Joint Design of Scheduling and Routing Based on Connected Coverage for Optimal Sensor Network Lifetime

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ABSTRACT

We consider information retrieval in a wireless sensor network deployed to monitor a spatially corrected random filed. The measured data are sent to an access point through multi-hop transmissions. We address the joint design of sensor scheduling and information routing in each data collection to optimize a performance measure: network lifetime. We first formulate this problem as an integer programming based on the connected coverage in sensor networks. We then derive an upper bound for the network lifetime which provides a measure for the performance of suboptimal methods. After that, we propose a suboptimal method for node scheduling and data routing to maximize the network lifetime. In the proposed method, instead of treating them as two separated optimization problems, the scheduling and routing are integrated into a single algorithm: when scheduling the sensors for area coverage, we take into account not only the network geometry information but also the energy consumed for the data transmission; when designing the information routing, we consider the role of each sensor in the scheduling since some sensors have crucial importance on the area coverage and should be treated specially in the routing. We study the performance of the proposed method by comparing its result with the lifetime upper bound and the separated design methods. Numerical examples demonstrate the performance of the proposed method.

Keywords: Network lifetime, scheduling, routing, coverage, connectivity, wireless sensor networks

1. INTRODUCTION

A wireless sensor network consists of a large number of sensor nodes each capable of sensing, processing and data transmission. Each node is energy constrained and in many scenarios is infeasible to recharge or replace the batteries. Therefore, network lifetime is a key characteristic of a wireless sensor network which indicates the maximum utility a sensor network can provide, and it needs to be carefully addressed when designing a wireless sensor network.[1,2] In this paper, we consider the problem of information retrieval in a wireless sensor network deployed to monitor a spatially correlated random field. We take into account the scenario that the measured data by the sensors are sent to an access point through multi-hop transmission. Our goal is to jointly design the schemes for sensor scheduling and information routing such that the network lifetime can be maximized.

Due to node redundancy and the spacial correlation of the underlying signal field, we assume that when the access point receives a measurement from a sensor, it can reconstruct, for a given quality-of-service (QoS) requirement, every point within a disk area of a coverage range centered at the sensor. The coverage range is related to the specified QoS. Therefore, to solve the field reconstruction problem, we optimally schedule the sensors for each data collection such that the monitored area is fully covered and the network lifetime is maximized.

In order to save the transmission energy, we use multi-hop transmission, instead of signal-hop transmission, to send the measurements from each sensor to the access point. We assume that the transmitter can adjusted its transmission power level such that only the minimum level of energy is used for the intended receiver within the transmission range. Hence, we need to design an energy-efficient information routing scheme to prolong the network lifetime.

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The node scheduling and information routing are related to the problems of coverage and connectivity in sensor networks. In this paper, we observe that to maximize the network lifetime, the scheduling and routing cannot be treated as two separate problems. They are related with each other. For example, when we select a set of sensors to cover a signal field, certain sensor nodes have crucial roles to cover some area; hence, to prolong the network lifetime, we intent to schedule these nodes for sensing only. That is, when we design the routing scheme, we should try to avoid selecting these nodes as relays. Therefore, the relation between the scheduling and the routing should be studied carefully, and these two schemes should be designed jointly to maximize the network lifetime.

In these paper, we first formulate this problem as an integer programming. In the problem formulation, instead of directly designing the data transmission path for each active sensor, we look for the optimal assignments of flow to each link[15] and data generation rate to each sensor to maximize the network lifetime under the conditions of flow conservation, energy limitation, and full area coverage. We then derive an upper bound for the network lifetime which provides a measure for the performance of suboptimal methods. After that, we propose a suboptimal method for node scheduling and data routing to maximize the network lifetime, the performance of which is close to the lifetime upper bound. In the proposed method, instead of treating them as two separate optimization problems, the scheduling and routing are integrated into a single algorithm: when scheduling the sensors for area coverage, we take into account not only the network geometry information but also the energy consumed for the data transmission; when designing the information routing, we consider the role of each sensor in the scheduling since some sensors have crucial importance on the area coverage and should be treated specially in the routing. We study the performance of the proposed method by comparing it with separate design methods. Numerical examples demonstrate the performance of the proposed method.

1.1 Related Work

The research work on sensor node scheduling and coverage can be found in Ref. 2-11. The problem of sensor node scheduling to maximize the lifetime of a wireless sensor network has been studied in Ref. 2-4 where distributed scheduling protocols are proposed that exploit both channel state and residual energy information. In Ref. 5 we address the problem of network lifetime maximization for QoS specific information retrieval for the reconstruction of a spatially correlated random field. We assume there exist single-hop transmissions between sensors and the access point. In Ref. 6 an upper bound of network lifetime to achieve α portion of the area coverage is derived. In Ref. 7 the authors devise a fully decentralized and localized density control algorithm, the goal of which is to maintain coverage using a minimal number of sensor nodes. The methods in Ref. 8-10 focus on maximizing the number of disjoint cover sets. A method for energy-efficient target coverage is proposed in Ref. 11 that allows sensors to participate in multiple cover sets. All of the above work only solves the coverage problem.

