Energy-Constrained Decentralized Best-Linear-Unbiased Estimation via Partial Sensor Noise Variance Knowledge

Jwo-Yuh Wu, Qian-Zhi Huang, and Ta-Sung Lee

***Abstract*—This letter studies the energy-constrained MMSE decentralized estimation problem with the best-linear-unbiased-estimator fusion rule, under the assumptions that 1) each sensor can only send a quantized version of its raw measurement to the fusion center (FC), and 2) exact knowledge of the sensor noise variance is unknown at the FC but only an associated statistical description is available. The problem setup relies on maximizing the reciprocal of the MSE averaged with respect to the prescribed noise variance distribution. While the considered design metric is shown to be highly nonlinear in the local sensor bit loads, we leverage several analytic approximation relations to derive an associated tractable lower bound; through maximizing this bound, a closed-form solution is then obtained. Our analytical results reveal that sensors with bad link quality are shut off to conserve energy, whereas the energy allocated to those active nodes is proportional to the individual channel gain. Simulation results are used to illustrate the performance of the proposed scheme.**

***Index Terms*—Convex optimization, decentralized estimation, energy efficiency, quantization, sensor networks.**

I. Introduction

LOW energy/power cost is a critical concern for various application-specific designs of sensor networks [17], [18]. In the decentralized estimation scenario, wherein each sensor can transmit only a compressed version of its raw measurement to the fusion center (FC) owing to bandwidth and power limitations, several energy-efficient estimation schemes have been reported in the literature [1], [9], [13]–[16] . Since the transmission energy is proportional to the message length [2], [11], all these works are formulated within a quantization bit assignment setup, with the optimal bit load determined via the knowledge of *instantaneous* local sensor noise characteristics, e.g., the noise variance if the fusion rule follows the best-linear-unbiased-estimator (BLUE) principle [7, Ch. 6]. To maintain the estimation performance against the variation of sensing conditions, repeated update of the noise profile is therefore needed: this inevitably incurs more training overhead and hence extra energy consumption. The design of distributed estimation algorithms independent of the instantaneous noise parameters remains an open problem [15, p. 419]. Relying on partial noise variance knowledge in the form of the statistical distribution, the problem of minimizing total transmission energy under an allowable average distortion level [measured in terms of a mean-square-error (MSE)-based criterion averaged with respect to the prescribed distribution] is recently considered in [14].

This letter complements the study of [14] by addressing the counterpart problem: how to find the optimal bit load which minimizes the average distortion under a fixed total energy budget. The main contribution of this letter can be summarized as follows: 1) while the design metric, in the form of the reciprocal of the MSE averaged with respect to the distribution, is shown in [14] to be highly nonlinear in the sensor bit load, we leverage several analytic approximation relations to derive an associated tractable lower bound; 2) by maximizing this lower bound, the problem can be further formulated in the form of convex optimization which yields a closed-form solution. Our analytic results reveal that, toward utmost estimation accuracy under a limited energy budget, sensors with bad link quality should be shut off, and energy allocated to those active nodes should be proportional to the individual channel gain; a similar energy conservation policy is also found in the previous works [9], [14], [15]. Numerical simulation evidences the effectiveness of the proposed scheme: it outperforms the uniform allocation strategy in an energy-limited environment.

II. System Scenario

Consider a wireless sensor network, in which N spatially deployed sensors cooperate with an FC for estimating an unknown deterministic parameter θ. The local observation at the ith node is

$$x_i = \theta + n_i, \quad 1 \le i \le N \tag{2.1}$$

where n_i is a zero-mean measurement noise with variance σ_i^2. Due to bandwidth and power limitations, each sensor quantizes its observation into a b_i-bit message, and then transmits this locally processed data to the FC to generate a final estimate of θ. In this letter, the uniform quantization scheme with nearest-rounding [11], [12] is adopted; the quantized message at the ith sensor can thus be modeled as

$$m_i = x_i + q_i, \quad 1 \le i \le N \tag{2.2}$$

where q_i is the quantization error uniformly distributed with zero mean and variance $\sigma_{q_i}^2 = R^2/(12 \cdot 4^{b_i})$ [11], [12], where $[-R/2, R/2]$ is the available signal amplitude range common to all sensors. The adopted quantizer model (2.2) and the uniform quantization error assumption, though being valid only when the number of quantization bits is sufficiently large [11], are widely used in the literature due to analytical tractability. Assume that

