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Adaptive quantization for distributed estimation in cluster-based wireless sensor networks☆

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ABSTRACT

In this paper, the problem of parameter estimation in cluster-based wireless sensor networks is studied. Particularly, we focus on how to choose a suitable threshold in the one-bit adaptive quantization scheme. An adaptive quantization scheme for parameter estimation in cluster-free sensor networks is extended to this scenario. Intra-cluster and inter-cluster maximum likelihood estimators (MLEs) as well as the corresponding Cramér–Rao lower bounds (CRLBs) are derived. Due to the energy constraint of sensors, the performance–energy tradeoff of parameter estimation is also investigated. Simulation results show that parameter estimation in cluster-based sensor networks with adaptive quantization can be more energy-efficient than that in cluster-free sensor networks, while achieving close performance as the number of sensors increases.

1. Introduction

Distributed estimation in wireless sensor networks has sparked great research interest in recent years [1–12]. A key feature of distributed estimation is that sensors collaborate to estimate a scalar parameter, a signal vector or others under the inherent limitations of sensor networks (such as limited energy and constrained bandwidth). The main design goal is to save energy while achieving acceptable estimation performance.

For distributed estimation in sensor networks, the estimation performance depends on the choice of threshold in the one-bit quantization of samples [2,11,12]. There are two basic strategies for the selection of threshold: (1) fixed quantization in local sensors. For instance, the cases with the single threshold and a fixed set of different thresholds were studied [2]. (2) adaptive quantization in local sensors. For instance, each local sensor dynamically adjusts its threshold based on the data received from other sensors [11]. Three adaptive quantized schemes including step size-fixed, step size-variable, and maximum-likelihood schemes were proposed in [12].

Motivated by energy constraint of sensors, energy-efficient distributed estimation algorithms have been widely pursued [5–7]. It is worthwhile to mention that different topologies of sensor networks lead to different energy consumption and estimation performance [8–10]. It has been shown that the tradeoff between estimation performance and energy consumption exists under certain conditions [9].

In this paper, the energy-efficient distributed estimation problem in cluster-based sensor networks based on one-bit quantized observations is considered. It is worthwhile to mention that comparing with sensors sending original observations to cluster heads [13], sensors under consideration will quantize observations into one-bit messages and then send messages to cluster heads. To design a more energy-efficient and less complex distributed estimation scheme than the scheme with adaptive quantization in [11], a cluster-based adaptive quantization scheme is proposed. Different from linear-operation collaboration for cluster-based sensor networks in [14], two kinds of maximum likelihood estimators (MLEs), i.e. the intra-cluster MLE and the inter-cluster MLE, are derived to obtain an accurate estimate of the parameter. Their corresponding CRLBs are also derived to benchmark the estimation

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performance. Considering the energy constraint of sensors, the tradeoff between estimation performance and energy consumption is investigated through formulating an optimization problem.

2. Cluster-based adaptive quantization

Consider a densely-deployed sensor network, which consists of M locally distributed sensors and a fusion center, to reconstruct the underlying physical parameter of interest. It is assumed that the observation noises $\{w(i), i = 1, b, \ldots, M\}$ are independent and identically distributed Gaussian random variables with zero mean and variance σ^2.

Each sensor takes an observation of an unknown and deterministic scalar parameter:

$$x(i) = \theta + w(i), i = 1, 2, \ldots, M, \tag{1}$$

where θ and $x(i)$ denote the scalar parameter and an observation from the sensor i, respectively.

Subject to severe bandwidth and energy limitations, local observations should be quantized before being transmitted. This leads to a set of binary observations $b(i, \tau_k)$, where k and τ_k denote the time index and a threshold, respectively. If τ_k is constant, it means that the threshold is fixed; if τ_k is time-varying, it means that the threshold is adaptive. It has been shown that distributed estimation with an adaptive threshold can achieve better performance than that with a fixed threshold [11]. The adaptive quantization scheme in [11] is summarized as follows. The scheme uses the one-bit quantizer and defines a random threshold τ_1 at the sensor 1, which usually is set to zero. Thus, the sensor 1 generates a binary observation b_1:

$$b_1 = \text{sgn}\{x(1)\}, \tag{2}$$

where the function sgn{} is defined as

$$\text{sgn}\{x\} = \begin{cases} 1, & x \geq 0; \\ -1, & x < 0. \end{cases} \tag{3}$$

Then, b_1 is transmitted to the fusion center. The wireless communication channel is assumed to be shared on a time-division basis. Therefore, the information bit of each sensor can be received by the subsequent sensors. For the sensor n, the binary observation b_n is generated as follows:

$$b_n = \text{sgn}\{x(n) - \tau_n\}, \tag{4}$$

where $\tau_n = \Delta \sum_{i=1}^{n-1} b_i$ and $n \geq 2$, Δ denotes a positive step size parameter. The sensor n will receive the information bits of the preceding sensors $\{1, 2, \ldots, n-1\}$.