Some research work on energy efficient routing in wireless sensor networks can be found in Ref. 12-14. The approaches in these papers are to find the path to the destination that minimizes the total consumed energy. In Ref. 15, instead of directly looking for the energy efficient path, they optimally design the flow assignment on each link to maximize the network lifetime. The problem of sensor scheduling is not considered in the above work.

The coverage based on multi-hop transmission has been investigated in Ref. 7 and 16-20. In Ref. 7 and 16, the authors investigate the relationship between coverage and connectivity and prove that the condition that the communication range is at least twice of the sensing range is both necessary and sufficient to ensure that the coverage implies connectivity. In Ref. 17 and 18 the authors address the optimization problem of selecting a minimum set of sensors that ensures both coverage and connectivity. They combine coverage and connectivity in a single algorithm. However, they do not use the network lifetime as a performance measure. In Ref. 19 the authors consider the problem of connected target coverage to maximize the network lifetime. They create a tree to represent the data transmissions from sensors to the sink, and develop a heuristic algorithm to maximize the number of such cover trees. However, in this paper we address the problem of area coverage. We formulate the routing problem into the energy constrained optimal flow assignment which is more general than creating cover trees. In Ref. 20 the authors also address the problem of maximizing network lifetime while providing coverage and connectivity in wireless sensor networks. Different from the above problem formulation the authors divide the sensor nodes into mutually exclusive connected cover sets, and they try to maximize the number of such sets. They separate the original problem into two sub-optimal problems and solve them individually.

2. PROBLEM FORMULATION

We assume a set of sensors $S = \{s_1, \ldots, s_N\}$ are randomly deployed in a connected area $\mathcal{D}$. Each sensor has a coverage range R_s and a maximum communication range R_c. The sink (access point) is denoted by s_D. Such a sensor network and the sink can be modeled as an undirected graph $G = (V, X)$, where $V = S \cup \{s_D\}$ and X is the set of edges. There exists a edge $(i, j) \in X$ between nodes s_i and s_j if and only if the distance between s_i and s_j is within the maximum communication range R_c.

We consider the problem of data collection to reconstruct the whole area. That is, we need to schedule the sensors for data measuring such that the selected sensors cover the area; we also need to design the transmission rout such that the measured data can be sent to the sink through multi-hop transmissions. Since each sensor is energy constrained, our task is to optimally design the schemes for scheduling and routing to maximize the network lifetime. Here, we define the network lifetime as the number of data collections that can be processed from the instant the sensor network is deployed to the instant that either we cannot find a set of sensors that cover the monitored area or the measured data in the cover set cannot be transmitted to the access point.

In order to formulate the lifetime maximization problem, we correspond each data collection process to a weighted undirected graph $G_k = (V_k, X_k)$, $k = 1, \ldots, K$, where K is the total number of data collections that can be supported by the whole sensor network. In the vertex set V_k, we associate each node s_i with a data generation function $g_k^{(i)}$ that is defined as: during the k-th data collection, if the i-th sensor is selected for data measuring, $g_k^{(i)} = 1$ (we assume all the sensors generate the same length of measurement packages); otherwise, $g_k^{(i)} = 0$. In the edge set X_k, we associate each edge (i, j) with a flow $q_k^{(i,j)}$, which can be positive number, negative number, or zero, as follows.

- If $q_k^{(i,j)} = 0$, there is no flow through the edge (i, j).
- If $q_k^{(i,j)} > 0$, there exists flow from node s_i to s_j. The amount of flow is $|q_k^{(i,j)}|$.
- If $q_k^{(i,j)} < 0$, there exists flow from node s_j to s_i. The amount of flow is $|q_k^{(i,j)}|$.

The similar definition exists for $q_k^{(j,i)}$ that satisfies $q_k^{(i,j)} = -q_k^{(j,i)}$. Here, we consider the scenario that the transmission package cannot be split. Hence, $q_k^{(i,j)}$ is a integer number.

2.1 Coverage, Flow, and Energy Constraints

Based on the above graph model, the three conditions that should be guaranteed while maximizing the network lifetime can be formulated as the conditions of coverage constraint, flow conservation, and energy constraint, and are discussed as follows, respectively.

2.1.1 Coverage Constraint

We denote by C_k the set of sensors that are selected to measuring the signal field in the k-th data collection, i.e.,

$$C_k = \{s_i | s_i \in V_k, \text{and } g_k^{(i)} = 1\}. \tag{1}$$

Then, to satisfy the coverage condition, we require the set C_k to be a cover set, i.e., the sensor nodes s_i's in the cover set C_k satisfy

$$\bigcup_{s_i \in C_k} \mathcal{A}(s_i) \supseteq \mathcal{D} \quad \text{for} \quad k = 1, \ldots, K, \tag{2}$$

where $\mathcal{A}(s_i)$ represents the coverage area of s_i.

