Network Lifespan Enlargement for Assessment in Multihop Wireless Sensor Networks

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Abstract

In energy limited wireless sensor networks, both local quantization and multihop transmission are essential to save transmission energy and thus prolong the network lifetime. The goal is to maximize the network lifetime, defined as the estimation task cycles accomplished before the network becomes nonfunctional. The network lifetime optimization problem includes three components: Optimizing source coding at each sensor node, optimizing source throughput at each sensor node. Optimizing multihop routing path. Source coding optimization can be decoupled from source throughput and multihop routing path optimization and is solved by introducing a concept of equivalent 1-bit Mean Square Error (MSE) function. Based on optimal source coding, multihop routing path optimization is formulated as a linear programming problem, which suggests a new notion of character-based routing. It is also seen that optimal multihop routing improves the network lifetime bound significantly compared with single-hop routing for heterogeneous networks. Furthermore, the gain is more significant when the network is denser since there are more opportunities for multihop routing. Also, the gain is more significant when the observation noise variances are more diverse.

Keywords—Sensor Networks; Lifetime Maximization; 1-bit MSE

Introduction

Wireless Sensor Networks (WSN), consisting of a large number of geographically distributed sensor nodes, have many current and future envisioned applications, such as environment monitoring, battlefield surveillance, health care, and home automation. Though each sensor is characterized by low power constraint and limited computation and communication capabilities due to various design considerations such as small battery size, bandwidth and cost, potentially powerful networks can be constructed to accomplish various high level tasks via sensor cooperation[1], such as distributed estimation, distributed detection and target localization and tracking.

Decentralized estimation using ad hocs WSN is also recently addressed, which is based on successive refinements of local estimates maintained at individual sensors. At each iteration, the sensor exchange quantized messages with their immediate neighbors, and then each sensor uses this information to refine its local estimate. In this context, decentralized estimation of deterministic parameters in linear data models was considered in using the notion of consensus averaging. Decentralized estimation of parameter vectors [2],[3] in general data models was considered using Best Linear Unbiased Estimator (BLUE).

In energy limited WSN, both local quantization and multihop transmission are essential to save transmission energy and thus prolong the network lifetime. To maximize the network lifetime for the estimation application, three factors are needed to be optimized together: source coding i.e., quantization level of each observation, source throughput i.e., total number of observations or total information bits generated by each sensor and multihop routing path to transmit the observations from all sensors to the fusion centre. This problem can be formulated as a Non-Linear Programming problem (NLP). Further, source coding optimization can be decoupled from source throughput and multihop routing optimization and solved by introducing the concept of equivalent 1-bit MSE function. It is noted that the proposed algorithm determines the optimal quantize locally at each sensor without knowing other sensors’ information. Thus it can be implemented in a distributed manner. On the other hand, the source throughput and multihop routing needs to be optimized jointly and it can be formulated as a Linear Programming (LP) [4] problem based on optimal source coding. It is interesting to note that the solution implies a character- based routing, where a sensor node only relays other sensor observations that are more accurate than its observations, which is different from the traditional distance-based routing, where the sensor nodes closer to the fusion center relay information for sensor nodes farther away from the fusion center. Each sensor can observe the phenomenon, quantize and transmit its observation to the Fusion Center (FC) via multihop wireless channel, and the fusion center makes the final estimation based on all the messages. The data from a sensor can be relayed by received multiple sensors. Meanwhile, a sensor can relay data for multiple sensors.

System Model and Preliminaries

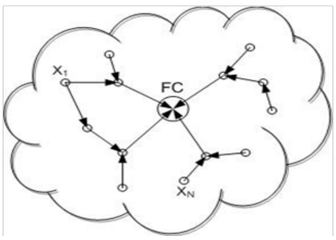

Fig2.1-System model of a sensor network with fusion center

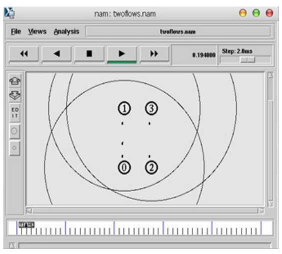

Fig 2.2-Network simulation in Ns-2

A dense network is consider including N distributed sensor nodes and a fusion center, denoted as node N+1, to observe and estimate an unknown parameter Θ. Fig 2.1 shows the system model of the network and Fig 2.2 gives the simulation of the network in network simulator.

