DISTRIBUTED CENSORING WITH ENERGY CONSTRAINT IN WIRELESS SENSOR NETWORKS

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ABSTRACT

In wireless sensor networks (WSNs), energy is always precious for sensor nodes. To save energy, censoring is introduced to cut the total number of transmission by only transmitting informative data. This algorithm, however, ignores the energy consumption during the delivery of parameters, which can be significant comparing to the saved power. In this paper, we consider the adaptive censoring from the energy perspective. A distributed censoring algorithm with energy constraint is developed that allows sensor nodes to make autonomous decisions on whether to transmit the incoming data. We show that with the proposed algorithm, the overall energy consumption of the WSNs is reduced, while the performance loss in terms of estimation error is negligible. Simulation results validate its effectiveness.

Index Terms— Distributed censoring, energy constraint, recursive least squares, wireless sensor networks.

1. INTRODUCTION

Wireless sensor networks (WSNs) become popular in recent years, thanks to technology advances in sensors, communications and computations. The applications of WSNs include environmental monitoring, industrial control, smart home, etc. [1], where sensor nodes are deployed over a geographical area of interest to sense the environment, and a fusion center (FC) is applied to collect data. The nature of sensor nodes determines that the energy is always a critical constraint when deploying WSNs. Reducing the data transmission can be an effective way to reduce the energy consumption [2].

There are a number of data-reduction techniques used in parameters estimation with WSNs, such as collaborative data covariance-based dimensionality reduction using convex optimization [3] [4], measurement quantization [5] and compressive sensing [6]. However, these proposed protocols either require collaboration among sensors in the data-reduction step, or require several rounds of sensor nodes to FC communication for effective data-reduction. Censoring has recently been employed to select data for estimation of parameters and dynamical processes in resource-constrained WSNs [7] [8]. Authors in [9], [10] and [11] confirmed that estimation accuracy of sensors in the data-reduction step, or require several rounds of sensor nodes to FC communication for effective data-reduction. Censoring has recently been employed to select data for estimation of parameters and dynamical processes in resource-constrained WSNs [7] [8]. Authors in [9], [10] and [11] confirmed that estimation accuracy of sensors in the data-reduction step, or require several rounds of sensor nodes to FC communication for effective data-reduction.

The rest of this paper is organized as follows. Section II introduces the framework of distributed censoring method with energy constraint for WSNs. Performance analysis of the proposed censoring approach is presented in Section III. Section IV shows the simulation results, and Section V concludes the paper.

Notations: Lower-(upper-) case boldface letters denote column vectors (matrices). Calligraphic symbols are reserved for sets, while symbol (·)T stands for transposition. φ(t) = (1/(2π)) exp(−t2/2) denotes the standardized Gaussian probability density function (PDF) and Q(z) = ∫−∞z φ(t)dt denotes the associated complementary cumulative distribution function. Vector I denotes the identity matrix. Positive definiteness (semi-definiteness) of a symmetric matrix B is denoted as B ⪰ 0 (respectively, B ⪯ 0). An estimation for parameters θ will be represented as ˆθ.

2. SYSTEM MODEL AND PROBLEM FORMULATION

Consider a WSN with K sensor nodes {Sk}Kk=1 randomly deployed over a geographical area. Unknown parameters θ ∈ ℜp, where p is the length of parameters, are related to the measurement yk ∈ ℜ at each sensor node by the linear regression model [12] [13]

\[ y_k = \mathbf{h}_k^T \theta + v_k, \quad k = 1, \ldots, K, \tag{1} \]

where the regressors {h_k}Kk=1 are known at the FC, and v_k denotes uncorrelated, zero-mean, Gaussian distributed noise. Without loss of generality, we assume that the noise variance is σ2 for all K sensors.

If all \( y_k \) are available at the FC, the maximum likelihood estimation of China under Grant No. 61671436 and the Science and Technology Commission Foundation of Shanghai under Grant No. 17511104902.

