Energy-efficient Quantization and Transmission in Distributed Estimation

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***Abstract*— In this paper, we investigate the problem of energy-efficient distributed estimation in wireless sensor networks. In an inhomogeneous sensing and transmission environment, the minimization of total energy is jointly determined by the optimal quantization and transmission scheduling. In order to minimize the total energy under the mean squared error (MSE) and total transmission time constraints, we design a joint algorithm which iteratively computes the optimal quantization lengths and transmission times. We proved that the algorithm is convergent. Simulations show that the iteration converges quickly, and significant energy saving can be achieved when compared with the uniform quantization and transmission scheme.**

Keywords-distributed estimation, energy efficient, quantizaion, transmission scheduling.

I. INTRODUCTION

Consider a distributed wireless sensor network (WSN) as shown in Fig.1, local sensors cooperate with a fusion center (FC) in estimating an unknown parameter in the environment. The local sensors are in charge of observation and sending the compressed data to the FC, and the FC aggregates the data and generates a final estimation. Due to the specific application environment, sensor networks face serious energy and bandwidth constrains. Thus we must design the best estimation scheme under the limited energy and bandwidth.

Usually the transmission energy consumption is effected by two important factors: the length of transmission data and the time of the transmission. In [1], the authors derived some universal decentralized estimation schemes under the ideal channel models. Based on the case of inhomogeneous sensing environment and different channel gains, the authors in [2] and [3] optimally choose the quantization lengths for all sensors by taking into account their local SNRs and the channel gains. They set the data length equals to the constellation size in order to minimize the delay, although we know that the transmission delay is not a severe constraint in sensor networks sometimes. Since timely knowledge of the instantaneous noise profiles will be too costly to acquire, the authors in [4] provide an energy-efficient decentralized estimation solution by considering the long-term noise variance information. However in their transmission model, all the sensors use the same bit rate, which implies each sensor's transmission time is uniquely determined by the length of transmission data. Therefore, none of these proposed solutions jointly optimize the quantization lengths and transmission times, so they remain to be developed.

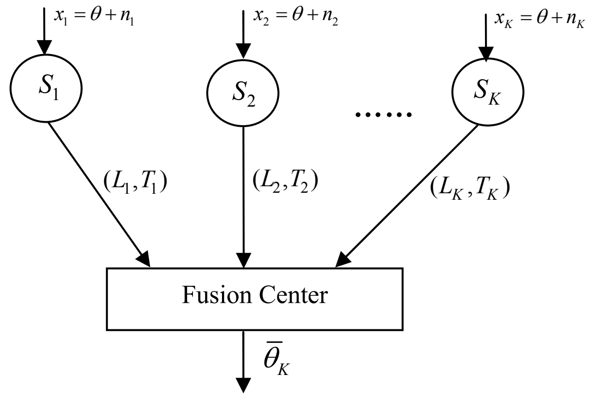

Figure 1. Sensor network with a fusion center.

The information theory tells us that, the longer time it is used to transmit a message, the less energy it needs [5]. When the total transmission time is given, there is an optimal time scheduling for each sensor. The MoveRight algorithm [7] is such an algorithm that can find the optimal scheduling of the sensors' transmission times quickly. In this paper, we will extend the MoveRight algorithm to optimize the transmission times of all the sensors when the quantization lengths are given.

In this paper, we propose a variable-length Time Division Multiple Access (TDMA) scheme and use the uncoded MQAM as the modulation scheme for all the sensors. We first deduce a closed-expression of optimal quantization with transmission time fixed via convex optimization. Then we merge the quantization optimization and transmission time scheduling together to form an iterative joint optimization algorithm. We do some analysis of the convergence property and show the energy saving performance through some simulation results.

The paper is organized as follows: Section II introduces the system model. Section III discusses the quantization and transmission scheduling with minimized energy cost. Section IV shows the performance of our algorithm via some simulation results. Finally we carried out a brief summary in section V.