Here, we introduce the concept of the subregion: a subregion is a set of points such that two points belong to the same subregion if and only if they are in the coverage area of the same set of sensors.[5] Then, we can divide the whole monitored area into a set of disjoint subregions $\{\mathcal{F}_1, \ldots, \mathcal{F}_L\}$ such that

$$\bigcup_{l=1}^{L} \mathcal{F}_l = \mathcal{D} \quad \text{and} \quad \mathcal{F}_i \cap \mathcal{F}_j = \emptyset \quad \text{for} \quad i \neq j. \tag{3}$$

Based on the relationship between subregions and sensor nodes, we associate each subregion with a subset F_l including all sensors that cover the subregion $F_l = \{s_{n_1}, \ldots, s_{n_l}\}$. Then, we can define a boolean variable $b_k^{(i)}$ for $i = 1, \ldots, N$ and $k = 1, \ldots, K$, such that

$$b_k^{(i)} = \begin{cases} 1, & s_i \in C_k \\ 0, & s_i \notin C_k \end{cases} . \tag{4}$$

Hence, the coverage condition can be written as

$$\sum_{i: s_i \in F_l} b_k^{(i)} \geq 1, \forall l, \quad \text{for} \quad k = 1, \ldots, K, \tag{5}$$

which means in each cover set, there exists at least one sensor that covers each subregion.

2.1.2 Flow Conservation

The flow conservation condition represents that for each node $s_i \in V_k - \{s_D\}$, the sum of the incoming flows and the data generated by this node equals the sum of the outgoing flows from this node. The flow conservation guarantees that all the data measured by the selected sensors can be sent to the access point through multi-hop transmissions.

According to the definition of $q_k^{(i,j)}$ and $g_k^{(i)}$, the flow conservation condition can be formulated as

$$\sum_{j: s_j \in S^{(i)}} q_k^{(i,j)} = g_k^{(i)}, \forall i \in V_k - \{s_D\}, \quad \text{for} \quad k = 1, \ldots, K, \tag{6}$$

where $S^{(i)}$ denotes the set of neighbors of s_i, i.e., $S^{(i)} = \{s_j \mid (i, j) \in X_k\}$.

To further understand the flow conservation condition (6), we divide $S^{(i)}$ into two sets $S^{(i)}_{\text{out},k}$ and $S^{(i)}_{\text{in},k}$, where $S^{(i)}_{\text{out},k}$ represents the set of the neighbors that the flows leaving s_i go into, i.e., $S^{(i)}_{\text{out},k} = \{s_j | q_k^{(i,j)} > 0\}$; and $S^{(i)}_{\text{in},k}$ represents the set of the neighbors from which the flows go into s_i, i.e., $S^{(i)}_{\text{in},k} = \{s_j | q_k^{(i,j)} < 0\}$. Then, the equation (6) can be rewritten as

$$-\sum_{j: s_j \in S^{(i)}_{\text{in},k}} q_k^{(i,j)} + g_k^{(i)} = \sum_{j: s_j \in S^{(i)}_{\text{out},k}} q_k^{(i,j)}, \tag{7}$$

in which the first term on the left hand side represents the incoming flows to s_i, the second term on the left hand side is the data generated by s_i, and the term on the right hand side is the outgoing flows from s_i.

2.1.3 Energy Constraint

Each sensor has an initial energy $E_0^{(i)}$. The energy constraint requires that during all the data collections, the total consumed energy by each sensor cannot be larger than its initial energy. Here, we consider that each sensor consumes energy in sensing, receiving and transmitting data.

- We denote e_s as the energy consumed by each sensor to measure a package of data. Then, in the k-th data collection, the energy consumed by s_i for data sensing is $e_s \cdot g_k^{(i)}$.
- We denote e_r as the energy consumed to receive a package. Then, in the k-th data collection, the energy consumed by s_i for data receiving is $e_r \cdot \left(-\sum_{j: s_j \in S^{(i)}_{\text{in},k}} q_k^{(i,j)}\right)$.
- We denote $e_t^{(i,j)}$ as the energy consumed to transmit a package from node s_i to s_j, which is related to the distance between s_i and s_j. Here, we use the energy transmission model

$$e_t^{(i,j)} = \varepsilon_t + \alpha \cdot d_{ij}^{\beta} \tag{8}$$

  where ε_t represents the energy dissipation of the transmitter electronics, d_{ij} is the distance between s_i and s_j, and β is the path loss factor. Then, in the k-th data collection, the energy consumed by s_i for data transmission is $e_t^{(i,j)} \cdot \sum_{j: s_j \in S^{(i)}_{\text{out},k}} q_k^{(i,j)}$.