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estimation of $\theta$ would be the least squares (LS) estimator \[15\]
\[
\hat{\theta}_{ls}(K) = \left( \sum_{k=1}^{K} h_k h_k^T \right)^{-1} \sum_{k=1}^{K} y_k^* h_k. \tag{2}
\]

The performance of the estimator is assessed by the covariance matrix \[C(K) = \sigma^2 \left( \sum_{k=1}^{K} h_k h_k^T \right)^{-1} \] \[15\].

In general, LS solution can only deal with a batch of data samples. To deal with the large datasets, we would like to reduce the overall computational complexity of the estimation task as well as the total number of utilized observations $y_k^*$ and/or $h_k$ \[11\].

Data censoring can be applied to reduce the number of observations adopted for estimation. With $R_k$ denoting the censoring interval, a generic censoring rule to select data in (1) is given by
\[
y_k = \begin{cases} 
\ast, & \text{if } y_k^* \in R_k, \\
y_k^*, & \text{otherwise}.
\end{cases} \tag{3}
\]

where $\ast$ denotes an unspecified value. If $y_k^* \in R_k$, the value of $y_k^*$ is censored and we only know that $y_k \in R_k$ for the set $R_k$; otherwise, the exact measurement $y_k = y_k^*$ is obtained as the incoming data contains additional information that previous observations may not have \[11\].

Fig. 1 illustrates the data censoring in WSNs. In this setup, sensor nodes transmit their observations to the FC. Inter-sensor transmission is not considered. Instead of transmitting all observations, a total of $\bar{K}(<K)$ sensor nodes are selected to transmit their measurements to FC during one estimation period.

To deal with the impact of the initial estimation on estimation performance, we assume a multiple time slots scenario. Fig. 2 illustrates the data censoring with $T = 3$ time slots in WSNs. During each time slot, only $K = 10$ sensor nodes are selected to transmit their measurements to FC. Additionally, censoring is performed independently at each sensor node during each time slot.

The energy constraint, on the other hand, is critical to WSNs. A fair data selection method should consider the energy consumption during the data transmission. In WSNs, the energy consumed by the transceiver and the signal processing unit can be considered as a constant. The energy dissipated is approximately $\epsilon_{elec} = 400\, \text{mJ/byte}$ to run the transmitter or receiver circuitry. The energy consumption by the power amplifier, on the other hand, greatly depends on the Euclidean distance $d_k$ between the sensor node $k$ and the FC. A simplified model of energy consumption per byte of the power amplifier is $\epsilon_{amp} d_k^2$, where $\epsilon_{amp} = 800\, \text{nJ/byte/m}^2$. As the data received and transmitted are usually short messages, we assume that the data length of the packet is $m$ bytes for both transmitter and receiver. Thus, the total transmitting energy consumption would be $m \epsilon_{elec} + m \epsilon_{amp} d_k^2$; the total receiving energy consumption is $m \epsilon_{elec}$ \[16\].

To simplify notation, we normalize the energy in terms of receptions, that is to say, each reception consumes a unit of energy, while each transmission from sensor $k$ to FC consumes \[17\]
\[
E_k = 1 + \beta d_k^2, \tag{5}
\]

where $\beta = \epsilon_{amp}/\epsilon_{elec} > 0$.

During each time slot $t = 1, \cdots, T$, $s_k^*$ is the selection vector at time slot $t$ which can be obtained by solving the following optimization problem
\[
s_k^* = \arg \min_{s \in \{0,1\}^K} \sum_{k=1}^{K} \left[ \alpha_{tk} (y_k^* - s_k h_k^T \theta)^2 + (1 - \alpha_{tk}) s_k E_k \right] \tag{6a}
\]

s.t. \[\sum_{k=1}^{K} s_k \leq \bar{K}, \tag{6b}\]