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II. SYSTEM MODEL

Consider a WSN with K distributed sensors deployed to estimate an unknown parameter θ. The k^{th} sensor observes a noisy version of θ given by:

$$x_k = \theta + n_k, \quad 1 \le k \le K \tag{1}$$

where n_k denotes the zero-mean noise with variance σ_k^2. We assume that noise variances are independent across sensors. For the limitation of bandwidth, each sensor should compress its observation x_k to a L_k-bit length message m_k and send to the FC. In this paper we use a uniform quantization scheme with nearest-rounding which can be modeled as:

$$m_k = x_k + \Delta_k, \quad 1 \le k \le K \tag{2}$$

here Δ_k refers to zero-mean quantization error with variance $\delta_k^2 = W^2/(12\cdot 4^{L_k})$ [6]. $[-W/2, W/2]$ is the signal range that sensors can observe. The FC performs the Best Linear Unbiased Estimator (BLUE) to recover θ :

$$\bar{\theta}_K = \bar{\theta}_K(m_1, m_2, \cdots, m_K) = \left(\sum_{k=1}^{K}\frac{1}{\delta_k^2+\sigma_k^2}\right)^{-1}\sum_{k=1}^{K}\frac{m_k}{\delta_k^2+\sigma_k^2}, 1 \le k \le K\,. \tag{3}$$

The corresponding MSE is [3]:

$$D = \mathrm{E}\left(\left|\bar{\theta}_K - \theta\right|^2\right) \le \left(\sum_{k=1}^{K}\frac{1}{\delta_k^2+\sigma_k^2}\right)^{-1} = \left(\sum_{k=1}^{K}\frac{1}{\sigma_k^2 + W^2\cdot 4^{-L_k}/12}\right)^{-1}\,. \tag{4}$$

Considering the possible errors in actual transmission, when the bit error rate (BER) is below a certain threshold, the total MSE will be one constant factor increase when compared to the benchmark measure [3]. Thus in the following, we will use D to denote the MSE due to BER for convenience.

Assume the observation noise to be Gaussian distribution, then the noise variance can be modeled as follows:

$$\sigma_k^2 = \gamma + \alpha z_k, \quad 1 \le k \le K\,, \tag{5}$$

here γ denotes the minimal observation noise power throughout the entire network; α refers to the variance of each sensor's noise power. $z_k \sim \chi_1^2$ is chi-squared distribution with degree 1.

III. QUANTIZATION AND TRANSMISSION SCHEDULING WITH MINIMIZED ENERGY COST

We assume the sensors send data to the fusion center with MQAM (constellation size b_k) at an identical transmission symbol rate B, then the transmission time for the k^{th} sensor to send the L_k bits data is $T_k = L_k/(Bb_k)$, and the transmission energy [3] is given by:

$$E_k(L_k, b_k) = \frac{4}{3}N_f N_0 G_k \frac{L_k}{b_k}\left(2^{b_k}-1\right)\ln\frac{2}{p_b^k}, \tag{6}$$

here p_b^k is BER and $G_k := d_k^{\kappa}$ is the path-loss, where κ is the path-loss constant and d_k is the transmission distance. If we substitute b_k with $b_k = L_k/(BT_k)$, (6) becomes

$$E_k(L_k, T_k) = \frac{4}{3}N_f N_0 B G_k T_k\left(2^{\frac{L_k}{BT_k}}-1\right)\ln\frac{2}{p_b^k}\,. \tag{7}$$