Based on the above discussion, in the k-th data collection, the total energy consumed by s_i, denoted by $E_{u,k}^{(i)}$, is

$$E_{u,k}^{(i)} = e_s \cdot g_k^{(i)} - e_r \cdot \sum_{j:j \in S_{\text{in},k}^{(i)}} q_k^{(i,j)} + e_r^{(i,j)} \cdot \sum_{j:j \in S_{\text{out},k}^{(i)}} q_k^{(i,j)}. \tag{9}$$

Then, the energy constraint condition is formulated as

$$\sum_{k=1}^{K} E_{u,k}^{(i)} \leq E_0^{(i)}, \forall s_i \in V_k - \{s_D\}. \tag{10}$$

2.2 Optimization Formulation

According to the above discussion, the energy constrained network lifetime maximization problem based on connected coverage can be presented as: Given an area $\mathcal{D}$, an access point s_D, and a set of networked sensors $\{s_1, \ldots, s_N\}$, which is modeled as an undirected graph $G(V, X)$, find a sequence of undirected weighted graphs $\{G_1(V_k, X_k), \ldots, G_K(V_k, X_k)\}$ such that K is maximized, and the coverage condition, flow conservation, and energy constraint are satisfied.

Mathematically, this optimization problem can be formulated as

$$\begin{aligned}
&\text{Maximize} \qquad K \\
&\text{Subject to} \\
&\sum_{i:s_i \in F_l} b_k^{(i)} \geq 1, \quad \forall\, l, \quad \text{for} \quad k = 1, \ldots, K; \\
&\sum_{j:s_j \in S^{(i)}} q_k^{(i,j)} = g_k^{(i)}, \quad \forall\, s_i \in V_k - \{s_D\}, \quad \text{for} \quad k = 1, \ldots, K; \\
&\sum_{k=1}^{K} E_{u,k}^{(i)} \leq E_0^{(i)}, \quad \forall\, s_i \in V_k - \{s_D\}; \\
&b_k^{(i)} \in \{0, 1\}, \quad g_k^{(i)} \in \{0, 1\}, \quad q_k^{(i,j)} \text{ is integer.}
\end{aligned}$$

This optimization problem is an integer programming problem, the solution of which is NP-hard.[21] In the following, we first derive an upper bound for the network lifetime to achieve full area coverage and connectivity under the condition that the communication range r_c is no less than twice the coverage range r_s. We then propose a suboptimal method for lifetime maximization.

3. NETWORK LIFETIME UPPER BOUND

In this section, we derive an algorithm to compute the lifetime upper bound for the above optimization problem. This upper bound provides a benchmark to the suboptimal methods for network lifetime maximization. To derive the upper bound, we consider the scenario that the sensor's maximum communication range is no less than twice of the sensor's coverage range, i.e., $R_c \geq 2R_s$. This condition is both necessary and sufficient to ensure that the coverage implies connectivity.[7] Therefore, we redefine the network lifetime as the time span from the instant the network is deployed till the instant we cannot find a sensor set covering the whole area or the sensors in the cover set do not have enough energy to transmit the measured data to the sink. The algorithm is derived as follows.

We first divide the whole area into a set of disjoint subregions $\{\mathcal{F}_1, \ldots, \mathcal{F}_L\}$. We associate each subregion with a subset F_l of all sensor nodes that cover the subregion, i.e., $F_l = \{s_1^{(l)}, \ldots, s_{N_l}^{(l)}\}$. Since we want to cover the whole area, the basic idea of the proposed algorithm to derive a lifetime upper bound is that: (i) first, for each subregion, we calculate a lifetime upper bound of this subregion (this upper bound is also an upper bound for the whole sensor network); then, (ii) among all the subregions, we find the minimum value of all these upper bounds. This minimum value is the lifetime upper bound we derive for the whole sensor network. Here, we define the lifetime of a subregion as the number of data collections that can be supported by the energy of all the sensors that cover the subregion.

In order to cover subregion $\mathcal{F}_l$, at least one sensor $s_i^{(l)} \in F_l$ should be selected to measure the signal field, and the measurements are transmitted to the sink s_D. The other sensors in F_l can be used as relays for the transmission. Therefore, when we calculate the lifetime upper bound of subregion $\mathcal{F}_l$, instead of considering only the minimum energy consumed by a single sensor $s_i^{(l)}$ for transmission, we consider the minimum energy consumed by all the sensors in F_l for data measuring and transmission. According to the above discussion, the proposed algorithm to derive the lifetime upper bound includes three steps:

Step 1: For each subregion $\mathcal{F}_l$, find a path for each $s_i^{(l)} \in F_l$, consisting of only the sensors in F_l, that consumes minimum energy to transmit data from $s_i^{(l)}$ to sink s_D.

