

MULTI-HOP PROGRESSIVE DECENTRALIZED ESTIMATION OF DETERMINISTIC VECTOR IN WIRELESS SENSOR NETWORKS

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ABSTRACT

This paper presents a novel scheme for estimating an unknown deterministic vector in a multi-hop progressive decentralized fashion in a wireless sensor network. Under this scheme, each sensor performs the best linear unbiased estimation of the unknown vector using the data measured by the sensor and the estimations received from its up stream sensors, and the estimation at each sensor is first quantized and then forwarded to its down stream sensor. The final estimation of the unknown vector resides at a fusion center. The number of quantization bits assigned to each sensor is computed off-line via an optimization algorithm that minimizes the network transmission energy subject to a pre-determined upper bound on the mean square error of the final estimation at the fusion center. This optimization algorithm utilizes any given routing tree from all sensors to the fusion center. Comparing to the conventional non-progressive schemes, the proposed progressive scheme yields a significant amount of energy saving.

1. INTRODUCTION

In this paper, we consider a wireless sensor network where each sensor is capable of sensing, data processing and wireless communication. A specific task for this network is to estimate an unknown vector based on the data vectors measured by all sensors. The classical approach to this task is such that a fusion center collects the data from all sensors and then performs the best estimation of the unknown vector. The communication from all sensors to the fusion center can be costly in terms of both spectral usage and energy usage. To reduce the energy consumption for communication, it is desirable for each sensor to transmit a limited number of bits. By assuming that each sensor can deliver a given number of bits (say, B_k bits by sensor k) to the fusion center, researchers in [1]-[4] have recently developed algorithms to optimize the choice of B_k in terms of minimum transmission energy from all sensors.

However, there are deficiencies in those works. The algorithms in [1]-[4] only handle the estimation of a scalar parameter as opposed to vector parameter. Furthermore, when sensors are spread out in a field, the sensors far away from the fusion center must consume much more energy than the sensors near the fusion center to deliver each bit to the fusion center if each sensor transmits data directly to the fusion center as in the case considered in [1]-[4]. In order to overcome those deficiencies, we propose a novel scheme called multi-hop progressive distributed scheme in this paper. For convenience, we will refer to this scheme as proposed progressive (PP) scheme, and to those in [1]-[4] as non-progressive (NP) scheme.

In the PP scheme, we allow data to be transmitted from each sensor to the fusion center via a multi-hop route. In fact, we let each sensor receive from, and transmit to, only its neighboring sensor(s). For many potential applications, sensor networks are relatively stationary, and hence a routing tree from all sensors to the fusion center can be established and utilized for distributed estimation. It is known (e.g., see [5]) that for large networks, multi-hop routing allows concurrent co-channel transmissions and hence is more efficient in spectral usage (than the case where the spectrum is divided orthogonally among all sensors). Since the distance between adjacent sensors is generally much smaller than that from most sensors to the fusion center, the PP scheme is also expected to consume less transmission energy than the NP scheme. In the PP scheme, each sensor performs the BLUE (best linear unbiased estimation) of the unknown parameter based on the estimations received from its up stream sensors and the data measured by itself, and the estimation by each sensor is first quantized and then forwarded to its down stream sensor. For the PP scheme, we have also developed an algorithm to optimize the bit allocation to each sensor in terms of minimum transmission energy by all sensors subject to an upper bound on the MSE (mean square error) of the final estimation at the fusion center.

In Section 2, we present the PP scheme for 1-D network. For easy understanding, we first consider the case of scalar parameter and then the case of vector parameter. In Section 3, we extend the PP scheme to 2-D and 3-D networks. In Section 4, the performance of the PP scheme is illustrated.

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More details of this work are available in [6] and [7].

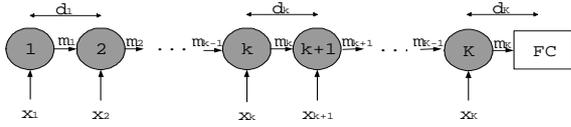


Fig. 1. Illustration of the multi-hop progressive decentralized estimation scheme for a 1-D network. The square on the far right is the fusion center.