The total amount of required transmission energy is:

$$E = \sum_{k=1}^{K}E_k(L_k, T_k)\,. \tag{8}$$

3.1 Problom Formulation

Our goal is to minimize the total energy under the target MSE performance and total transmission time constraints. This leads to the following optimization problem:

$$\begin{aligned}
\text{Minimize} \quad & \sum_{k=1}^{K}E(L_k, T_k) \\
\text{Subject to:} \quad & \left(\sum_{k=1}^{K}\frac{1}{\sigma_k^2 + W^2\cdot 4^{-L_k}/12}\right)^{-1} \le D \\
& \sum_{k=1}^{K}T_k \le T,\ T_k \ge 0,\ \ L_k \ge 0,\ \ \forall k,
\end{aligned} \tag{9}$$

where $\sigma_k^2 = \gamma + \alpha z_k$, if p_b^k's in (7) are the same for all sensors, problem (9) can be simplified:

$$\begin{aligned}
\text{Minimize} \quad & \sum_{k=1}^{K}\left(2^{\frac{L_k}{BT_k}}-1\right)T_k G_k \\
\text{Subject to:} \quad & \sum_{k=1}^{K}\frac{1}{\gamma+\alpha z_k + W^2\cdot 4^{-L_k}/12} \ge \frac{1}{D} \\
& \sum_{k=1}^{K}T_k \le T,\ T_k \ge 0,\ \ L_k \ge 0,\ \ \forall k,
\end{aligned} \tag{10}$$

Quantization based on the instantaneous noise profile is an energy-efficient scheme. However it may causes costly extra energy consumption since frequent training/update is needed. Thus we will exploit an alternative way, in which only the long-term information of the noise profile is considered:

$$\int_{\mathbf{z}}\sum_{k=1}^{K}\frac{1}{\gamma+\alpha z_k + W^2\cdot 4^{-L_k}/12}p(\mathbf{z})d\mathbf{z} \ge \frac{1}{D},$$

where $\mathbf{z} := [z_1 \cdots z_K]^T$ with $p(\mathbf{z})$ refers to the associated distribution of observation noise power. The inequality above can be simplified as [4]:

$$\sum_{k=1}^{K}2^{-L_k} \le M := \frac{\sqrt{12\alpha}K}{W}\left[Q^{-1}\left(\frac{1}{cND}\right)-\sqrt{\frac{\gamma}{\alpha}}\right], \tag{11}$$

where $c := \sqrt{\frac{2\pi}{\alpha}}\cdot\frac{e^{\gamma/2\alpha}}{\sqrt{\gamma+W^2/12}}$, then problem (10) can be translated to the following problem with a modified MSE performance constraint:

$$\text{Minimize} \quad \sum_{k=1}^{K}\left(2^{\frac{L_k}{BT_k}}-1\right)T_k G_k$$

$$\text{Subject to:} \quad \sum_{k=1}^{K} T_k \le T$$

$$\sum_{k=1}^{K} 2^{-L_k} \le M$$

$$0 \le T_k \le T, \quad L_k \ge 0, \forall k, \qquad (12)$$

where

$$M=\frac{\sqrt{12\alpha}K}{W}\left[Q^{-1}\left(\frac{1}{cND}\right)-\sqrt{\frac{\gamma}{\alpha}}\right], \quad c=\sqrt{\frac{2\pi}{\alpha}}\cdot\frac{e^{\gamma/2\alpha}}{\sqrt{\gamma+W^2/12}}.$$

3.2 Optimal Solution

In problem (12), since the two sets of variables $\{L_k\}_{k=1}^{K}$ and $\{T_k\}_{k=1}^{K}$ couple with each other in the objective function, it is difficult to work out a closed-form solution in a mathematical way. Fortunately, $\{L_k\}_{k=1}^{K}$ and $\{T_k\}_{k=1}^{K}$ belong to two independent constraint sets, so it may work if we optimize one set of variables with the other fixed. When both sets of variables are optimized, an iterative algorithm can be developed to jointly optimize (12).