Step 2: Based on the minimum energy paths obtained in Step 1, for each subregion, calculate its lifetime upper bound.

Step 3: Among all the upper bounds for the subregions, find the minimum value, which is the lifetime upper bound for the whole sensor network.

The step 1 (looking for the minimum energy path for each $s_i^{(l)} \in F_l$) and the step 2 (calculating the lifetime upper bound of each subregion) are discussed in details as follows.

3.1 Minimum Energy Path

For sensor $s_i^{(l)} \in F_l$, its measurement is transmitted to the sink s_D through a path P. We observe that all possible paths from $s_i^{(l)}$ to s_D are in one of the following forms:

- $P^{(1)} = (s_i^{(l)}, \ldots, s_j^{(l)}, s_D)$
- $P^{(2)} = (s_i^{(l)}, \ldots, s_j^{(l)}, s_k, \ldots, s_D)$

where, $\{s_i^{(l)}, \ldots, s_j^{(l)}\} \subset F_l$, and $s_k \notin F_l$. This classification can be explained as: in path $P^{(1)}$, the measured data by $s_i^{(l)}$ are transmitted to the sink using only the sensors in F_l as relays; in path $P^{(2)}$, the data are first transmitted to the sensors not in F_l, and then to the sink. Then, from all the possible paths $P = (s_i^{(l)} \ldots s_j^{(l)})$ that consist of only the sensors in F_l, we find the path that costs the minimum transmission energy, and associate this path to the sensor $s_i^{(l)}$ as its minimum energy path $P_i^{(l)}$.

To derive an algorithm to find this minimum energy path $P_i^{(l)}$, we first define a set that includes all the sensors that are nearest to the sensors in F_l. We denote this set as $S_C^{(l)}$. This set can be calculated as follows. For every sensor $s_i^{(l)} \in F_l$, we find a sensor $s_{C,i}^{(l)}$ that is outside F_l, i.e., $s_{C,i}^{(l)} \in S - F_l$, such that

$$s_{C,i}^{(l)} = \arg \min_{s \in S - F_l} \text{dist}\left(s, s_i^{(l)}\right). \tag{11}$$

Then, we collect all $s_{C,i}^{(l)}$'s into $S_C^{(l)}$, i.e., $S_C^{(l)} = \{s_{C,1}^{(l)}, \ldots, s_{C,N_l}^{(l)}\}$. Here, we assume all $s_{C,i}^{(l)}$'s are distinct. Otherwise, we only keep one $s_{C,i}^{(l)}$ in the set for all the same $s_{C,i}^{(l)}$'s. Then, to find $P_i^{(l)}$, we only consider the candidate paths $(s_i^{(l)} \ldots s_j^{(l)} s_k)$, where $\{s_i^{(l)}, \ldots, s_j^{(l)}\} \subset F_l$, and $s_k \in S_C^{(l)} \cup \{s_D\}$. This result is based on the following proposition.

Proposition: For any paths $P_m^{(l)} = (s_i^{(l)} \ldots s_j^{(l)} s_m)$ where $\{s_i^{(l)}, \ldots, s_j^{(l)}\} \subset F_l$, and $s_m \in S - F_l$, we can always find a path $P_k^{(l)} = (s_i^{(l)} \ldots s_h^{(l)} s_k)$ where $\{s_i^{(l)}, \ldots, s_h^{(l)}\} \subset F_l$, and $s_k \in S_C^{(l)}$ such that transmission energy for $P_k^{(l)}$ is smaller or equal to the transmission energy for $P_m^{(l)}$.

Then, for each $s_i^{(l)} \in F_l$, we can find its associated minimum energy path $P_i^{(l)}$ that represents the path which costs minimum energy of the sensors in F_l to send the measurements from $s_i^{(l)}$ to s_D through multi-hop transmissions. As an output, we have a list of such paths: $P_1^{(l)}, \ldots, P_{N_l}^{(l)}$.

3.2 Lifetime Upper Bound of Subregion

Based on the minimum energy paths, we derive an upper bound of the lifetime for subregion $\mathcal{F}_l$. According to the method in the above section, we obtain a set of minimum energy paths $\{P_1^{(l)}, \ldots, P_{N_l}^{(l)}\}$, and $E_i^{(l)}$ is transmission energy of path $P_i^{(l)}, i = 1, \ldots, N_l$. We first find the path, denoted by $P_m^{(l)}$, that has the minimum transmission energy, i.e.,

$$m = \arg\min_i E_i^{(l)}. \tag{12}$$

We observe that $E_m^{(l)}$ is the minimum energy costed by the sensors in F_l to transmit the data from any sensor $s_i^{(l)} \in F_l$ to the sink. Then, a lifetime upper bound of the subregion $\mathcal{F}_l$ can be obtained by dividing the whole energy of the sensors in F_l by $E_m^{(l)}$, i.e.,

$$\frac{\sum_{\{i:s_i \in F_l\}} E_0^{(i)}}{E_m^{(l)}}. \tag{13}$$

Here, $\sum_{\{i:s_i \in F_l\}} E_0^{(i)}$ is the total initial energy of the sensors covering subregion $\mathcal{F}_l$. Therefore, the upper bound for the whole sensor network is

$$\min_{\mathcal{F}_l} \frac{\sum_{\{i:s_i \in F_l\}} E_0^{(i)}}{E_m^{(l)}}. \tag{14}$$