2. THE PP SCHEME FOR 1-D NETWORK

2.1. Scalar Parameter

We first consider the case of scalar parameter estimation. A simple 1-D sensor network is shown in Fig. 1 where there are totally K sensors. The input to the k th sensor consists of x_k and m_{k-1} . Here, x_k is the measurement at the k th sensor, which is modelled as

$$x_k = \theta + n_k \quad (1)$$

where θ is the unknown parameter to be estimated, and n_k is the noise with the k -dependent variance $\sigma_{n_k}^2$. And m_{k-1} is the quantized estimation received from sensor $k-1$. The output from the k th sensor is denoted by m_k which is quantized from the BLUE of θ at sensor k . Let the variances of x_k and m_{k-1} be denoted by $\sigma_{x_k}^2$ and $\sigma_{m_{k-1}}^2$, respectively. Obviously, $\sigma_{x_k}^2 = \sigma_{n_k}^2$. Then, assuming $B_{k-1} > 0$, the BLUE of θ based on x_k and m_{k-1} at sensor k is

$$\hat{\theta}_k = \left(\frac{1}{\sigma_{m_{k-1}}^2} + \frac{1}{\sigma_{x_k}^2} \right)^{-1} \left(\frac{m_{k-1}}{\sigma_{m_{k-1}}^2} + \frac{x_k}{\sigma_{x_k}^2} \right) \quad (2)$$

With B_k bits for quantization of $\hat{\theta}_k$, we have m_k as the output of sensor k . Assume that $\hat{\theta}_k$ is bounded within $[-W, W]$, then the variance of quantization error at sensor k is $\sigma_{q_k}^2 = \frac{c_k W^2}{2^{2B_k}} \leq \frac{W^2}{2^{2B_k}}$ where $c_k \leq 1$. The variance of m_k is given by

$$\sigma_{m_k}^2 = \sigma_{q_k}^2 + \sigma_{\hat{\theta}_k}^2 \leq \frac{W^2}{2^{2B_k}} + \left(\frac{1}{\sigma_{m_{k-1}}^2} + \frac{1}{\sigma_{x_k}^2} \right)^{-1} \quad (3)$$

To determine B_k for all k , we will formulate a criterion that minimizes a measure of the network transmission energy subject to a MSE constraint. The details are shown next.

Since (3) is a nonlinear recursion for $\sigma_{m_k}^2$, it is hard to find the exact form of $\sigma_{m,K}^2$ which is the MSE of the final estimate m_K transmitted to the fusion center. But we can use the following inequality:

$$\sigma_{m_k}^2 \leq \frac{W^2}{2^{2B_k}} + \frac{\sigma_{m_{k-1}}^2}{4} + \frac{\sigma_{x_k}^2}{4} \quad (4)$$

which follows from (3) and $2\sigma_{m_{k-1}}\sigma_{x_k} \leq \sigma_{m_{k-1}}^2 + \sigma_{x_k}^2$. The above inequality recursion leads to

$$\begin{aligned} MSE &\doteq \sigma_{m,K}^2 \quad (5) \\ &\leq \sum_{k=1}^K \left(\frac{1}{4} \right)^{K-k} \frac{W^2}{2^{2B_k}} + \sum_{k=2}^K \left(\frac{1}{4} \right)^{K-k+1} \sigma_{x_k}^2 \\ &\quad + \left(\frac{1}{4} \right)^{K-1} \sigma_{x_1}^2 \doteq MSE_B. \end{aligned}$$

Assume that the communication channel between sensors has additive white Gaussian noise with power spectral density N_k , and the channel power attenuation factor is $a_k = d_k^r$ where d_k is the transmission distance from sensor k to sensor $k+1$ and r is the path loss exponent. Then, to transmit B_k bits reliably from sensor k to sensor $k+1$, the minimum required transmission energy E_k must satisfy the following, based on Shannon theory:

$$E_k = a_k N_k (2^{B_k} - 1) < a_k N_k 2^{B_k} \quad (6)$$

Under a practical coding and modulation scheme, the right side of (6) should be multiplied by a factor larger than one but independent of k . This factor, however, does not affect our theory on the choice of B_k .