A. Optimizing $\{T_k\}_{k=1}^{K}$ while $\{L_k\}_{k=1}^{K}$ are given

While $\{L_k\}_{k=1}^{K}$ are invariable, optimization problem (12) can be simplified as the following:

$$\text{Minimize} \quad \sum_{k=1}^{K}\left(2^{\frac{L_k}{BT_k}}-1\right)G_k T_k$$

$$\text{Subject to:} \quad \sum_{k=1}^{K} T_k = T, \quad 0 \le T_k \le T, \forall k. \qquad (13)$$

Noting that in (13), inequality constraint $\sum_{k=1}^{K} T_k \le T$ has been converted into equality constraint, for it can be proved that the best time scheduling follows $\sum_{k=1}^{K} T_k = T$. Otherwise we can prolong any sensor's transmission time to make $\sum_{k=1}^{K} T_k = T$, the energy will be lower. Besides, it is assumed L_k >0, $\forall k$ in (13) because if some L_k =0, obviously the optimal T_k =0. So the sensors whose $L_k = 0$ has been removed.

Since the objective function in (13) exactly meet the four conditions of MoveRight Algorithm [7], we can solve problem (13) by resorting to this packet-scheduling algorithm.

In problem (13), all the data can be considered to have arrived at time 0. Let S_k be the start time of the k^{th} sensor's transmission, $S_1 = 0$, $S_K + T_K = T$. We further assume $S_{K+1} = T$ for expression convenience. The MoveRight algorithm optimize $\{T_k\}_{k=1}^{K}$ via stepwise iterations. The pseudo code of the algorithm is:

Algorithm 1:

MoveRight( )

Initialize i =0, $S_k^{\,0} = k-1$, $T_k^i = S_{k+1}^i - S_k^i, \forall k$. $S_{K+1}^0 = T$.

Repeat

  $i = i+1$;

  for $k = 1:K-1$ **do**

    adjust S_{k+1}^{i-1} to S_{k+1}^i with $T_k^{i-1} + T_{k+1}^{i-1}$ fixed.

    update $T_k^i = S_{k+1}^i - S_k^{i-1}$.

    update $T_{k+1}^{i-1} = S_{k+2}^{i-1} - S_{k+1}^i$.

  end for

Until $T_k^i = T_k^{i-1}$ for all $k = 1:K$.

B. Optimizing $\{L_k\}_{k=1}^{K}$ while $\{T_k\}_{k=1}^{K}$ are given

Problem (12) can be translated into the following quantization optimization problem with $\{T_k\}_{k=1}^{K}$ fixed:

$$\text{Minimize} \quad \sum_{k=1}^{K}\left(2^{\frac{L_k}{BT_k}}-1\right)T_k G_k$$

$$\text{Subject to:} \quad \sum_{k=1}^{K} 2^{-L_k} \le M, \quad L_k \ge 0, \forall k. \qquad (14)$$

where M is the same as defined in (11).

The objective function and the constraints are both convex (if we ignore the integer requirement on L_k), it is thus a convex optimization problem. Form the Lagrangian as:

$$G(L_1,\cdots L_K,\lambda,\mu_1,\cdots,\mu_K) = \sum_{k=1}^{K}\left(2^{\frac{L_k}{BT_k}}-1\right)T_k G_k + \lambda\left(\sum_{k=1}^{K} 2^{-L_k} - M\right) - \sum_{k=1}^{K}\mu_k L_k. \qquad (15)$$

The relevant KKT conditions are given as:

$$\frac{G_k \ln 2}{B} 2^{\frac{L_k}{BT_k}} - \lambda \ln 2 \cdot 2^{-L_k} - \mu_k = 0, \forall k \qquad (16)$$

$$\lambda\left(\sum_{k=1}^{K} 2^{-L_k} - M\right) = 0, \qquad (17)$$

$$\lambda \ge 0, \mu_k \ge 0, \mu_k L_k = 0, L_k \ge 0, \forall k. \qquad (18)$$

If $\lambda = 0$, (16) implies $\mu_k = \frac{G_k \ln 2}{B} 2^{\frac{L_k}{BT_k}} > 0$, $\forall k$, thus $L_k = 0, \forall k$. When $M \ge K$, this case is the optimal solution, which means when D becomes so large that $M \ge K$, the MSE performance constraint can be satisfied even if all the sensors remain silent. We can also prove that if $M < K$, then $\lambda > 0$, otherwise it will conflict with the constraint in (14).

