OPTIMAL TRANSMISSION CODEBOOK DESIGN IN FADING CHANNELS FOR THE DECENTRALIZED ESTIMATION IN WIRELESS SENSOR NETWORKS

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ABSTRACT

In this paper, we design the near optimal transmission codebook for decentralized estimation in wireless sensor networks with uniform quantizations and digital communications over orthogonal Rayleigh fading channels. We start from deriving the maximum likelihood estimator (MLE) for arbitrary transmission codebook with known and unknown channel state information (CSI) at the fusion center (FC). Because the MLE is not a convex problem in the system we considered, it is not trivial to obtain an analytical expression of either its mean square error or Cramer-Rao lower bound (CRLB). By analyzing the likelihood function, we convert the optimal transmission codebook design minimizing the CRLB to a two-stage optimization problem, where the problem in each stages is convex. It is shown that the estimation accuracy with our designed codebooks and MLE is superior to that with available transmission schemes. The proposed codebook suggests that the sensors should use orthogonal codes to transmit different observations for unknown CSI, while the optimal codebook for known CSI is not orthogonal.

Index Terms— Decentralized estimation, wireless sensor networks, codebook design

1. INTRODUCTION

Wireless sensor networks (WSNs) consist of a number of sensors spatially deployed in a field to observe physical parameters such as temperature, humidity. The estimation for parameters in WSNs is usually performed decentralized, which means that there exists a fusion center (FC) in the network, and the sensors transmit their locally processed observations to FC without inter-communications [1]. The FC will generate the final estimation with received signals.

The decentralized estimation problem has drawn much more attention since wireless sensors are widely deployed. With the assumption of ideal communication and binary symmetrical channels, [2] gives the mean square error (MSE) bound of the estimation and discusses the power scheduling problem, [3, 4] study the quantizer design for the sensors, and [5,6] propose the estimation schemes under the strict bandwidth constraint that sensors can only transmit 1 bit for each observation.

In practical WSNs, the received signals of the FC often experience fading channels [7]. Coded transmissions are usually applied to improve the communication reliability. Differ from traditional digital communication systems, the transmission codebook is not designed for binary data, but for original observations in the decentralized estimation problems with WSNs. Some recent works [8–10] have considered schemes which map the observations of the sensors (quantized or not) to codes or waveforms directly. Among them, [8] gives a practical coding scheme, which uses orthogonal waveforms to represent each quantization value in synchronous multiple-access channels (MACs) where the signals from sensors arrive the FC simultaneously. [9] finds that the analog amplify-and-forward (AF) transmission may outperform the digital systems with the traditional separate source-channel coding scheme, especially in additive white Gaussian noise (AWGN) MACs. [10] analyzes the AF scheme in orthogonal channels, and finds that although multiple sensors can offer the diversity gain, the estimation MSE can not approach to 0 when the number of sensors is unbounded. As far as authors known, the optimal transmission schemes for both orthogonal and nonorthogonal MACs are still unknown.

In this paper, we propose a method to design the near optimal transmission codebooks for decentralized estimation in wireless sensor networks with digital communications over orthogonal fading MACs. We consider uniform quantizer and maximum likelihood estimator (MLE) which are optimal for estimating parameters with unknown statistics. After obtained the likelihood function, we study the codebook design to minimize the Cramer-Rao lower bound (CRLB). Based on the geometrical interpretation of the CRLB, this non-convex optimization problem is transformed to a two-stage optimization problem, where the problems in both stages are convex and can be solved analytically or numerically by efficient algorithms.

It is shown that the estimation accuracy using the proposed codebooks with MLE is superior to that with available transmission schemes, such as natural binary codes and analog AF transmission in orthogonal fading MACs. Moreover, the proposed codebook with unknown CSI suggests that the sensors should use orthogonal codes to transmit different observations, which means that the type-based multiple-access (TBMA) for decentralized estimation in non-orthogonal MACs [8] is also optimal in orthogonal MACs with unknown CSI.