It is therefore meaningful to set up the following criterion for determination of B_k :

$$\min_{\{B_k\}} \sum_{k=1}^K a_k^2 N_k^2 2^{2B_k} \quad (7)$$

subject to

$$MSE_B \leq MSE_0 \quad (8)$$

where (7) is the L_2 -norm of an upper bound of the minimum required network transmission energy, and MSE_0 is a pre-specified tolerance of the upper bound on the MSE at the fusion center. An equivalent form of (8) is

$$\sum_{k=1}^K \left(\frac{1}{4} \right)^{K-k} \frac{1}{2^{2B_k}} \leq \eta \quad (9)$$

where

$$\eta = \frac{1}{W^2} \left(MSE_0 - \sum_{k=2}^K \left(\frac{1}{4} \right)^{K-k+1} \sigma_{x_k}^2 - \left(\frac{1}{4} \right)^{K-1} \sigma_{x_1}^2 \right).$$

Then, by applying the fact that for any real numbers x_i and y_i , $(\sum_i x_i^2)(\sum_i y_i^2) \geq (\sum_i x_i y_i)^2$ with equality when $x_i = \lambda y_i$, we can show [6] that a close-form solution to the above optimization problem is

$$B_k = \frac{1}{2} (k - K + \log_2 \lambda - \log_2(a_k N_k))^+ \quad (10)$$

$$\lambda = \frac{1}{\eta} \sum_{k=k_0}^K a_k N_k 2^{k-K} \quad (11)$$

where $(x)^+ = x$ if $x \geq 0$ and $(x)^+ = 0$ if $x < 0$. Note that we require B_k to be nonnegative. In practice, B_k need to be rounded up to the nearest integer.

2.2. Vector Parameter

For the case of vector parameter, we now model the observation at each sensor as follows:

$$\mathbf{x}_k = \mathbf{G}_k \boldsymbol{\theta} + \boldsymbol{\omega}_k. \quad (12)$$

where $\boldsymbol{\theta} = [\theta_1, \theta_2, \dots, \theta_M]^T$ is the vector parameter to be estimated, \mathbf{x}_k is a $N \times 1$ observed data vector at sensor k , \mathbf{G}_k is a $N \times M$ known matrix with full column rank and $N \geq M$, and $\boldsymbol{\omega}_k$ is the observation noise vector at sensor k .

The PP scheme for the vector case hinges on the QR decomposition $\mathbf{G}_k = \mathbf{Q}_k \mathbf{R}_k$ where \mathbf{Q}_k is a tall $N \times M$ unitary matrix and \mathbf{R}_k is upper triangular. We can now write

$$\mathbf{y}_k \doteq \mathbf{Q}_k^H \mathbf{x}_k = \mathbf{R}_k \boldsymbol{\theta} + \boldsymbol{\nu}_k \quad (13)$$

where $\boldsymbol{\nu}_k = \mathbf{Q}_k^H \boldsymbol{\omega}_k$. The s th row of (13) can be written as

$$y_{k,s} = r_{k,s,s} \theta_s + \sum_{j=s+1}^M r_{k,s,j} \theta_j + \nu_{k,s}. \quad (14)$$

where $r_{k,i,j}$ is the (i, j) th element of \mathbf{R}_k .

At sensor k , the estimate of the s th component θ_s of $\boldsymbol{\theta}$ is denoted by $\hat{\theta}_{k,s}$, which is computed from $y_{k,s}$ and $m_{k-1,s}$ sequentially with respect to s . Here, $m_{k-1,s}$ is the s th element of \mathbf{m}_{k-1} . Specifically, we let

$$z_{k,s} \doteq \frac{y_{k,s} - \sum_{j=s+1}^M r_{k,s,j} \hat{\theta}_{k,j}}{r_{k,s,s}} \quad (15)$$

The variance of $z_{k,s}$ is given by

$$\sigma_{z_{k,s}}^2 = (\sigma_{\nu_{k,s}}^2 + \sum_{j=s+1}^M r_{k,s,j}^2 \sigma_{\hat{\theta}_{k,j}}^2) / r_{k,s,s}^2 \quad (16)$$