When $\lambda > 0$, (17) can be translated to :

$$\sum_{k=1}^{K} 2^{-L_k} - M = 0 . \qquad (19)$$

If L_k =0, then $\mu_k = \frac{G_k \ln 2}{B} - \lambda \ln 2 \geq 0$ implies $G_k \geq B\lambda$. We can also prove that $G_k \geq B\lambda \Rightarrow L_k$ =0, otherwise L_k >0 $\Rightarrow$ μ_k =0 $\Rightarrow$ $G_k/(B\lambda)$ = $2^{-L_k(1+1/BT_k)}$ <1 . Similarly, it can be proved that $G_k < B\lambda \Rightarrow L_k$ >0, μ_k =0 and $2^{-L_k} = (\frac{G_k}{B\lambda})^{\frac{BT_k}{1+BT_k}}$. From (19), we have:

$$M = \sum_{k=1}^{K} 2^{-L_k} = \sum_{G_k < B\lambda} 2^{-L_k} + \sum_{G_k \geq B\lambda} 1 \ . \tag{20}$$

Without loss of generality, we assume $G_{K+1} = \infty$ and $G_1 \leq G_2 \leq \cdots \leq G_K < G_{K+1} = \infty$. Equation (20) leads to:

$$\begin{cases} \sum_{k=1}^{K^*} (\frac{G_k}{B\lambda^*})^{\frac{BT_k}{BT_k+1}} + K - K^* = M \\ G_{K^*} < B\lambda^*, G_{K^*+1} \geq B\lambda^* \end{cases} , \tag{21}$$

where (K^*, λ^*) is a solution of (21). The next theorem demonstrates that (K^*, λ^*) is the unique solution.

Theorem I: Assume that (K^*, λ^*) is a solution of (21), and (K_1, λ_1) is a solution of (21)'s first equation,

(1) If $K_1 < K^*$, then $G_{K_1+1} < B\lambda_1$.

(2) If $K_1 > K^*$, then $G_{K_1} \geq B\lambda_1$.

Proof: Define $g(K', \lambda') = \sum_{k=1}^{K'} [1 - (\frac{G_k}{B\lambda'})^{\frac{BT_k}{BT_k+1}}]$ .Then $g(K', \lambda')$ is monotonically increasing in λ' because of $\frac{\partial g(K', \lambda')}{\partial \lambda'} > 0$.

(1) If $K_1 < K^*$, then $K - M = g(K^*, \lambda^*) = g(K_1, \lambda^*) + \sum_{k=K_1+1}^{K^*} [1 - (\frac{G_k}{B\lambda^*})^{\frac{BT_k}{BT_k+1}}] = g(K_1, \lambda_1)$,

Thus $g(K_1, \lambda_1) - g(K_1, \lambda^*) \geq 0 \Rightarrow \lambda_1 \geq \lambda^*$;

$K_1 < K^* \Rightarrow K_1 + 1 \leq K^* \Rightarrow G_{K_1+1} \leq G_{K^*} < B\lambda^* \leq B\lambda_1 \Rightarrow G_{K_1+1} < B\lambda_1$. This proved (1).

(2) If $K_1 > K^*$, then $K - M = g(K_1, \lambda_1) = g(K^*, \lambda_1) + \sum_{k=K^*+1}^{K_1} [1 - (\frac{G_k}{B\lambda_1})^{\frac{BT_k}{BT_k+1}}] = g(K^*, \lambda^*)$ .Assume $G_{K_1} < B\lambda_1$, then $g(K^*, \lambda^*) - g(K^*, \lambda_1) = \sum_{k=K^*+1}^{K_1} [1 - (\frac{G_k}{B\lambda_1})^{\frac{BT_k}{BT_k+1}}] > 0 \Rightarrow \lambda^* > \lambda_1$. But $B\lambda_1 > G_{K_1} \geq G_{K^*+1} \geq B\lambda^* \Rightarrow \lambda_1 > \lambda^*$, which leads to a conflict, thus $G_{K_1} \geq B\lambda_1$. This proved (2).