System model

First, each sensor k can make observations on an unknown parameter Θ. The observations are corrupted by additive noise and described by

$$X_k = \theta + n_k \qquad k=1,\ldots\ldots N \qquad (1)$$

It is assumed that the observation noise of all sensors (k= 1,…..N) are zero mean, spatially uncorrelated with variance , while the noise at each sensor node is assumed to be temporally independent and identically distributed (i.i.d), otherwise unknown. Assume there are K received observations (m1,m2,m3,…..mk) at the fusion center, then the fusion center produces a final estimation of by combing all of available observations using a fusion function f: =f(m1,m2,…mk). The quality of estimation is measured by the MSE criterion.

Blue Estimation Rule

If the fusion center has the knowledge of the sensor noise variance (k=1,2,…..K) and the sensors can perfectly send their observations xk(k=1,2,…..N) to the fusion center, the BLUE estimator for Θ is known to be

$$\theta' = (\sum_{k=1}^{k} 1/\sigma^2)^{-1}(\sum_{k=1}^{k} x_k/\sigma_k^{\ 2}) \qquad (2)$$

And the estimation MSE of the BLUE estimator is

$$E(\theta' - \theta)^2 = (\sum_{k=1}^{k} 1/\sigma_k^{\ 2})^{-1} \qquad (3)$$

But the BLUE scheme is impractical for WSN because of high communication cost (bandwidth and energy). Instead of sending the real-valued observations to the fusion center directly, quantization at the local sensors is essential to reduce the communication cost. In this paper, a probabilistic quantization scheme is adopted at each sensor to make the local quantization, as well as a quasi-BLUE estimation scheme at the fusion center to make the final estimation. Notice that is an unbiased estimator of because every mk is unbiased. Moreover, the estimation MSE of the quasi-BLUE estimator is

$$E(\theta' - \theta)^2 = (\sum_{k=1}^{k} 1/\pi_k^{\ 2}(\sigma_k^{\ 2}, b_k^{\ 2}\ ))^{-1} \qquad (4)$$

Energy Model

Assume sensor nodes can adjust their transmission power to control the transmission range. The energy consumed by sensor I to reliably transmit a b-bit message to sensor j is

$$e(b) = c.b.d^{a}_{\ i,j} \qquad (5)$$

Where c is a system constant denoting the energy required by a transmitter amplifier to transmit 1-bit one meter, is the path loss exponent depending on the medium properties and di,j is the distance between sensor i and sensor j.

Network Lifetime for Estimation

Function based Network Lifetime

For the estimation algorithm, the network is considered functional if it can produce an estimation satisfying a given distortion requirements Dr. Otherwise it is nonfunctional. The network lifetime L is defined as the estimation task cycles accomplished before the network becomes nonfunctional, where each time when the sensor network makes an estimation is denoted as an estimation task cycle.

$$L \le D_r * (\sum_{k=1}^{N} \sum_{i=1}^{M_k} (1/\pi^2(\sigma_k{}^2, b_{k,i}{}^2)))$$

Nonlinear Programming (NLP) formulation

Model, the wireless sensor network as a directed graph G(V, E) where V is the set consisting of all the N sensor nodes and the fusion center (node N+1), i.e., V=[1, N+1], E is the set of directed links in the network. The link cost to transmit a unit bit information from node i to node j denoted as Ci,j depends on the distance di,j between them based on the energy model

$$Ci, j = c.d^a{}_{i,j} \text{ ifdi, j R} \qquad (7)$$

$$= +\infty \text{ otherwise}$$

Where c,α are as defined before and R is the maximum transmission range. According to network lifetime bound the network lifetime maximization problem can be formulated as a nonlinear programming (NLP) problem as follows:

$$MaximizeD_r * (\sum_{k=1}^{N} \sum_{i=1}^{M_k} (1/\pi_k{}^2(\sigma_k{}^2, b_{k,i}{}^2))^{-1} \qquad (8)$$

Separation of source coding optimization with Multihop routing Optimization

The objective function depends only on the source throughput and the source coding scheme but does not depend on how the source is transmitted to the fusion center. On the other hand, the flow conservation and energy constraint only depends on source throughput sk but does not depend on the source coding. Thus, given the source throughput sk of each sensor node, the source coding optimization is independent of the multihop routing optimization.