2. SYSTEM MODELS

Consider a WSN which consists of N sensors and a FC in a field to measure a parameter θ with unknown statistics, where there are no inter-sensor communications. The sensors transmit their quantized observations to FC over Rayleigh fading channels. Assume that ideal orthogonal multiple-access protocols, such as TDMA and FDMA, are applied to the sensors, *i.e.* the FC can separate received signals from sensors.

The observation for the unknown parameter θ of the i-th sensor is

$$x_i = \theta + n_{s,i},\ i = 1, \cdots, N, \tag{1}$$

where $n_{s,i} \sim \mathcal{N}(0, \sigma_s^2)$ is the independent identically distributed (i.i.d.) Gaussian observation noise with zero mean and variance σ_s^2.

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For digital communications, sensors will quantize the observation then perform the source coding, channel coding, and modulation. This can be described as mapping the quantized observations of the sensors to a sequence of transmission symbols with length L. We apply a function $\mathbf{c}(x)|\mathbb{R} \rightarrow \mathbb{C}^L$ to represent the quantization, coding and modulation. For convenience, the transmission energy of the symbols is normalized to 1, *i.e.* $\mathbf{c}(x)^{\mathrm{H}}\mathbf{c}(x) = 1, \quad \forall x \in \mathbb{R}$.

Function $\mathbf{c}(x)$ can be applied to represent any processing which maps the observation to transmission symbols. We consider the uniform quantization since it is optimal for parameter with unknown statistics. For an M-level uniform quantizer, define the dynamic range of the quantizer as $[-W, +W]$, all the possible quantized values of the observation can be written as $S_m = m\Delta - W$, where $m = 0, \cdots, M-1$, and $\Delta = 2W/(M-1)$ is the quantization interval.

The observation of the sensors will be rounded to the nearest S_m, therefore $\mathbf{c}(x)$ is a piecewise constant function and can be described as,

$$\mathbf{c}(x) = \begin{cases} \mathbf{c}_0, & -\infty < x \leq S_0 + \frac{\Delta}{2} \\ \mathbf{c}_m, & S_m - \frac{\Delta}{2} < x \leq S_m + \frac{\Delta}{2} \\ \mathbf{c}_{M-1}, & S_{M-1} - \frac{\Delta}{2} < x < +\infty \end{cases}, \tag{2}$$

where $\mathbf{c}_m = [c_{m,1}, \cdots, c_{m,L}]^{\mathrm{T}}, m = 0, \cdots, M-1$ is the transmission symbols according to the quantized observation S_m.

Define the transmission codebook as $\mathbf{C}_t = [\mathbf{c}_0, \cdots, \mathbf{c}_{M-1}]$, and its correlation matrix as $\mathbf{R}_c = \mathbf{C}_t^{\mathrm{H}}\mathbf{C}_t$.

Based on the orthogonal channel assumption, the FC can separate and perfectly synchronize to the received signals from sensors. Assume that the channel is block fading, which means that the channel coefficients are invariant during the period each sensor transmits one observation. After matched filtering and symbol-duration spaced sampling, we can denote L received samples corresponding to the L transmitted symbols as

$$\mathbf{y}_i = \sqrt{\mathcal{E}_d} h_i \mathbf{c}(x_i) + \mathbf{n}_{c,i},\ i = 1, \cdots, N, \tag{3}$$

where $\mathbf{y}_i = [y_{i,1}, \cdots, y_{i,L}]^{\mathrm{T}}$, $h_i \sim \mathcal{CN}(0, 1)$ is the channel coefficient, $\mathbf{n}_{c,i} \sim \mathcal{CN}(0, \sigma_c^2\mathbf{I})$ is Gaussian receiver thermal noise, and $\mathcal{E}_d$ is the transmission power of each observation.

3. CODEBOOK DESIGN

In the sequel, we will first derive the MLE with known and unknown CSI. Then by analyzing the likelihood function, we formulate the optimal codebook design problem through minimizing CRLB of the estimation.