Theorem I not only proves the uniqueness of (K^*, λ^*) , but also provides us a way to search (K^*, λ^*) quickly: we can design a binary search algorithm for both K and λ with the complexity of $O(N \log K)$, where N is the complexity of searching λ with a fixed K .

When we got (K^*, λ^*) , the optimal L_k is given as:

$$L_k = \begin{cases} \frac{BT_k}{BT_k+1} \log(\frac{B\lambda^*}{G_k}), & k \leq K^* \\ 0, & k \geq K^* + 1 \end{cases} . \tag{22}$$

It's worth noting that the optimal L_k in (22) is a real number, which is the theoretically optimal lower bound. In the actual application, we can round L_k up to the closest integer that is larger than L_k .

C. Iterative Optimization of $\{L_k\}_{k=1}^K$ and $\{T_k\}_{k=1}^K$

Since the two sets of variables $\{L_k\}_{k=1}^K$ and $\{T_k\}_{k=1}^K$ are coupled in the objective function of problem (12), one possible way to find out the joint optimal solution is brute-force search, however the exponential-level complexity is obviously unfeasible for large size sensor networks. Thus we resort to an iterative algorithm which converges at least to a stationary point of the total energy, and yields the optimal solution of $\{L_k\}_{k=1}^K$ and $\{T_k\}_{k=1}^K$. The joint iterative algorithm goes like this: at every iteration step, we first optimize $\{L_k\}_{k=1}^K$ with $\{T_k\}_{k=1}^K$ fixed, then optimize $\{T_k\}_{k=1}^K$ with the solved $\{L_k\}_{k=1}^K$. The process repeats until the total energy converges to a stationary value. The pseudo code is as follow:

Algorithm 2:

Joint_Optimization( )

1 **Initialize** $\{L_k^0\}_{k=1}^K, \{T_k^0\}_{k=1}^K$, i=0;
2 **repeat**
3 i=i+1
4 **for** k = 1:K **do**
5 Update $\{L_k^{(i)}\}_{k=1}^K$ use (21) based on $\{T_k^{(i-1)}\}_{k=1}^K$.
6 **end for**
7 **for** k = 1:K **do**
8 Update $\{T_k^{(i)}\}_{k=1}^K$ use MoveRight based on $\{L_k^{(i)}\}_{k=1}^K$.
9 **end for**
10 Calculate $E^{(i)}$ based on $\{L_k^{(i)}\}_{k=1}^K$ and $\{T_k^{(i)}\}_{k=1}^K$.
11 **until** $\left|E^{(i)} - E^{(i-1)}\right| < \varepsilon$ for given tolerance ε .

a) Convergence property: The conclusions of part A and B show that line 4~6 and 7~9 in algorithm 2 can both reduce the total energy consumption, so $E^{(i)}$ is the non-increasing function of iteration times i . As $E^{(i)}$ has a lower bound (optimal value), $E^{(i)}$ will converge to a stationary-value.

b) Convergence speed: There are two plans in each iteration step: updating $\{L_k^{(i)}\}_{k=1}^K$ first or updating $\{T_k^{(i)}\}_{k=1}^K$ first. Their convergence speeds and performance will be distinguished in the following simulation result.