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the channel link between the ith sensor and the FC is corrupted by a zero-mean additive noise v_i with variance σ_v^2. The received data from all sensor outputs can thus be expressed in a vector form as[1]

$$[y_1 \cdots y_N]^T = [1 \cdots 1]^T \theta + \underbrace{[n_1 \cdots n_N]^T}_{:=\mathbf{n}} + \underbrace{[q_1 \cdots q_N]^T}_{:=\mathbf{q}} + \underbrace{[v_1 \cdots v_N]^T}_{:=\mathbf{v}} \quad (2.3)$$

where $(\cdot)^T$ denotes the transpose. This letter focuses on linear fusion rules for parameter recovery. More specifically, by assuming that the noise components $\{\mathbf{n}, \mathbf{q}, \mathbf{v}\}$ in (2.3) are mutually independent and the respective samples n_i's, q_i's, and v_i's are also independent across sensors, the parameter θ is retrieved via the BLUE [7, p. 138] scheme via

$$\hat{\theta} = \left(\sum_{i=1}^{N} \frac{y_i}{\sigma_i^2 + \sigma_v^2 + \beta 4^{-b_i}}\right) \left(\sum_{i=1}^{N} \frac{1}{\sigma_i^2 + \sigma_v^2 + \beta 4^{-b_i}}\right)^{-1} \quad (2.4)$$

and the incurred MSE is thus [7, p. 138]

$$E|\hat{\theta} - \theta|^2 = \left(\sum_{i=1}^{N} \frac{1}{\sigma_i^2 + \sigma_v^2 + \beta 4^{-b_i}}\right)^{-1}, \text{ where } \beta := R^2/12. \quad (2.5)$$

A commonly used statistical description for sensing noise variance is [9], [15]

$$\sigma_i^2 = \delta + \alpha z_i, \quad 1 \le i \le N \quad (2.6)$$

where δ models the network-wide noise variance threshold, α controls the underlying variation from the nominal minimum, and $z_i \sim \chi_1^2$ are i.i.d. central Chi-Square distributed random variables each with degrees-of-freedom equal to one [8, p. 24]. The proposed energy-constrained BLUE-based estimation scheme is based on the noise variance model (2.6) and is discussed next.

III. Main Results

A. Problem Setup

We assume that the ith sensor sends the b_i-bit message m_i by using QAM with a constellation size 2^{b_i}. The consumed energy is thus [2], [15]

$$E_i = w_i(2^{b_i} - 1), \text{ for some } w_i,\ 1 \le i \le N \quad (3.1)$$

and the energy density w_i is defined as [2]

$$w_i := \rho d_i^{\kappa_i} \cdot \ln(2/P_b) \quad (3.2)$$

in which ρ is a constant depending on the noise profile, d_i is the distance between the ith node and the FC, κ_i is the ith path loss exponent, and P_b is the target bit error rate assumed common to all sensor-to-FC links. With (3.1), the energy allocated to the ith sensor is thus determined by the number of quantization bits b_i. For a fixed set of sensing noise variances σ_i^2's, the problem of decentralized BLUE, under an allowable total energy budget E_T, can be formulated as

$$\begin{aligned} &\text{Minimize } \left(\sum_{i=1}^{N} \frac{1}{\sigma_i^2 + \sigma_v^2 + \beta 4^{-b_i}}\right)^{-1} \\ &\text{subject to } \sum_{i=1}^{N} w_i(2^{b_i} - 1) \le E_T \\ &\text{and } b_i \in \mathbb{Z}_0^+,\ 1 \le i \le N \end{aligned} \quad (3.3)$$

or equivalently

$$\begin{aligned} &\text{Maximize } \sum_{i=1}^{N} \frac{1}{\sigma_i^2 + \sigma_v^2 + \beta 4^{-b_i}} \\ &\text{subject to } \sum_{i=1}^{N} w_i(2^{b_i} - 1) \le E_T \\ &\text{and } b_i \in \mathbb{Z}_0^+,\ 1 \le i \le N \end{aligned} \quad (3.4)$$

where $\mathbb{Z}_0^+$ denotes the set of all nonnegative integers. To obtain a universal solution irrespective of instantaneous noise conditions, we will consider the following optimization problem, in which the equivalent distortion cost function in (3.4) is instead averaged with respect to the noise variance statistic characterized in (2.6):