3.1. Maximum Likelihood Estimator

Given θ, the received signals from different sensors are statistically independent. The MLE can be obtained by maximizing the likelihood function. If the CSI is known to the receiver of FC, we have,

$$\hat{\theta}_c = \arg\max_\theta \log p(\mathbf{Y}|\mathbf{h}, \theta) = \arg\max_\theta \sum_{i=1}^{N} \log p(\mathbf{y}_i|h_i, \theta), \tag{4}$$

while if the CSI is unknown to the receiver, we have

$$\hat{\theta}_n = \arg\max_\theta \log p(\mathbf{Y}|\theta) = \arg\max_\theta \sum_{i=1}^{N} \log p(\mathbf{y}_i|\theta), \tag{5}$$

where $\mathbf{Y} = [\mathbf{y}_1, \cdots, \mathbf{y}_N]$ and $\mathbf{h} = [h_1, \cdots, h_N]^{\mathrm{T}}$.

The conditional probability density function (PDF) $p(\mathbf{y}_i|h_i, \theta)$ can be obtained by utilizing total probability theorem,

$$p(\mathbf{y}_i|h_i, \theta) = \int_{-\infty}^{+\infty} p(\mathbf{y}_i|h_i, x) p(x|\theta) \mathrm{d}x, \tag{6}$$

where $p(x|\theta)$ is the PDF of Gaussian distribution $\mathcal{N}(\theta, \sigma_s^2)$, which depends on the observation model, and $p(\mathbf{y}_i|h_i, x)$ is the PDF of vector complex Gaussian distribution $\mathcal{CN}(\sqrt{\mathcal{E}_d} h_i \mathbf{c}(x), \sigma_c^2\mathbf{I})$ according to the received signal model.

If CSI is unknown at the FC, $p(\mathbf{y}_i|x)$ can be derived based on $p(\mathbf{y}_i|h_i, x)$ as,

$$\begin{aligned} p(\mathbf{y}_i|x) &= \int_{\mathbb{C}} p(\mathbf{y}_i|h_i, x) p(h_i) \mathrm{d}h_i \\ &= \alpha \exp\left(-\frac{\|\mathbf{y}_i\|_2^2}{\sigma_c^2} + \frac{\mathcal{E}_d|\mathbf{y}_i^{\mathrm{H}}\mathbf{c}(x)|^2}{\sigma_c^2(\mathcal{E}_d + \sigma_c^2)}\right), \end{aligned} \tag{7}$$

where $\alpha = 1/(\pi^L(\mathcal{E}_d + \sigma_c^2)\sigma_c^{2(L-1)})$ and $p(h_i)$ is the PDF of complex Gaussian distribution $\mathcal{CN}(0, \sigma_c^2\mathbf{I})$.

Utilizing total probability theorem, the likelihood function without CSI is then,

$$\log p(\mathbf{Y}|\theta) = \sum_{i=1}^{N} \log\left(\int_{-\infty}^{+\infty} p(\mathbf{y}_i|x) p(x|\theta) \mathrm{d}x\right). \tag{8}$$

Ignoring all the items independent from the MLE, the MLE with and without CSI can be respectively written as,

$$\begin{aligned} \hat{\theta}_c = \arg\max_\theta \sum_{i=1}^{N} \log\Bigg(\int_{-\infty}^{+\infty} &\exp\left(-\frac{(x-\theta)^2}{2\sigma_s^2}\right) \\ &\exp\left(-\frac{2\sqrt{\mathcal{E}_d}\Re\{h_i \mathbf{y}_i^{\mathrm{H}}\mathbf{c}(x)\}}{\sigma_c^2}\right)\mathrm{d}x\Bigg), \end{aligned} \tag{9}$$

and

$$\begin{aligned} \hat{\theta}_n = \arg\max_\theta \sum_{i=1}^{N} \log\Bigg(\int_{-\infty}^{+\infty} &\exp\left(-\frac{(x-\theta)^2}{2\sigma_s^2}\right) \\ &\exp\left(\frac{\mathcal{E}_d|\mathbf{y}_i^{\mathrm{H}}\mathbf{c}(x)|^2}{\sigma_c^2(\mathcal{E}_d + \sigma_c^2)}\right)\mathrm{d}x\Bigg). \end{aligned} \tag{10}$$