3.3 Computational Complexity

We analyze the computational complexity of using the proposed method to calculate the lifetime upper bound. For subregion $\mathcal{F}_l$, there are N_l sensors covering this subregion. For each $s_i^{(l)} \in F_l$, we first find a minimum energy path to sink s_D consisting of only the sensors in F_l. We can use Dijkstra's algorithm to find such a path, the computational complexity of which is $O(N_l^2)$.[22] Since we need to find a minimum energy path for all $s_i^{(l)} \in F_l$, the computational complexity is $O(N_l^3)$. It can be verified that the number N_l is in the order of $(\pi R_c^2/|\mathcal{D}|) \cdot N$, where N is the number of deployed sensors, $|\mathcal{D}|$ is the size of the monitored area, and πR_c^2 is the size of the coverage area of each sensor. The number of subregions is in the order of N^2. Therefore, the total computational complexity is $O\{\left((\pi R_c^2/|\mathcal{D}|) \cdot N\right)^3 \cdot N^2\} = O\{(R_c^2/|\mathcal{D}|)^3 \cdot N^5\}$.

4. NETWORK LIFETIME MAXIMIZATION METHOD

In this section, we derive a suboptimal method to maximize the network lifetime. In the above derivation of lifetime upper bound, we observe that the upper bound is determined by the subregions that have small lifetime. Here, we define the lifetime of a subregion as the maximum number of data collections to reconstruct that subregion that can be provided by the sensors covering that subregion. We also call those subregions with small lifetime the sparsely covered subregions, since the subregions covered by less number of sensors tend to have smaller lifetime.

Based on this observation, the basic idea of the proposed suboptimal method is that, we first identify the most sparsely covered subregion (critical subregion), and cover it first. Among all the sensors that cover the critical subregion, we find a sensor and the corresponding path from that sensor to the sink to cover the critical subregion according to certain criterion. When designing this criterion, we consider the effects of the consumed energy for transmission, the residual energy, and the geometry information of the sensors. The main procedure of the method is described as follows.

1. We create a communication network among all the live sensors and the sink. There exists a link between a pair of nodes if their distance is smaller than or equal to the sensor's maximum communication range.

2. We divide the whole monitored area into a set of disjoint subregions according to the position of live sensors and their coverage range.

3. We identify a critical subregion according to certain criterion.

4. Among all the sensors that cover the critical subregion, we choose a sensor to cover the critical subregion and determine its associated path to the sink according to certain criterion.

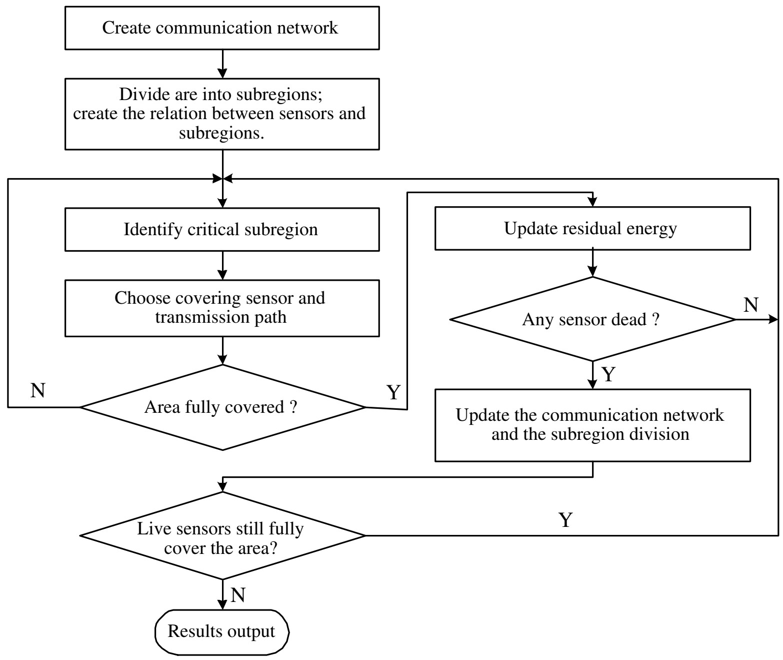

Figure 1. Flow chart of the suboptimal algorithm for lifetime maximization.