$$\begin{aligned} &\text{Maximize } \int_{\mathbf{z}} \sum_{i=1}^{N} \frac{1}{\tilde{\delta} + \alpha z_i + \beta 4^{-b_i}} p(\mathbf{z}) d\mathbf{z} \\ &\text{subject to } \sum_{i=1}^{N} w_i(2^{b_i} - 1) \le E_T \\ &b_i \in \mathbb{Z}_0^+,\ 1 \le i \le N \end{aligned} \quad (3.5)$$

where $\tilde{\delta} := \delta + \sigma_v^2$ and $\mathbf{z} := [z_1 \cdots z_N]^T$ with $p(\mathbf{z})$ denoting the associated distribution. To solve (3.5), the first step is to find an analytic expression of the equivalent mean MSE metric. Since $z_i \sim \chi_1^2$ is i.i.d. and $p_{\chi_1^2}(z) = (1/\sqrt{2\pi z}) \exp(-z/2) u(z)$ [8, p. 24], where $u(z)$ denotes the unit step function, it is straightforward to verify

$$\int_{\mathbf{z}} \sum_{i=1}^{N} \frac{1}{\tilde{\delta} + \alpha z_i + \beta 4^{-b_i}} p(\mathbf{z}) d\mathbf{z} = \frac{1}{\sqrt{2\pi}} \sum_{i=1}^{N} \int_0^\infty \frac{e^{-z_i/2}}{(\alpha z_i + \tilde{\delta} + \beta 4^{-b_i})\sqrt{z_i}} dz_i. \quad (3.6)$$

Equation (3.6) allows us to derive a closed-form expression for cost function in (3.5); this is done with the aid of the next lemma (see [14] and for a proof).

Lemma 3.1: The following result holds:

$$\int_0^\infty \frac{e^{-z_i/2}}{(\alpha z_i + \tilde{\delta} + \beta 4^{-b_i})\sqrt{z_i}} dz_i = \frac{2\pi \cdot e^{(\tilde{\delta} + \beta 4^{-b_i})/2\alpha} \cdot Q\left(\sqrt{(\tilde{\delta} + \beta 4^{-b_i})/\alpha}\right)}{\sqrt{\alpha(\tilde{\delta} + \beta 4^{-b_i})}} \quad (3.7)$$

where $Q(x) := \int_x^\infty (e^{-t^2/2}/\sqrt{2\pi}) dt$ is the Gaussian tail function. □

[1]As in [1], [9], and [15], we assume orthogonal channel access among all the sensor-to-fusion links, which can be realized via, e.g., TDMA or CDMA with orthogonal spreading.

Based on (3.6) and (3.7), problem (3.5) can be equivalently rewritten as

$$\text{Maximize } \sqrt{2\pi}\cdot\sum_{i=1}^{N}\frac{e^{(\tilde{\delta}+\beta 4^{-b_i})/2\alpha}\cdot Q\left(\sqrt{(\tilde{\delta}+\beta 4^{-b_i})/\alpha}\right)}{\sqrt{\alpha(\tilde{\delta}+\beta 4^{-b_i})}}$$
$$\text{under } \sum_{i=1}^{N} w_i(2^{b_i}-1)\le E_T, \text{ and } b_i\in_0^+,\ \forall i. \quad (3.8)$$

The optimization problem (3.8) appears rather formidable to tackle because the cost function is highly nonlinear in b_i. In what follows, we will propose an alternative formulation which is more tractable and can yield an analytic solution.

B. Alternative Formulation

The proposed approach is grounded on the following approximation to $Q(\cdot)$ function [10, p. 115]:

$$Q(x)\approx\frac{1}{\sqrt{2\pi}}\left[\frac{e^{-x^2/2}}{(1-\pi^{-1})x+\pi^{-1}\sqrt{x^2+2\pi}}\right]. \quad (3.9)$$