The difference between two likelihood functions comes form the difference between $p(\mathbf{y}_i|h_i, x)$ and $p(\mathbf{y}_i|x)$, where the former depends on the real part of $\mathbf{y}_i^{\mathrm{H}}\mathbf{c}(x)$ and the latter depends on the magnitude of it. Substitute (3) to $\mathbf{y}_i^{\mathrm{H}}\mathbf{c}(x)$, we have

$$\mathbf{y}_i^{\mathrm{H}}\mathbf{c}(x) = \sqrt{\mathcal{E}_d} h_i \mathbf{c}(x_i)^{\mathrm{H}}\mathbf{c}(x) + \mathbf{n}_{c,i}^{\mathrm{H}}\mathbf{c}(x) \tag{11}$$

It can be found that the cross-correlations between two transmission codes, which are the elements of $\mathbf{R}_c$, play a key role in the likelihood functions. In the sequel, we apply a two-stage optimization to design the optimal $\mathbf{R}_c$. We will first find an ideal form of the conditional PDF $p(\mathbf{y}_i|h_i, x)$ or $p(\mathbf{y}_i|x)$ which can minimize CRLB. Then we design $\mathbf{R}_c$ with which the actual conditional PDF statistically approaches its ideal form.

3.2. Optimal Form of $p(\mathbf{y}_i|x)$ and $p(\mathbf{y}_i|h_i, x)$

Regarding the log-likelihood function as a function of θ defined as $L(\theta)$, the CRLB of the estimation, depending on the curvature of $L(\theta)$, is

$$\mathrm{Var}[\hat{\theta}] \geq \left(-\mathrm{E}\left[\frac{\partial^2 L(\theta)}{\partial \theta^2}\right]\right)^{-1}. \tag{12}$$

If the analytical expression of (12) can be obtained, we can design the optimal codebook by minimizing it. Unfortunately, it is not trivial to obtain the analytical expression for the decentralized estimation considered. In order to construct a tractable optimization, we fist analyze the likelihood functions.

Regarding $p(\mathbf{y}_i|h_i, x)$ or $p(\mathbf{y}_i|x)$ as a function of x and rewritten them as $f_i(x)$, it is shown from (6) and (8) that both likelihood functions can be written as,

$$L(\theta) = \sum_{i=1}^{N} \log\left(\langle p(x|\theta), f_i(x)\mathrm{d}x\rangle\right), \tag{13}$$

where

$$p(x|\theta) = \frac{1}{\sqrt{2\pi}\sigma_s} \exp\left(-\frac{(x-\theta)^2}{2\sigma_s^2}\right) \tag{14}$$

is a Gaussian function, and

$$\langle f(x), g(x)\rangle = \int_{-\infty}^{+\infty} f(x)g(x)\mathrm{d}x. \tag{15}$$

It follows from (13) that the likelihood function can be viewed as a correlation of two functions—$p(x|\theta)$ and $f_i(x)$, where the former one is deterministic given θ and the latter depends on $\mathbf{R}_c$. In order to make the problem solvable, we first relax $f_i(x)$ to be a general non-negative function, then substitute it to (12). Note that $f_i(x)$ is not a PDF any more due to this relaxation. After that, we formulate the optimization problem which minimizes (12) with relaxed $f_i(x)$ to find an optimal form of $f_i(x)$, which is denoted by $f^*(x)$.