5. We remove all the subregions covered by the chosen sensor from the set of the uncovered subregions. We repeat the above two steps until there is no uncovered subregions.

6. When we find a cover set and the associated paths, we update the residual energy of the sensors selected for sensing and relaying. If the live sensors can still cover the whole area, we repeat the above steps to find another set of sensors for data collection. Otherwise, the lifetime of the network is reached.

The flow chart of the method is shown in Figure 1. In this method, we need to answer two key questions: (i) how do we identify a critical subregion? (ii) how do we select a covering sensor and a path from this sensor to the sink? These questions are addressed as follows.

4.1 Critical Subregion

We define the critical subregion as the subregion with the minimum residual lifetime. The residual lifetime of a subregion is the maximum number of data collections to reconstruct the subregion that can be provided by the residual energy of sensors covering that subregion. Since it is difficult to compute the exact lifetime of each subregion, we use an upper bound to replace the lifetime. One way to calculate the upper bound of the residual lifetime is to use the method similar to we apply to find the lifetime upper bound in Section 3. We only need to replace the initial energy $E_0^{(i)}$ of each sensor with the current residual energy $E_r^{(i)}$.

However, this method to compute the residual lifetime of each subregion involves high computation complexity. Hence, we approximate the residual lifetime of each subregion as

$$\sum_{i\in F_l} \frac{E_r^{(i)}}{E_c^{(i)}} \tag{15}$$

where, $E_c^{(i)} = e_t^{(i,i_\mathrm{n})}$ represents the energy consumed for transmission from node s_i to s_{i_n}, and s_{i_n} is the node that is nearest to node i

$$i_\mathrm{n} = \arg\min_j \mathrm{dist}(i,j). \tag{16}$$

Therefore, the critical subregion is

$$\mathcal{F}_c = \arg\min_{F_l} \sum_{i\in F_l} \frac{E_r^{(i)}}{E_c^{(i)}}. \tag{17}$$

4.2 Covering Sensor and Transmission Path

When we identify a critical subregion, the next step is: from all the sensors that cover the critical subregion, we choose a sensor according to certain criterion to reconstruct the critical subregion. We also determine a path from the selected sensor to the sink for the data transmission. In the proposed method, we first define a cost for each link in the communication network. Then, for each sensor that covers the critical subregion, we find a minimum cost path from that sensor to the sink. The sensor whose path has the minimum cost is selected to cover the critical subregion, and the corresponding minimum cost path is selected for data transmission. Here, the cost of a path is defined as the sum of the cost of all the links in that path.

Hence, an important question is: how do we define the cost for each link? The definition of the cost of a link closely relates to the problem of which sensors we should choose as sensing and relaying in the current data collection such that we can prolong the network lifetime. We consider both the sensor's energy information and geometry information. we favor the sensors with large amount of residual energy to be chosen into the data collection; we favor the path consumed small amount of energy for data transmission from the sensor to the sink. We observe that the sensors covering the critical subregions have crucial roles to prolong the network lifetime. Hence, if a sensor is important to cover a critical subregion, we intend not to select that sensor as relays.

Based on the above discussion, for a link (i, j), we consider the following local sensor parameters to define the cost:

- $e_t^{(i,j)}$: unit transmission energy from node s_i to s_j.
- $E_r^{(i)}$: current residual energy of sensor s_i.
- $c_r^{(i)}$: critical value of sensor s_i (which is defined later).
- $E_r^{(j)}$: current residual energy of sensor s_j.
- $c_r^{(j)}$: critical value of sensor s_j.

The critical value of a sensor represents how important the sensor is to cover critical subregions. The smaller the critical value, the more important it is. The critical value of sensor s_i is defined as follows.

We denote $S_i = \{\mathcal{F}_{n_1}, \ldots, \mathcal{F}_{n_i}\}$ as a set of subregions that are covered by sensor s_i. For each subregion $\mathcal{F}_{n_l} \in S_i$, we denote $L_r^{(n_l)}$ as its residual lifetime, which is defined as

$$L_r^{(n_l)} = \sum_{j \in F_{n_l}} \frac{E_r^{(j)}}{E_c^{(j)}} \tag{18}$$

where, the consumed energy $E_c^{(j)}$ of s_j is defined the same as in (15). Then, we define the critical value $c_r^{(i)}$ as

$$c_r^{(i)} = \min_{n_l \in \{n_1, \ldots, n_i\}} L_r^{(n_l)}. \tag{19}$$

That is, we use the minimum value of the lifetime of the subregions in S_i as the critical value of sensor s_i. If a sensor is important to cover some critical subregions, we tend to prevent selecting it into the transmission path (using as relays). Hence, we favor the sensors with larger critical values.