Sourcecodingoptimization

In this section the source coding is optimized for a given source throughput sk of each sensor k e[1, N], i.e., find the optimal quantization level bk, I for each observation I of each sensor k to maximize the network lifetime bound. Mathematically the problem can be formulated as:

Equivalent 1-bit MSE function

A b-bit quantization sensor with estimation MSE $\pi^2(\sigma^2$ can be treated as b equivalent 1-bit sensor each with the same estimation MSE g(σ^2 ,b). That is why g(σ^2 ,b) is called equivalent 1-bit MSE function

$$g^2(\sigma^2, b) = b * \pi^2(\sigma^2, b) = b * (\sigma^2 + w^2 / (2b-1)^2) \qquad (9)$$

The optimal quantize for 8-bit data and floating precision data is given in Fig 4.1

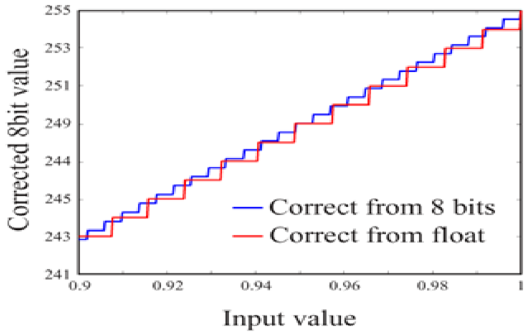

Fig 4.1 Optimal quantize Characteristics

Upper bound of Network Lifetime

Based on the definition, the network lifetime bound for estimation can be reformulated as a linear function of the source throughput. Given the source throughput Sk of all sensor nodes k € [1, N] and the estimation distortion requirement Dr, the bound of function based network lifetime for estimation is where g(σ_k^2) is the optimal 1-bit MSE function of sensor node k.

$$L <= Dr * \sum_{k=1}^{N} (s_k / (g_k^{opt} (\sigma^2))) \quad (10)$$

Joint Optimization of Source throughput and Multihop Routing

The total amount of data of each sensor can transmit and relay is limited by the energy supply of the sensor node, the source throughput of each sensor and the multihop routing path from each sensor to the sink need to be optimized together.

Linear Programming Formulation

The linear programming problem can be understood as the weighted data gathering problem since the objective function is the weighted sum of the amount of data generated at all sensors, where the weight of the data from sensor is the inverse of its corresponding optimal 1-bit MSE function.

$$Dr((\sum_{k=1}^{K} S_k (g^2 (\sigma^2))) \quad (11)$$

Character-based routing

The optimal structure for the weighted data gathering problem is character based routing, where the sensor node only relays data generated by sensor nodes with higher importance, i.e., bigger weight.

Simulation Results

In heterogeneous network, the network lifetime bound for estimation is maximized by optimal source coding and optimal multihop routing jointly.

Heterogeneous network

In this section, a heterogeneous sensor network with N sensors is simulated where the observation noise variance of each sensor is assumed to be

$$\sigma^2{}_k = \beta + \gamma z_k \text{ , k=1,....N} \quad (12)$$

Where β models the network-wide noise variance threshold, controls the underlying variation from sensor to sensor and zkis a Chi-Square distributed random variable with one degree of freedom. From the graphs, it is seen that single hop routing gives degraded result when compared to multihop routing.