where $y_k^*$, $h_k$, and $s_k$ are the measurement, regressor and the selection variable of sensor node $k$ at time slot $t$, respectively; $\alpha_{tk}$ (\(0 \leq \alpha_{tk} \leq 1\)) and $1 - \alpha_{tk}$ are the weights of estimation performance and transmission energy cost of sensor $k$ at time slot $t$, respectively. Comparing to estimation performance, if energy cost is more important for the WSNs, a smaller $\alpha_{tk}$ is chosen; otherwise, a larger $\alpha_{tk}$ is chosen. If energy cost is not considered, i.e., $\alpha_{tk} = 1$, problem (6) reduces to the original censoring problem (4).

In the next section, we derive an adaptive censoring algorithm for (6). Its performance is also discussed analytically.
3. PROPOSED DISTRIBUTED CENSORING ALGORITHM
WITH ENERGY CONSTRAINT

To deal with the optimization problem (6), we can include the constraint (6b) into the objective function with a Lagrange multiplier \( \lambda_t(\lambda_t > 0) \). In addition, replacing the binary constraint \{0, 1\} by the interval one \([0, 1]\) leads to a relaxed but convex alternative to (6). The updated quadratic optimization problem is given by

\[
s_t^*(\lambda_t) = \arg\min_{s_t \in [0, 1]^K} \sum_{k=1}^{K} (\alpha_{tk}(y_{tk} - s_{tk} h_{tk}^T \theta_{t-1}))^2 + (1 - \alpha_{tk}) s_{tk} E_{tk} + \lambda_t \left( \sum_{k=1}^{K} s_{tk} - K \right),
\]

where \( \theta_t \) is initialized to \( \theta_0 = \hat{\theta} \), and \( \theta_{t-1} \) is the estimated parameters after time slot \( t - 1 \), which is available to sensor nodes through downlink broadcasting.

Problem (7) can be decomposable into \( K \) separate problems for which the \( k \)-th sub-problem attains its minimum at

\[
s_{tk}^*(\lambda_t^*) = \frac{2 \alpha_{tk} y_{tk} h_{tk}^T \theta_{t-1} - (1 - \alpha_{tk}) E_{tk} - \lambda_t^*}{2 \alpha_{tk} h_{tk}^T \theta_{t-1}},
\]

where \( \lambda_t^* \) is the optimal Lagrange multiplier at time slot \( t \). Slicing \( s_{tk} \) leads to the selection \( s_{tk} = 1[y_{tk} > 0] \), where \( 1[y_{tk} > 0] \) denotes the indicator function. The condition \( s_{tk} > 0 \) can be rewritten as

\[
|y_{tk}| > \frac{(1 - \alpha_{tk}) E_{tk} + \lambda_t^*}{2 \alpha_{tk} h_{tk}^T \theta_{t-1}} = \tau_{tk}(\lambda_t^*),
\]

where \( \tau_{tk}(\lambda_t^*) \) is the optimal threshold of sensor \( k \) at time slot \( t \). The term \( y_{tk} \) and \( h_{tk}^T \theta_{t-1} \) must have the same signs; otherwise, \( s_{tk} = 0 \) since \( s_{tk}^* < 0 \).

The optimum \( \lambda_t^* \) should satisfy the inequality constraint (6b). Note that the number of uncensored measurements, \( \sum_{k=1}^{K} s_{tk} \), is a random variable. Bounding \( \sum_{k=1}^{K} s_{tk} \) not to exceed the desired value \( \hat{K} \), yields

\[
\sum_{k=1}^{K} \mathbb{E}[s_{tk}] = \sum_{k=1}^{K} \text{Pr}[|y_{tk}| > \tau_{tk}(\lambda_t^*)]
= K - \sum_{k=1}^{K} \mathbb{E} \left( \frac{-\tau_{tk}(\lambda_t^*) - h_{tk}^T \theta}{\sigma} \right) - \mathbb{E} \left( \frac{\tau_{tk}(\lambda_t^*) - h_{tk}^T \theta}{\sigma} \right)
= K - f(\lambda_t)
\leq \hat{K}.
\]

It is shown that \( f(\lambda_t) \) is a monotonically increasing function of \( \lambda_t \). Replacing \( \theta \) by \( \theta_{t-1} \), a one-dimensional grid search yields the desired \( \lambda_t^* \) [13].