Note that $\sigma_{\nu_{k,s}}^2 = \sigma_{\omega_k}^2$. Then, the BLUE $\hat{\theta}_{k,s}$ of θ_s is

$$\hat{\theta}_{k,s} = \left(\frac{m_{k-1,s}}{\sigma_{m_{k-1,s}}^2} + \frac{z_{k,s}}{\sigma_{z_{k,s}}^2} \right) / \left(\frac{1}{\sigma_{m_{k-1,s}}^2} + \frac{1}{\sigma_{z_{k,s}}^2} \right) \quad (17)$$

In order to transmit $\hat{\theta}_{k,s}$ for $s = 1, 2, \dots, M$ from sensor k to sensor $k+1$ over bandlimited wireless channel, we have to quantize $\hat{\theta}_{k,s}$. We will use $B_{k,s}$ bits to quantize $\hat{\theta}_{k,s}$ into $m_{k,s}$. Assume that $\hat{\theta}_{k,s}$ is bounded within $[-W_s, W_s]$. Then, the variance of the quantization error of $m_{k,s}$ is $\sigma_{Q_{k,s}}^2 = \frac{c_{k,s} W_s^2}{2^{2B_{k,s}}} \leq \frac{W_s^2}{2^{2B_{k,s}}}$ where $c_{k,s} \leq 1$. The variance of $m_{k,s}$ is then given by

$$\sigma_{m_{k,s}}^2 = \sigma_{\hat{\theta}_{k,s}}^2 + \sigma_{Q_{k,s}}^2 \quad (18)$$

We now develop an algorithm for computing the bit allocations, i.e., $B_{k,s}$. Similar to the scalar case, we can derive the following upper bound on $\sigma_{m_{k,s}}^2$ [7]:

$$\sigma_{m_{k,s}}^2 \leq \sum_{j=s}^M p_{k,s,j} \sigma_{m_{k-1,j}}^2 + q_{k,s} + \frac{W_s^2}{2^{2B_{k,s}}} \quad (19)$$

where

$$p_{k,s,j} = \begin{cases} 0, & j < s \\ \frac{1}{4}, & j = s \\ \frac{1}{4} \sum_{i=s+1}^j \frac{r_{k,s,i}^2}{4r_{k,s,s}^2} \prod_{l=i+1}^j \frac{r_{k,l-1,l}^2}{4r_{k,l-1,l-1}^2}, & j > s \end{cases} \quad (20)$$

and $q_{k,s} = \sum_{j=s}^M \frac{\sigma_{\nu_{k,j}}^2}{r_{k,j,j}^2} p_{k,s,j}$.

We want the MSE of the final quantized estimate \mathbf{m}_K of $\boldsymbol{\theta}$ to be upper bounded by a predetermined value MSE_0 , i.e., $MSE \doteq E\{(\mathbf{m}_K - \boldsymbol{\theta})^H (\mathbf{m}_K - \boldsymbol{\theta})\} \leq MSE_0$. Based on the inequality (19), we have an upper bound on the MSE :

$$MSE \doteq \sum_{s=1}^M \sigma_{m_{K,s}}^2 \leq \sum_{k=1}^K \sum_{s=1}^M h_{k,s} \frac{W_s^2}{2^{2B_{k,s}}} + \xi \doteq MSE_B \quad (21)$$

where $h_{K,s} = 1, 1 \leq s \leq M$, $h_{k,s} = \sum_{l=1}^s p_{k+1,l,s} h_{k+1,l}$, $k = K-1, \dots, 1, 1 \leq s \leq M$, and $\xi = \sum_{k=1}^K \sum_{s=1}^M h_{k,s} q_{k,s}$.