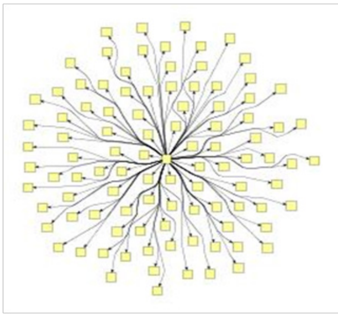

Fig 6.1 Distributed Sensor networks

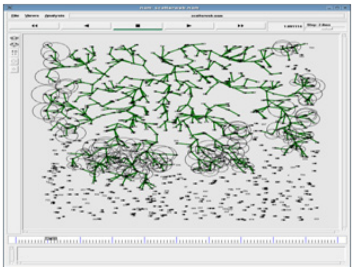

Fig 6.2 Communication between nodes

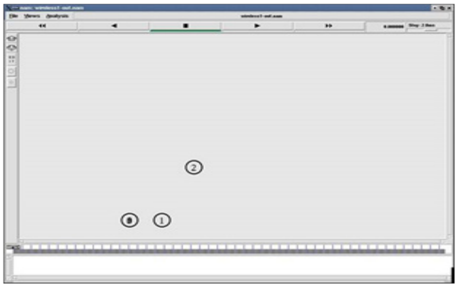

Fig 6.3 Sensor Network Distributed Scenario

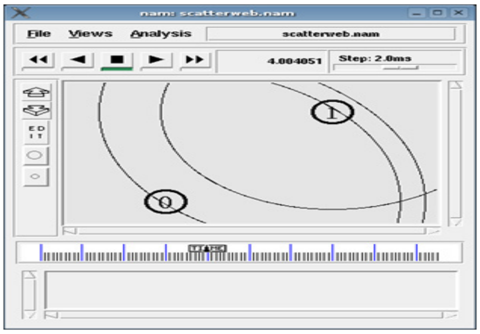

Fig 6.4 Communication between Sensor network nodes.

Fig 6.1 shows the distributed scenario of the sensor network where the nodes are distributed over an entire topographic range defined within the simulator. Fig 6.2 shows the simulation of the network and the communication between the sensor nodes. The sensor nodes transmit via multihop to the fusion center where the collaborative estimation of the measured parameter is done.

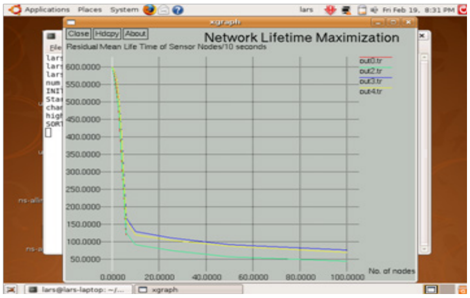

Fig 6.5 Network Lifetime Vs. No. of nodes

The graph shows the normalized lifetime of sensor network for different node distribution in the network. Thus from the Fig 6.5, it is seen that even the number of nodes increase, the network lifetime remains constant after a threshold level.

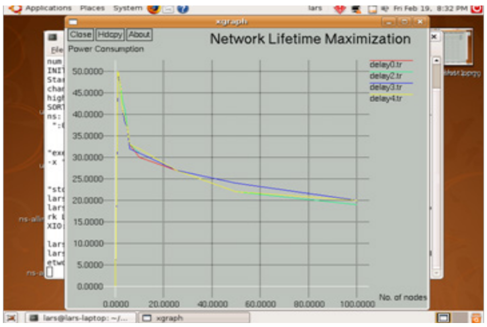

Fig 6.6 Network lifetime Maximization showing the rate of power consumption

Fig 6.6 shows the performance of the network with multihop and source coding(indicated in brown color), without source coding(indicated in green color), without multihop(blue-heterogeneous network), homogenous network(yellow), wireless sensor network without source coding and multihop routing(bluish green). Thus from Fig 6.6, it is seen that the network lifetime of a network with multihop and source coding is maximum and it remains constant after a threshold level.

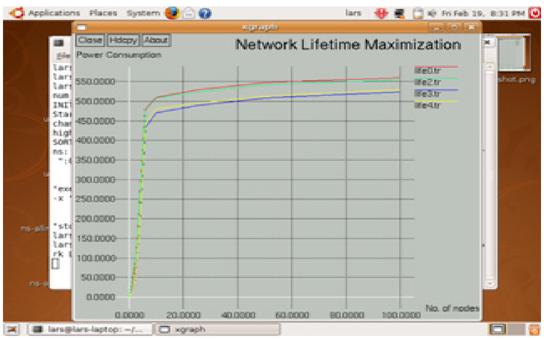

Fig 6.7 Network lifetime compared with delay.

Conclusion

In this paper, distributed estimation in energy-limited wireless sensor networks was discussed from lifetime-distortion perspective. From the application aspect, this paper deals with the estimation of task cycles the network can accomplish before the network becomes nonfunctional other than whether any individual sensor node is dead. Thus a concept of function-based network lifetime is introduced. Based on this concept, it is shown that the network lifetime bound maximization problem can be formulated as an NLP problem, where there are three factors needed to be optimized together: source coding at each sensor, i.e., quantization level for each observation, source throughput of each sensor, and multihop routing.

It is shown that the source coding can be optimized independently from the source throughput and multihop routing, and the optimal source coding is achieved by maximizing the equivalent 1-bit MSE function. Furthermore, that the optimal routing solution is character-based routing is found out, where a sensor node only relays data from sensor nodes with smaller observation noise variance. Different from the traditional distance-based routing, where the routing path is selected based on the distance to the destination, character-based routing explicitly takes into account the information character in the routing selection.

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