are similar. During $t \in [6, 11]$, the mobile fusion center is close to sensor 5 and sensor 5's data transmission consumes little energy. On the other hand, within the same interval, market based bit allocation can buy 5 bit information from sensor 5 at a cheap price and then is able to buy additional information from other sensors. That is why the MSE performance of the market based bit allocation with $E_0 = 1000$ provides better tracking performance than the bit allocation scheme with the total number of bits constraint. When E_0 is reduced to $E_0 = 500$, the fusion center can purchase less information from sensors and the tracking performance degrades. Among all simulated scenario the market based bit allocation scheme with $E_0 = 1000$ provides the closest estimation performance to that of the case where all $N = 9$ sensors transmit $M = 5$ bit information.

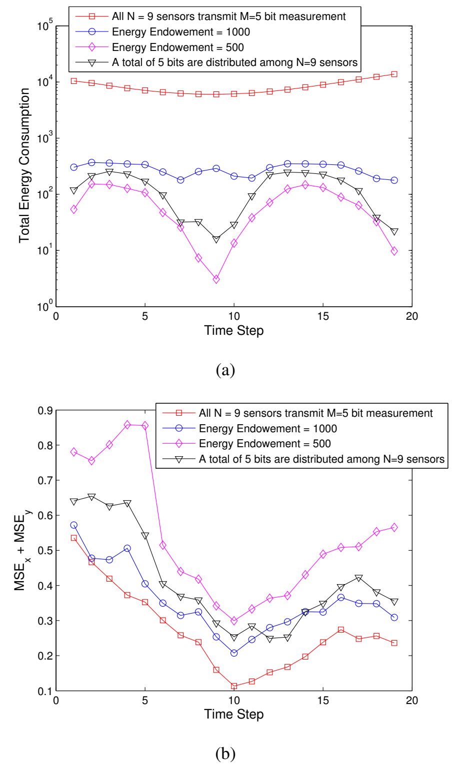

Fig. 2: (a) Total energy consumption (b) Summation of MSE on the positional estimates, MSE = MSE_x + MSE_y. The MSE at each time step is averaged over $T_{trials} = 100$ trials. $P_0 = 10^3$, $\sigma_n^2 = 1$. The initial state distribution of the target $p(\mathbf{x}_0)$ is Gaussian with $\mu_0 = [-8\ -8\ 2\ 2]$ and $\Sigma_0 = diag[\sigma_\theta^2\ \sigma_\theta^2\ 0.01\ 0.01]$ and $3\sigma_\theta = 2$ so the initial point of the target remains in the ROI with very high probability. The target motion follows a near constant velocity model with $q = 2.5 \times 10^{-3}$. Measurements are taken at regular intervals of $\Delta = 0.5$ seconds and the observation length is 10 s.. The number of particles used in the particle filter is $N_s = 5000$.

V. CONCLUSION

In this paper, we have studied a market based dynamic bit allocation scheme for target tracking in energy constrained wireless sensor networks using quantized data where the fusion center acts as a customer and sensors act as producers and the prices of purchasing bits from sensors and price of unit energy balances the market. The proposed scheme achieves tracking performance close to that of the case where all the sensors transmit information to the fusion center and reducing the total energy requirement. As a future work, we will consider scenarios where the wealth of sensors vary in time and the design of multiple-time steps ahead dynamic bit allocation policies are necessary.

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