Based on (3.9) and the following inequality:

$$\sqrt{(\tilde{\delta}+\beta 4^{-b_i})^2+2\pi\alpha(\tilde{\delta}+\beta 4^{-b_i})}\le(\tilde{\delta}+\beta 4^{-b_i})+\pi\alpha \quad (3.10)$$

we can reach after some manipulations the key lower bound of the cost function, shown at the bottom of the page. Note that, since equality in (3.10) is attained when $\alpha=0$, the lower bound (3.11) tends to be tight for small α; through simulation, it is found that, with the proposed solution [cf. (3.17)], the relative error incurred by (3.11) is at most 3.54% for $\alpha\le 0.5$. We will instead focus on maximizing the lower bound in (3.11), i.e.,

$$\text{Maximize } \sum_{i=1}^{N}\frac{4^{b_i}}{\beta+(\alpha+\tilde{\delta})4^{b_i}}$$
$$\text{subject to } \sum_{i=1}^{N} w_i(2^{b_i}-1)\le E_T$$
$$\text{and } b_i\in\mathbb{Z}_0^+,\ 1\le i\le N. \quad (3.12)$$

To facilitate analysis, we first observe that, since $b_i\in\mathbb{Z}_0^+$, it follows $\sum_{i=1}^N w_i(2^{b_i}-1)\le\sum_{i=1}^N w_i(4^{b_i}-1)$: this implies we can replace the total energy constraint in (3.12) by the following one without violating the overall energy budget requirement:

$$\sum_{i=1}^{N} w_i(4^{b_i}-1)\le E_T. \quad (3.13)$$

With the aid of (3.13) and by performing a change of variable with $B_i := 4^{b_i}-1$, the optimization problem becomes

$$\text{Maximize } \sum_{i=1}^{N}\frac{B_i+1}{(\alpha+\beta+\tilde{\delta})+(\alpha+\tilde{\delta})B_i}$$
$$\text{subject to } \sum_{i=1}^{N} w_iB_i\le E_T$$
$$\text{and } B_i\ge 0,\ 1\le i\le N. \quad (3.14)$$

In (3.14), the intermediate variable B_i is relaxed to be a nonnegative real number so as to render the problem tractable; once the optimal real-valued B_i (and hence b_i) is computed, the associated bit loads can be obtained through upper integer rounding, as in [9], [14], and [15]. The major advantage of the alternative problem formulation (3.14) is that it admits the form of convex optimization and can moreover lead to a closed-form solution, as is shown next.

C. Optimal Solution

By leveraging the standard Lagrange technique, the optimal solution to (3.14) can be obtained as follows. First of all, let us assume $w_1\ge w_2\ge\cdots\ge w_N$ without loss of generality, and define the function

$$f(K):=\frac{E_T\left(1+\frac{\beta}{\alpha+\tilde{\delta}}\right)^{-1}+\sum_{j=K}^{N}w_j}{\sqrt{w_K}\sum_{j=K}^{N}\sqrt{w_j}},\quad 1\le K\le N. \quad (3.15)$$

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 $K_1=1$ (the existence and uniqueness of such K_1 when otherwise is shown in the supplementary materials).[2] Then the optimal solution pair $(\lambda^{opt}, B_i^{opt})$ is given by

$$\sqrt{\lambda^{opt}}=\frac{\sqrt{\beta}}{\alpha+\tilde{\delta}}\left(\sum_{j=K_1}^{N}\sqrt{w_j}\right)\times\left(E_T+\left(1+\frac{\beta}{\alpha+\tilde{\delta}}\right)\sum_{j=K_1}^{N}w_j\right)^{-1} \quad (3.16)$$

and

$$B_i^{opt}=\begin{cases}0, & 1\le i\le K_1-1\\ \frac{1}{\alpha+\tilde{\delta}}\sqrt{\frac{\beta}{\lambda^{opt}w_i}}-\left(1+\frac{\beta}{\alpha+\tilde{\delta}}\right), & K_1\le i\le N.\end{cases} \quad (3.17)$$

With $B_i=4^{b_i}-1$ and $\tilde{\delta}=\delta+\sigma_v^2$, the optimal bit load b_i^{opt} can be directly obtained from (3.17).

[2]Available through the website http://www.cm.nctu.edu.tw/people/bio.php?PID=1446#personal_writing.

$$\sqrt{2\pi}\cdot\sum_{i=1}^{N}\frac{e^{(\tilde{\delta}+\beta 4^{-b_i})/2\alpha}\cdot Q\left(\sqrt{(\tilde{\delta}+\beta 4^{-b_i})/a}\right)}{\sqrt{\alpha(\tilde{\delta}+\beta 4^{-b_i})}}\ge\sum_{i=1}^{N}\frac{1}{(\tilde{\delta}+\beta 4^{-b_i})+\alpha}=\sum_{i=1}^{N}\frac{4^{b_i}}{\beta+(\alpha+\tilde{\delta})4^{b_i}} \quad (3.11)$$