Assume there are totally L wireless channels between sensor k and $k+1$. We further assume that the model of each channel is the same as in the scalar case. Then, the minimum energy E_k required to reliably transmit $\sum_{s=1}^M B_{k,s}$ bits from sensor k to sensor $k+1$ through L channel uses is given by the following expression according to the Shannon theory:

$$E_k = La_k N_k \left(2^{\frac{1}{L} \sum_{s=1}^M B_{k,s}} - 1 \right) \quad (22)$$

For any given $B_{k,s}$ for $s = 1, \dots, M$, the energy efficiency increases (i.e., E_k decreases) as L increases. However, the spectral efficiency $\frac{1}{L} \sum_{s=1}^M B_{k,s}$ in bits/second/Hertz decreases as L increases. So, in practice, there is always a tradeoff between energy efficiency and spectral efficiency.

According to the fact that for positive real numbers a_i , $\prod_{i=1}^n a_i \leq \sum_{i=1}^n a_i^n / n$, we can upper bound E_k by $E_k \leq La_k N_k 2^{\frac{1}{L} \sum_{s=1}^M B_{k,s}} \leq \frac{L}{M} a_k N_k \sum_{s=1}^M 2^{\frac{M}{L} B_{k,s}}$. We now aim to minimize the $L_{2L/M}$ norm of the upper bound on $E_{k,s}$ as a design approach to determine $B_{k,s}$, i.e.,

$$\min_{\{B_{k,s}\}} J \doteq \sum_{k=1}^K \sum_{s=1}^M \left(\frac{L}{M} \right)^{\frac{2L}{M}} a_k^{\frac{2L}{M}} N_k^{\frac{2L}{M}} 2^{2B_{k,s}} \quad (23)$$

subject to

$$MSE_B \leq MSE_0 \quad (24)$$

or equivalently

$$\sum_{k=1}^K \sum_{s=1}^M \frac{h_{k,s} W_s^2}{2^{2B_{k,s}}} \leq MSE_0 - \xi \doteq \eta \quad (25)$$

The solution to the above problem can be shown to be [7]:

$$\begin{aligned} B_{k,s} &= \frac{1}{2} \left(\log_2 \lambda + \log_2 (\sqrt{h_{k,s}} W_s) - \log_2 (A_k) \right)^+ \\ \lambda &= \frac{1}{\eta} \sum_{(k,s) \in S^+} \sqrt{h_{k,s}} W_s A_k \\ A_k &= \left(\frac{L}{M} \right)^{\frac{L}{M}} a_k^{\frac{L}{M}} N_k^{\frac{L}{M}} \end{aligned}$$

where $S^+ = \{(k, s) | B_{k,s} > 0\}$. The computations of $B_{k,s}$ and λ need to be performed iteratively until convergence. The iteration starts with a full S^+ (corresponding to $B_{k,s} > 0$ for all k and s). After convergence, $B_{k,s}$ is rounded up into an integer.

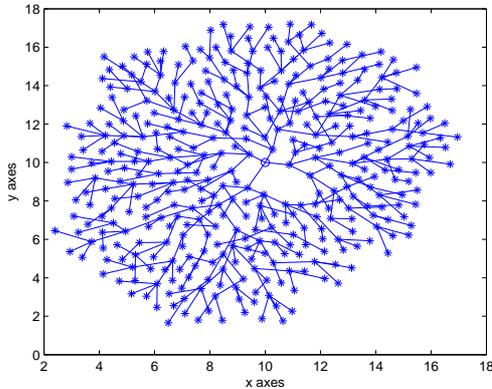


Fig. 2. An example of 2-D sensor network with a routing tree. The fusion center is denoted by the circle in the center. Here, there are 400 nodes, each denoted by *.

3. THE PP SCHEME FOR 2-D OR 3-D NETWORKS

For a 2-D or 3-D network, a routing tree must be first established as illustrated in Fig. 2 where each branch of the tree represents a path of data flow.