After some equivalent transformations (details will be shown in [11]), the optimization problem constructed with relaxed $f_i(x)$ can be derived as,

$$\begin{array}{ll} \min\limits_{f(x)} & J(f(x)) \\ \text{s.t.} & f(x) \geq 0, \forall x \in \mathbb{R}, \end{array} \tag{16}$$

where

$$J(f(x)) = \frac{\langle (x-\theta)^2 p(x|\theta), f(x)\rangle}{\langle p(x|\theta), f(x)\rangle}. \tag{17}$$

This is a variational problem, which can be transformed to a linear programming and be solved by K.K.T. conditions as [11],

$$f^*(x) = \alpha\delta(x-\theta), \tag{18}$$

where $\delta(x)$ is Dirac-δ function and α is an arbitrary constant.

In the sequel we will apply a robust approximation to design $\mathbf{R}_c$, which makes $p(\mathbf{y}_i|h_i, x)$ or $p(\mathbf{y}_i|x)$ approximates $f^*(x)$.

3.3. Optimal Correlation Matrix $\mathbf{R}_c$

For convenience, we take $p(\mathbf{y}|h_i, x)$ as an example to develop the codebook.

Given the ideal form of $f^*(x)$, we can formulate the following robust norm approximation problem to design $\mathbf{R}_c$

$$\begin{array}{ll} \min & \mathrm{E}\left[\|p(\mathbf{y}|h_i, x) - f^*(x)\|\right] \\ \text{s.t.} & \mathbf{R}_c \succeq 0, \end{array} \tag{19}$$

where the expectation is with respect to $\mathbf{n}_{c,i}$ and h_i, and "$\succeq 0$" means positive semi-definite.

The desired function to be approximated to, $f^*(x)$, is too ideal for $p(\mathbf{y}_i|h_i, x)$ which is not practical. Only if there is no observation noise, no quantization noise, and no communication error, $p(\mathbf{y}_i|h_i, x)$ can equal to $f^*(x)$. We relax $f^*(x)$ to $f^+(x) = \delta(x - x_i)$ because x_i is the optimal estimation of θ for sensors.

For digital communications, $\mathbf{c}(x)$ is piecewise constant in each interval $\mathbf{Q}_m = [S_m - \frac{\Delta}{2}, S_m + \frac{\Delta}{2}]$, which makes $p(\mathbf{y}|h_i, x)$ also piecewise constant with respect to x. Define $\mathbf{p} = [p_0, \cdots, p_{M-1}]^{\mathrm{T}}$ as the values of $p(\mathbf{y}|h_i, x)$ on all intervals, then the continuous function $p(\mathbf{y}|h_i, x)$ can be represented by vector $\mathbf{p}$.

If x_i belongs to interval $\mathbf{Q}_{m_i}$, then p_{m_i} will be a constant independent with $\mathbf{R}_c$. The reason is that when $x \in \mathbf{Q}_{m_i}$, $\mathbf{c}(x)$ will be the same as $\mathbf{c}(x_i)$ due to the quantization. Therefore, we remove p_{m_i} from vector $\mathbf{p}$ since it will not affect the codebook design. In other intervals, we have $f^+(x) = 0$. Then the robust approximation problem can be transformed into a least norm problem, which is

$$\min \mathrm{E}\left[\|\mathbf{p}\|_p\right], \tag{20}$$

where $\|\cdot\|_p$ is l_p norm.

Assume $\mathbf{R}_c = \mathrm{Toep}(1, r_1, \cdots, r_{M-1})$ as a Toeplitz matrix, then we just need to optimize its first row instead of the whole matrix. If l_2 norm is applied, (20) can be simplified as a standard semi-definite programming (Details will be presented in [11].),

$$\begin{array}{ll} \min & y \\ \text{s.t.} & \Re\{\mathbf{R}_c\} \succeq 0 \\ & -1 \leq \Re\{r_m\} \leq +1, \quad \forall m = 1, \cdots, M-1 \\ & \left(\begin{array}{c|c} \mathbf{\Lambda} & \mathbf{1} \\ \hline \mathbf{1}^{\mathrm{T}} & y \end{array}\right) \succeq 0, \end{array} \tag{21}$$

where $\mathbf{\Lambda} = \mathrm{diag}(1 + \frac{3\sigma_c^2}{4\mathcal{E}_d} - \Re\{r_1\}, \cdots, 1 + \frac{3\sigma_c^2}{4\mathcal{E}_d} - \Re\{r_{M-1}\})$, and

$$y \geq \sum_{m=1}^{M-1} \frac{1}{\left(1 + \frac{3\sigma_c^2}{4\mathcal{E}_d}\right) - \Re\{r_m\}}. \tag{22}$$