The above adaptive quantization scheme requires that every local sensor broadcast its packets and other local sensors including the fusion center listen and receive the packets. In contrary, a fixed quantization scheme only requires that every local sensor sends its packets to the fusion center [2]. Note that additional packets received by other local sensors are energy-consuming. Therefore, parameter estimation with the above adaptive quantization scheme consumes more energy than that with a fixed quantization scheme.

It is known that clustering can reduce energy consumption and improve energy efficiency in sensor networks. Therefore, we consider parameter estimation in cluster-based sensor networks with adaptive quantization. The sensor network is divided into many clusters. In each cluster, the cluster members communicate with the cluster head. All cluster heads communicate with the fusion center. To avoid interference between clusters, no information exchange across clusters is allowed. It is assumed that communication channels between any cluster head and its members are ideal. This assumption is reasonable when a cluster head and its cluster members are close to each other [10]. The cluster-based adaptive quantization scheme is described as follows. Each cluster adopts the above adaptive quantization scheme independently. The step size Δ_i will be assigned to the cluster i. The sensor j in the cluster i (denoted by (i, j)) generates a binary observation $b_{(i,j)}$:

$$b_{(i,j)} = \text{sgn}\{x(i, j) - \tau_{(i,j)}\}, \tag{5}$$

where $x(i, j)$ denotes the observation of the sensor j in the cluster i. The parameter $\tau_{(i,j)}$ is expressed as

$$\tau_{(i,j)} = \Delta_i \cdot \sum_{k=1}^{j-1} b_{(i,j)}, j \geq 2. \tag{6}$$

Because $b_{(i,j)}$ is equal to -1 or 1, it becomes a Bernoulli random variable with parameter

$$q(\theta, \tau_{(i,j)}) := Prob\{b_{(i,j)} = 1\} = \int_{\tau_{(i,j)}}^{+\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\theta)^2}{2\sigma^2}} dx. \tag{7}$$

3. Estimation performance

3.1. Intra-cluster MLE and inter-cluster MLE

To obtain an accurate estimate of the parameter at the fusion center, the cluster heads generate data by adopting the following intra-cluster MLE and then transmit the data directly to the fusion center. It is assumed that the channel between each cluster head and the fusion center is error-free. The intra-cluster MLE is essentially the MLE [11] working in each independent cluster.

Each cluster head, taking the cluster i for example, first calculates its corresponding joint probability mass function (PMF) of $\{b_{(i,1)}, \ldots, b_{(i,N_i)}\}$ as

$$P_{(b_{(i,1)}, \ldots, b_{(i,N_i)})} = \prod_{k=1}^{N_i} P(b_{(i,k)} | \tau_{(i,k)}), \tag{8}$$

where N_i denotes the number of cluster members in the cluster i. Then, its log-likelihood function is expressed as

$$L(\theta, i) = \sum_{k=1}^{N_i} \left\{ \frac{1 + b_{(i,k)}}{2} \cdot ln[q(\theta, \tau_{(i,k)})] + \frac{1 - b_{(i,k)}}{2} \cdot ln[1 - q(\theta, \tau_{(i,k)})] \right\}. \tag{9}$$

Note that $\hat{\theta}_i$ that maximizes the log-likelihood function $L(\theta, i)$ is the MLE. Thus, for the cluster head i, the intra-cluster MLE based on the above cluster-based adaptive quantization scheme, is expressed as

$$\hat{\theta}_i = arg\max_{\theta} L(\theta, i). \tag{10}$$

It has been shown that $\hat{\theta}_i$ can be obtained by employing the gradient-based iterative algorithm [2]. Each cluster head will obtain an estimate of the parameter $\hat{\theta}_i$. For example, if the sensor network consists of N clusters, N different estimates of θ will be obtained. Recall that no information exchange is allowed across clusters and thus it is impossible for the fusion center to obtain the real-time information, such as actual thresholds $\{\tau_{(i,k)}, k = 1, \ldots, N_i\}$ in any cluster. In other words, local estimates should be implemented in the cluster heads themselves, but not in the fusion center.

After obtaining the intra-cluster MLE, the following challenging problem arises: For the fusion center, how to get an accurate estimate of θ based on $(\hat{\theta}_1, \ldots, \hat{\theta}_N)$. Generally, the most direct method is the sample mean estimator (SME): $\hat{\theta} = N^{-1} \sum_{i=1}^{N} \hat{\theta}_i$. However, different weights should be assigned to obtain an accurate estimate. In this paper, we will introduce an inter-cluster MLE alternatively.