IV. SIMULATION

The performance of the algorithm applied in this paper will be evaluated by energy saving in percentage when compared with the uniform quantization and transmission scheduling scheme (UQTS). From the MSE performance constraint (11), the average length each sensor need is $\tilde{L} = \log(K/M)$. In the UQTS, we set quantization length $\tilde{L}$, and transmission time $\tilde{T} = T/K$. In the following simulations the number of sensors is set to be $K = 100$, The d_k in $G_k = d_k^{\kappa}$ is generated by uniform distribution, $d_k \sim U[1,10]$. We know the higher coefficient κ is, the larger the variance of G_k becomes.

Fig.2 shows the convergence performance of Algorithm2. With M =50 and κ =3.5, the energy saving converges to 73.45% after 20 iterations. It can be seen that, updating $\{L_k^{(i)}\}_{k=1}^{K}$ first converges faster than updating $\{T_k^{(i)}\}_{k=1}^{K}$ first. Therefore, in application updating quantization length can be done before that of transmission time. Considering the limit of actual computational capacity, 3-4 iterations can provide desirable convergence performance.

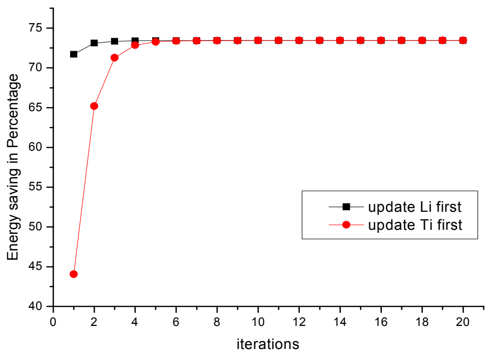

Figure 2. The convergence performance of Algorithm 2.

Fig.3 shows the energy-saving performance of the three ways in MSE change. Here we set κ =3.5. According to Fig.3, as MSE increases, optimization performance of quantization length is rising while that of transmission time goes down due to the decreasing of average quantization length $\tilde{L}$. Yet the performance of iterative joint optimization keeps rising.

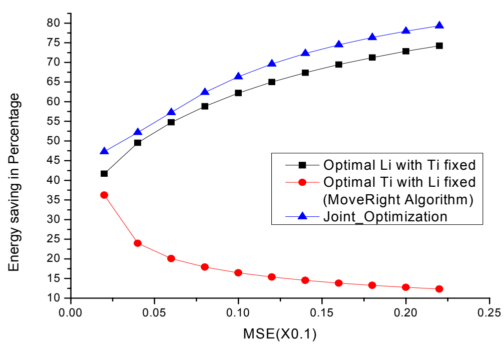

Figure 3. Percentage of energy saving w.r.t different MSE.

Finally with $M = K/8$, κ changes within 1~6. We know the higher κ is, the more heterogeneous the channel gains become. Fig.4 shows that all the three algorithms perform better when the channel gains become more heterogeneous.

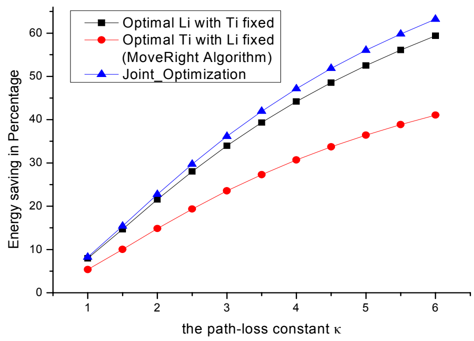

Figure 4. Percentage of energy saving w.r.t different κ.

V. CONCLUSION

Our paper provided a solution to the energy-efficient distributed estimation under the constraints of a target MSE performance and total transmission time. We derived a closed-expression of optimal quantization scheme under a fixed transmission scheduling. Combining our optimal quantization scheme with MoveRight algorithm, we designed an algorithm which optimizes quantization and transmission jointly. The joint algorithm will shut off the sensors suffering from poor channel quality, optimally choose the quantization lengths and transmission times for the active sensors through an iterative way. Simulation results show that the algorithm works well in the heterogeneous sensing and transmission environment, and more than 60% energy can be saving when compared with the uniform quantization and transmission scheme.

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