Problem (21) can be solved efficiently by numerical algorithms. If we apply l_∞ norm to (20) and utilize the Jensen inequality to simplify the problem, we can obtain an analytical solution as $\Re\{\mathbf{R}_c\} = \mathrm{Toep}(1, -\frac{1}{M-1}, \cdots, -\frac{1}{M-1})$(see also [11]).

Following the same approach, the optimization problem for designing $\mathbf{R}_c$ with unknown CSI can be derived as,

$$\begin{array}{ll} \min & \sum\limits_{m=1}^{M-1} \frac{1}{\left(\frac{3\sigma_c^2}{4\mathcal{E}_d} + 1\right)\left(\frac{3\sigma_c^2}{2\mathcal{E}_d} + 1\right) - r_m^* r_m} \\ \text{s.t.} & \mathbf{R}_c \succeq 0 \\ & 0 \leq r_m^* r_m \leq 1. \end{array} \tag{23}$$

We can find that its solution is $\mathbf{R}_c = \mathbf{I}$, since its objective function is monotone with respect to $r_m^* r_m$. It means that the sensors should assign orthogonal codes to each possible quantized observation. This orthogonal codebook was used by the type-based multiple-access (TBMA) in non-orthogonal channels [8]. Our solution implies that TBMA is optimal in orthogonal multiple-access fading channels when the CSI is unknown to the receiver. Whether it is optimal in general fading MACs will be studied in future works.

Obtained $\mathbf{R}_c$, we can use algorithms such as Cholesky-like factorization to find $\mathbf{C}_t$, since $\mathbf{R}_c$ is positive semi-definite. The length of the transmission symbols obtained by this way is equal or less than M.

4. SIMULATIONS

There are N sensors and a FC in the simulation scenarios. The observation SNR of local sensors is defined as $\gamma_s = 20\log_{10}(W/\sigma_s)$. The communication SNR is defined as $\gamma_c = 10\log_{10}(\mathcal{E}_d/N_0)$, where $N_0/2 = \sigma_c^2$ is the double-sided power spectrum density of the receiver noise in the FC. Note that we define the communication SNR based on $\mathcal{E}_d$, the energy consumed for transmitting one observation, for a fair comparison, because the code length of different codebooks is not identical.

The MSEs of the best linear unbiased estimator (BLUE) without quantization noise and communication error and the Quasi-BLUE with quantization noise [2] are also provided through simulations, which can be regarded as a performance lower bound.

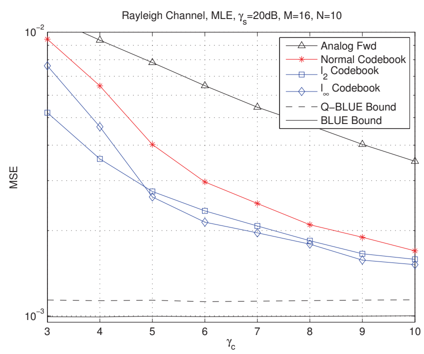

Fig. 1. MSE of the MLE with CSI

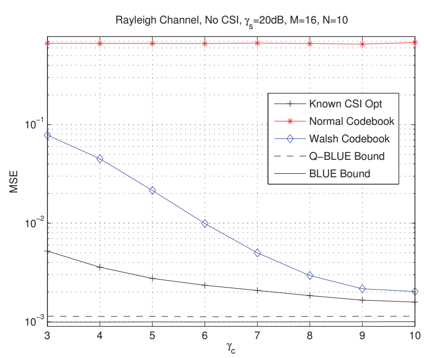

Fig. 2. MSE of the MLE without CSI

The codebook marked as *Normal Codebook* in the figures refers to the uncoded natural binary coding, which maps $M = 2^K$ quantization values to K-bit binary codes. The codebooks designed by l_2 and l_∞ norm are marked as l_2 *Codebook* and l_∞ *Codebook*. As for unknown CSI case, we apply Walsh codes to construct a codebook which makes $\mathbf{R}_c = \mathbf{I}$.