IV. Discussions and Simulation

1) We note that the minimal achievable average MSE is attained whenever all the raw sensor measurements with infinite-precision are available to the FC (i.e., the case when $b_i = \infty, 1 \le i \le N$). Hence, by setting $b_i = \infty$ in the mean MSE formula specified in (3.8), we have the following performance bound:

$$MSE_{\min}=\left[Ne^{(\delta+\sigma_v^2)/2\alpha}Q\left(\sqrt{(\delta+\sigma_v^2)/\alpha}\right)\sqrt{\frac{2\pi}{\alpha\left(\delta+\sigma_v^2\right)}}\right]^{-1}. \quad (4.1)$$

Formula (4.1) reveals the impacts of the noise model parameters α and δ on the estimation performance. Specifically, it is easy to see from (4.1) that the minimal MSE increases with α: this implies the estimation accuracy degrades as the sensing environment becomes more and more inhomogeneous. Furthermore, it can be checked that $MSE_{\min}$ also increases with the minimal noise power threshold δ. This is reasonable since a large δ implies poor measurement quality of *all* sensor data, and hence a less accurate parameter estimate.

2) Recall from (3.2) that the energy density factor w_i is proportional to the path loss gain d_i^{κ} (assuming $\kappa_i = \kappa$ throughout all links). Large values of w_i, therefore, correspond to sensors deployed far away from the FC (with large d_i), usually with poor background channel gains. In light of this point, the proposed optimal solution (3.17) is intuitively attractive: sensors associated with the $(K_1 - 1)$th largest w_i's are turned off to conserve energy. We note that a similar energy conservation strategy via shutting off sensors alone poor channel links is also found in [9], [14], and [15]. Also, we further note from (3.17) that, for those active nodes, the assigned message length is inversely proportional to $\sqrt{w_i}$. This is intuitively reasonable since sensors with better link conditions should be allocated with more bits (energy) to improve the estimation accuracy.

3) We compare the simulated performance of the proposed solution (3.17) against the uniform energy allocation scheme with bit load determined through

$$w_i(2^{b_i} - 1) = E_T/N, \quad 1 \le i \le N \quad (4.2)$$

In each run, we simply choose $w_i = d_i^{\kappa}$ with $\kappa = 3$, and d_i's are uniformly drawn from the interval [1, 10] as in [15]. In the following experiments, we set the number of sensors to be $N = 200$, link noise $\sigma_v^2 = 0.05$, and consider three different levels of total energy: $E_T = \gamma \sum_{i=1}^{N} w_i$ with $\gamma = 0.25$, 1, 3, which, respectively, correspond to the low, medium, and high energy regimes. With fixed $\delta = 2$, Fig. 1(a) shows the computed mean MSE as α varies from 0 to 8, whereas Fig. 1(b) depicts the MSE for fixed $\alpha = 2$ and $0.5 \le \delta \le 8$. The results show that, as expected, the estimation accuracy improves as E_T increases. Also, the proposed solution (3.17) outperforms (4.2), especially when E_T is small; it is thus more effective in an energy-limited environment.

4) The proposed energy allocation technique via minimizing the average distortion level can also be applied to the scenario considered in [3] and [4], where all sensors "amplify-and-forward" the local measurements for data fusion via BLUE. The resultant problem formulation and performance comparison with the proposed digital solution (3.17) is referred to the supplementary materials. We also note that other amplify-and-forward schemes include, e.g., [5] and [6], which instead assume the parameter of interest to be statistically Gaussian and follow a joint source-channel coding approach.

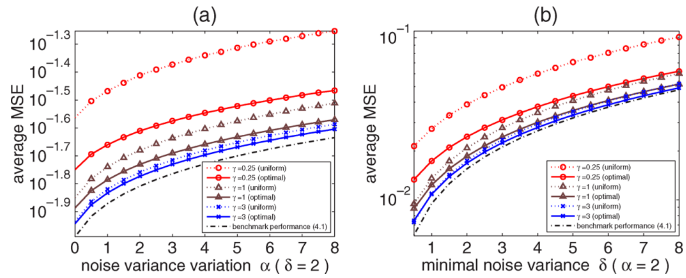

Fig. 1. Performance comparison of (3.18) with the uniform allocation scheme (4.2) at different energy levels.

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