Supposing that the optimum \( \lambda_t^* \) and estimation \( \hat{\theta}_{t-1} \) are available at each sensor, censoring can be implemented autonomously at each sensor with the following rule

\[
(y_{tk}, s_{tk}) = \begin{cases} (y_{tk}, 1), & \text{if } |y_{tk}| > \tau_{tk}(\lambda_t^*), \\ (*, 0), & \text{otherwise}. \end{cases}
\]

Applying recursive least squares (RLS) algorithm in FC with the censoring rule, yields [11]

\[
\hat{\theta}_n = \hat{\theta}_{n-1} + \frac{s_{tk}}{n} C_n h_{tk}(y_{tk} - h_{tk}^T \hat{\theta}_{t-1}),
\]

\[
C_n = \frac{1}{n-1} \left[ C_{n-1} - \frac{s_{tk} C_{n-1} h_{tk}^T h_{tk} C_{n-1}}{n-1} + \frac{h_{tk}^T C_{n-1} h_{tk}}{n-1} \right],
\]

where \( C_n \) is the sample estimation for \( C(K) \), and is typically initialized to \( C_0 = cI \) for some small positive \( c \).

The computation and communication steps that constitute censoring are tabulated as Algorithm 1. During each time slot, prior to censoring, the FC calculates the optimum \( \lambda_t^* \) and broadcasts it and \( \theta_{t-1} \) to all \( K \) sensors. Each sensor \( S_k \) autonomously decides its threshold \( \tau_{tk} \), and makes the censoring independently. Parameters estimation is performed in FC with RLS algorithm.

**Algorithm 1** Distributed Censoring with Energy Constraint

**Require**: \( h_{tk}, \hat{K}; S_k \) knows \( h_{tk}, y_{tk}^* \)

1: initialize \( n = 1 \), \( \hat{\theta}_0 = \hat{\theta} \), \( C_0 = cI \)
2: for \( t = 1, 2, \ldots, T \) do
3: FC: Finds \( \lambda_t^* \) from (10), broadcasts \( (\lambda_t^*, \hat{\theta}_{t-1}) \)
4: for \( k = 1, 2, \ldots, K \) do
5: \( S_k \): Receives \( (\lambda_t^*, \hat{\theta}_{t-1}) \), gets threshold \( \tau_{tk}, y_{tk} \) and \( s_{tk} \)
6: end for
7: for \( k = 1, 2, \ldots, K \) do
8: FC: Updates \( C_n \) and \( \hat{\theta}_n \) using (12), \( n \leftarrow n + 1 \)
9: end for
10: FC: \( \hat{\theta} \leftarrow \hat{\theta}_n \)
11: end for
12: FC: Set \( \hat{\theta} = \hat{\theta}_T \)

Next, we study the performance of the proposed method in terms of convergence.

**Proposition 1**: The Cramér-Rao lower bound (CRLB) for the variance of distributed censoring method with energy constraint is given by

\[
\mathbf{I}_{T/K}(\theta) = \sum_{t=1}^{T} \sum_{k=1}^{K} \tau_{tk}(\theta) h_{tk} h_{tk}^T,
\]

where

\[
\tau_{tk}(\theta) = \frac{1}{\sigma^2} \left\{ \frac{1 - [Q(z_{1tk}) - Q(z_{2tk})]}{1 - [Q(z_{1tk}) - Q(z_{2tk})]} + \frac{z_{1tk} \phi(z_{1tk}) - z_{2tk} \phi(z_{2tk})}{1 - [Q(z_{1tk}) - Q(z_{2tk})]} \right\},
\]

\[
z_{1tk} = -\frac{\tau_{tk} - h_{tk}^T \theta}{\sigma}, \quad z_{2tk} = \frac{\tau_{tk} - h_{tk}^T \theta}{\sigma}.
\]

**Proof of Proposition 1**. Both the proposed algorithm and [13] are based on distributed censoring method. Compared to [13], the proposed method considers multiple time slots scenario and the energy cost is taken into account, which only changes the value of \( \tau_{tk} \). According to the Appendix C of [13], the CRLB of the proposed approach is obtained.