The performance of analog amplify-forward transmission [9] is also evaluated for comparison.

Fig. 1 shows the MSEs of different transmission codebooks when CSI is known to the receiver; while Fig. 2 depicts the MSEs when CSI is unknown. It is shown that the codebooks we designed can improve the estimation accuracy evidently. Note that the performance of the MLE with natural binary coding is the worst when CSI is unknown. This is because the MLE without CSI depends on the magnitude of the elements in $\mathbf{R}_c$ rather than the phase of them. As a result, the natural binary coding introduces phase ambiguity to the MLE, which dramatically increases MSE.

5. CONCLUSIONS

In this paper, we introduce a novel method to design the transmission codebook for the decentralized estimation in WSNs. We consider digital communications and orthogonal Rayleigh fading channels. Based on the geometrical interpretation of the CRLB, we transform the non-convex optimization problem to design the transmission codebook into a two-stage convex optimization problem. Simulations show that the codebook designed can improve estimation accuracy of the decentralized estimation, compared with that using traditional transmission schemes.

Furthermore, it indicates by the designed codebooks that the TBMA, which uses orthogonal codebooks, is optimal in orthogonal MACs if CSI is unknown to the FC. Nevertheless, if CSI is known, orthogonal codebooks are not optimal any more.

6. REFERENCES

[1] J.-J. Xiao, A. Ribeiro, Z.-Q. Luo, and G. B. Giannakis, "Distributed compression-estimation using wireless sensor networks," *IEEE Signal Processing Mag.*, vol. 23, no. 7, 2006.

[2] J.-J. Xiao, S. Cui, Z.-Q. Luo, and A. J. Goldsmith, "Power scheduling of universal decentralized estimation in sensor networks," *IEEE Trans. on Signal Processing*, vol. 54, no. 2, 2006.

[3] W. M. Lam and A. R. Reibman, "Design of quantizers for decentralized estimation systems," *IEEE Trans. on Communications*, vol. 41, no. 11, 1993.

[4] P. Venkitasubramaniam, L. Tong, and A. Swami, "Score-function quantization for distributed esitmation," in *40th Annual Conference on Information Sciences and Systems, 2006*, 2006.

[5] A. Ribeiro and G. B. Giannakis, "Bandwidth-constrained distributed estimation for wireless sensor networks—part I: Gaussian case," *IEEE Trans. on Signal Processing*, vol. 54, no. 3, 2006.

[6] Z.-Q. Luo, "An isotropic universal decentralized estimation scheme for a bandwidth constrained ad hoc sensor network," *IEEE Journal on Selected Areas in Communications*, vol. 23, no. 4, 2005.

[7] T. Aysal and K. Barner, "Constrained decentralized estimation over noisy channels for sensor networks," *IEEE Trans. on Singal Processing*, vol. 56, no. 4, 2008.

[8] G. Mergen and L. Tong, "Type based estimation over multiaccess channels," *IEEE Trans. on Signal Processing*, vol. 54, no. 2, 2006.

[9] M. Gastpar and M. Vetterli, "Source-channel communication in sensor networks," *Lecture Notes in Computer Science*, vol. 2634, 2003.

[10] S. Cui, J.-J. Xiao, A. J. Goldsmith, Z.-Q. Luo, and H. V. Poor, "Estimation diversity and energy efficiency in distributed sensing," *IEEE Trans. on Signal Processing*, vol. 55, no. 9, 2007.

[11] X. Wang and C. Yang, "Decentralized estimation over fading channels in wireless sensor networks — optimal codebook design," journal paper in preparation.