Let each sensor in the network have a unique label k where $k = 1, 2, \dots, K$. For convenience, we assume the fusion center has a label $k = K + 1$. The set containing the up stream sensors of sensor k is denoted by \mathcal{C}_k , and the size of \mathcal{C}_k is denoted by e_k . Sensor k computes the estimate $\hat{\theta}_k$ of the vector parameter θ using its local measurement x_k and the data $\{m_l, l \in \mathcal{C}_k\}$ received from \mathcal{C}_k . Then, sensor k uses $B_{k,s}$ bits to quantize the s th element $\hat{\theta}_{k,s}$ of $\hat{\theta}_k$ into $m_{k,s}$ where $s = 1, \dots, M$, which are to be transmitted to its down stream sensor. One can verify that

$$\hat{\theta}_{k,s} = \frac{\sum_{l \in \mathcal{C}_k} \frac{m_{l,s}}{\sigma_{m_{l,s}}^2} + \frac{z_{k,s}}{\sigma_{z_{k,s}}^2}}{\sum_{l \in \mathcal{C}_k} \frac{1}{\sigma_{m_{l,s}}^2} + \frac{1}{\sigma_{z_{k,s}}^2}} \quad (26)$$

where $z_{k,s} = (y_{k,s} - \sum_{j=s+1}^M r_{k,s,j} \hat{\theta}_{k,j}) / r_{k,s,s}$. Likewise, we can obtain

$$\sigma_{m_{k,s}}^2 \leq \sum_{l \in \mathcal{C}_k} \sum_{j=s}^M p_{k,s,j} \sigma_{m_{l,j}}^2 + q_{k,s} + \frac{W_s^2}{2^{2B_{k,s}}} \quad (27)$$

where

$$p_{k,s,j} = \begin{cases} 0, & j < s \\ \frac{1}{(1+e_k)^2}, & j = s \\ \frac{1}{(1+e_k)^2} \sum_{i=s+1}^j \frac{r_{k,s,i}^2}{(1+e_k)^2 r_{k,s,s}^2} \times \\ \prod_{l=i+1}^j \frac{r_{k,l-1,l}^2}{(1+e_k)^2 r_{k,l-1,l-1}^2}, & j > s \end{cases} \quad (28)$$

and $q_{k,s} = \sum_{j=s}^M \frac{\sigma_{v_{k,j}}^2}{r_{k,j,j}^2} p_{k,s,j}$. Notice that (20) is a special case of (28) by simply setting $e_k = 1$. Then, at the fusion center whose label is $k = K + 1$, the MSE is bounded as follows:

$$\begin{aligned} MSE &\doteq \sum_{s=1}^M \sigma_{m_{K+1,s}}^2 \leq \sum_{k=1}^K \sum_{s=1}^M h_{k,s} \frac{W_s^2}{2^{2B_{k,s}}} + \xi \doteq MSE_B \\ \xi &= \sum_{k=1}^K \sum_{s=1}^M h_{k,s} q_{k,s} \end{aligned}$$

where $h_{l,s} = \frac{1}{e_{K+1}^2}$, $l \in \mathcal{C}_{K+1}$, $s = 1, \dots, M$; $h_{l,s} = \sum_{j=1}^M p_{k,j,s} h_{k,j}$, $l \in \mathcal{C}_k$, $s = 1, \dots, M$. With the above defined $h_{k,s}$, the previous procedure for computing $B_{k,s}$ and λ is now also valid for 2-D or 3-D networks.

4. PERFORMANCE EVALUATION

We now compare the performance of the PP scheme with that of the NP scheme in [1]. For comparison, we also include a uniform progressive (UP) scheme for which a constant number of bits for each sensor is assigned.

We will consider a 2-D network of 400 sensors as shown in Fig. 2. This network is constructed in such a way that the distance between a parent sensor and its child sensor is $D\delta$ where δ is uniformly distributed within the range $[0.5, 1.5]$ and D is unspecified. We further assume that $W = 1$, $\sigma_{x_k}^2 = 0.05$, $r = 4$, and $N_k = 1$.

Under the constraint $MSE_0 = 0.0043$ at the fusion center, Fig. 3 compares the bit allocations by the NP, PP and UP schemes. The figure shows the number of bits for each sensor versus the Euclidean distance (divided by D) from the sensor to the fusion center. For the UP scheme, each sensor is allocated with the same number of bits. We see that the number of bits allocated by either the PP scheme or the UP scheme for a sensor at medium or high distance is much higher than that by the NP scheme. This is because of the short transmission range for each sensor under the progressive scheme. We also see that the PP scheme allocates a much smaller number of bits for each sensor at medium or high distance than the UP scheme. This is because of the optimization used in developing the PP scheme. Compared to the PP scheme, the NP scheme collects too little information from sensors at medium or high distance and the UP scheme collects too much information from sensors at medium or high distance.