4. NUMERICAL RESULTS

In this section, we examine the proposed distributed censoring method with energy constraint. Simulations are done for the model in (1) with \( K = 100 \), \( K = 20 \) and SNR=30 dB. The regressors \( h_{tk} \) and parameters vector \( \theta \) are picked uniformly over \([-1, 1] \) with dimension \( p = 10 \), \( \alpha_{tk} \) is constant for each sensor node at each time slot. During all the simulations in this paper, there are \( K \) sensor
nodes randomly deployed in 1km × 1km area, the FC is located at (0.5km, 0.5km).

In the first experiment, we would like to check the algorithm performance in terms of modeling accuracy, which is defined as normalized mean-square error (NMSE = ||\hat{\theta}_t - \theta||^2 / ||\theta||^2). The convergence of estimation in terms of NMSE is shown in Fig. 3, where the x-axis and y-axis represent time slot and NMSE, respectively; the black dashed line shows the NMSE of randomly selected method; the red solid line reveals the performance of the proposed algorithm with \( \alpha_{tk} = 0.1 \); the blue dashed line indicates the performance of distributed censoring method and the magenta dashed line represents the NMSE performance of all data method. From this figure, we observe that the NMSE of all data method benchmarks the performance of other methods, the proposed method performs slightly worse than distributed censoring method but slightly better than randomly selected method.

Next, we study the energy efficiency of the proposed algorithm. Energy consumptions of different estimation methods at each time slot are shown in Fig. 4, where the x-axis and y-axis represent time slot and energy consumed, respectively; the legends are the same as the first simulation’s. As Fig. 4 shows, the method using all data has the largest energy consumption because all data must be transmitted from sensors to FC. Energy consumptions of distributed censoring method and randomly selected method are basically the same, since the energy cost is not taken into account in both methods. The proposed method consumes the least energy than other methods. Because it not only considers the convergence performance, but also takes the energy cost into account.

In the third simulation, we would like to verify the convergence speed of the proposed algorithm with different \( \alpha_{tk} \)'s. In Fig. 5, the red solid line, black dashed line and blue dashed line represent the performance of the proposed method with \( \alpha_{tk} = 0.1 \), \( \alpha_{tk} = 0.05 \) and \( \alpha_{tk} = 0.03 \), respectively. We observe that when \( \alpha_{tk} \) is small, the proposed algorithm converges slowly and eventually reaches a larger convergence value. When \( \alpha_{tk} \) is large, it converges quickly and has a lower bound. Thus, the choice of \( \alpha_{tk} \) is an important factor affecting the performance of the proposed method.

In the fourth simulation, we would like to continue our investigation of different \( \alpha_{tk} \)'s in terms of energy consumed. The legends are the same as the third simulation’s. As Fig. 6 shows, the smaller the \( \alpha_{tk} \), the more important the energy consumption is in WSNs, the less energy is consumed. Appropriate choice of \( \alpha_{tk} \) can achieve the trade-off between estimation performance and energy consumption.

5. CONCLUSIONS

In this paper, a distributed censoring method with energy constraint for parameters estimation in WSNs is explored. The energy cost is considered based on the distributed censoring algorithm. The overall energy consumption of WSNs is reduced, with little estimation performance loss. Simulations demonstrate that the proposed algorithm achieves a good trade-off between estimation performance and energy consumption.
6. REFERENCES