Fig. 4 shows the total normalized transmission energy consumed by the network, i.e., $\sum_{1 \leq k \leq K} E_k/D^r$, versus the target MSE_0 . We see that the PP scheme requires the least amount of energy throughout the whole MSE_0 region. At high MSE_0 , the PP scheme and the NP scheme consume approximately the same energy because almost all bits are allocated to the sensors right next to the fusion center.

We then evaluate the progressive scheme for the vector parameter estimation. We assume that θ has 10 elements, i.e., $M = 10$. We set $W_s = 1$. We choose G_k to be 20×10 matrices of i.i.d. Gaussian random variables with zero mean and variance of 10. We also choose $\sigma_{\omega_k}^2 = 0.05$, $N_k = 1$ and $\alpha = 4$. We choose $L = M$ initially unless mentioned otherwise later.

Under $MSE_0 = 1.0 \times 10^{-5}$ at the fusion center, Fig. 5 shows the average transmission energy per sensor, i.e., $E_{node} = \frac{1}{K} \sum_{k=1}^K E_k/D^r$, versus the size K of the network. We see that E_{node} decreases with K . However, as the network becomes very large, the change becomes negligible. This is because the information from far away sensors is heavily filtered out as it moves towards the fusion center. This phenomenon is directly due to a finite number of bits allocated to each sensor.

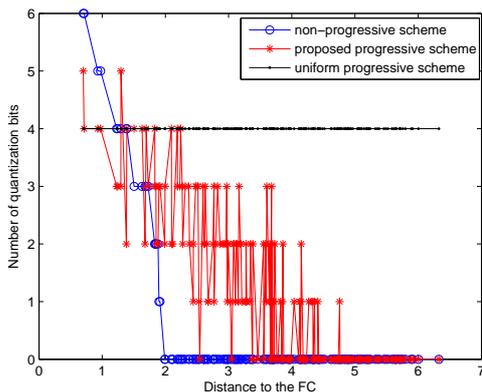


Fig. 3. The number of quantization bits allocated for each sensor versus the normalized Euclidean distance from the sensor to the fusion center. $MSE_0 = 0.0043$. The network used is Fig. 2.

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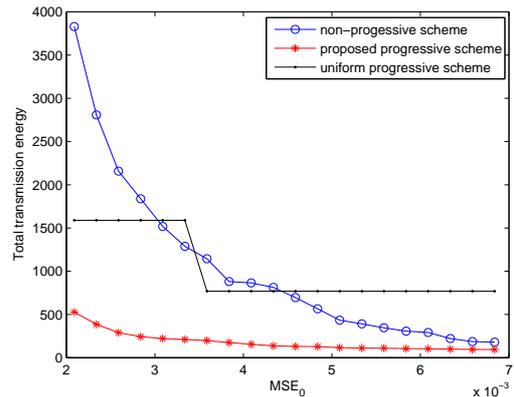


Fig. 4. Total amount of normalized transmission energy consumed by the network versus MSE_0 . The network used is Fig. 2.

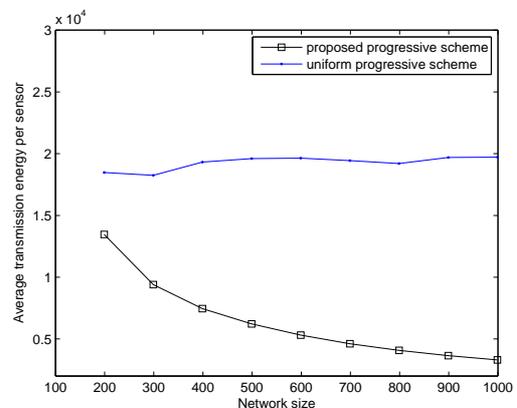


Fig. 5. The average amount of normalized energy per sensor versus the number of sensors in the network. $MSE_0 = 1.0 \times 10^{-5}$. The network used is Fig. 2.

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