According to the above discussion, we define the link cost as

$$\text{cost}(i, j) = \left(e_t^{(i,j)}\right)^{x_1} \cdot \left(E_r^{(i)}\right)^{-x_2} \cdot \left(c_r^{(i)}\right)^{-x_3} + (e_r)^{y_1} \cdot \left(E_r^{(j)}\right)^{-y_2} \cdot \left(c_r^{(j)}\right)^{-y_3}. \tag{20}$$

Here, e_r is the unit receiving energy. x_k and y_k, $k = 1, 2, 3$, are integer constants. They represent the weights of each parameters.

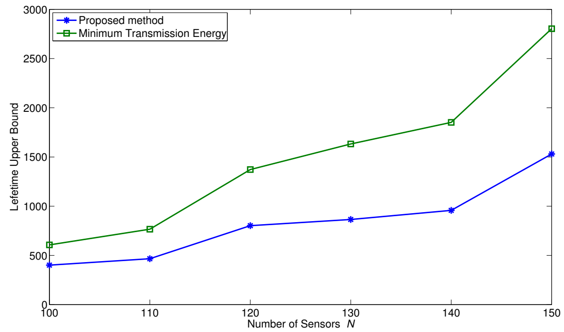

Figure 2. Lifetime upper bound vs. number of sensors

4.3 Computational Complexity

We analyze the computational complexity of using the proposed method to search a cover set and the corresponding transmission paths from sensors to the sink in each data collection. To find a cover set and the corresponding paths, we apply two steps: (i) identifying a critical subregion and (ii) finding the minimum cost path. When N sensors are deployed, the number of subregions is in the order of N^2; hence, to identify a critical subregion, the computational complexity is $O(N^2)$. To find the minimum cost path, we can use Dijkstra's algorithm, the computational complexity of which is $O(N^2)$.[22] These two steps are repeated until all subregions are covered. The number of the iterations is approximately in the order of $|\mathcal{D}|/(\pi R_c^2)$. Therefore, the total computational complexity is $O\{(|\mathcal{D}|/R_c^2) \cdot N^2\}$.

5. NUMERICAL EXAMPLES

In this section we use numerical examples to evaluate the performance of the proposed method for network lifetime optimization. In these examples sensor nodes are deployed in a 20×20 area randomly following a uniform distribution. Each sensor has a disk coverage area with range R_s and a maximum communication range R_c which is equal to the twice of the coverage range. The initial energy for each sensor is the same. For the energy consumption due to the transmission, we use the model that $e_t^{(i,j)} = \alpha \cdot d_{ij}^{\beta}$ (refer to Equation (8) for the explanation of the notation). Here, we set $\alpha = 0.01$ and $\beta = 2$. Each value in the figures is obtained by averaging the results of 100 randomly generated network topologies.

In the first example, we study the performance of the proposed algorithm to derive the network lifetime upper bound. We compare the derived upper bound with another upper bound obtained by minimum transmission energy (MTE) algorithm. This method is also based on dividing the monitored area into a set of disjoint subregions. In MTE, the lifetime upper bound of subregion $\mathcal{F}_l$ is derived as

$$\sum_{i \in F_l} \{E_0^{(i)}/E_c^{(i)}\} \tag{21}$$

where $E_0^{(i)}$ is the initial energy of sensor s_i, and $E_c^{(i)}$ is the transmission energy from s_i to its nearest node (refer to Equation (16) for the definition of the nearest node). Hence, $E_0^{(i)}/E_c^{(i)}$ is an upper bound of the number of data collections that can be supported by sensor s_i (we omit the energy consumed for data measuring). Therefore, it is easy to verify that Equation (21) is a lifetime upper bound of subregion $\mathcal{F}_l$. Then, the lifetime upper bound of the whole sensor network is

$$\min_{\mathcal{F}_l} \sum_{i \in F_l} \{E_0^{(i)}/E_c^{(i)}\}. \tag{22}$$

The result of the comparison of the upper bound obtained by the proposed method with the upper bounds obtained by MTE with respect to the number of sensors is shown in Figure 2. Here we set the coverage to be 4 and the initial energy to be 15. From this result we observe that both upper bounds increase with the number of the deployed sensors, as we expected. And the upper bound obtained by the proposed method is much tighter than the upper bound obtained by MTE. For example, when the number of sensors is 140, the upper

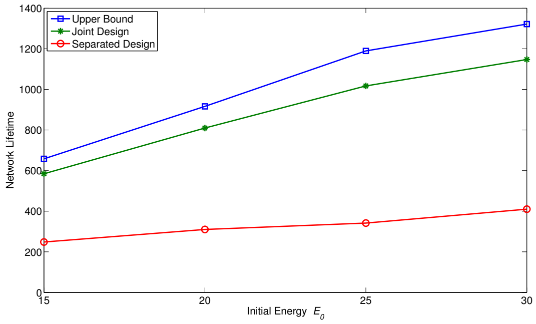

Figure 3. Network lifetime vs. initial energy

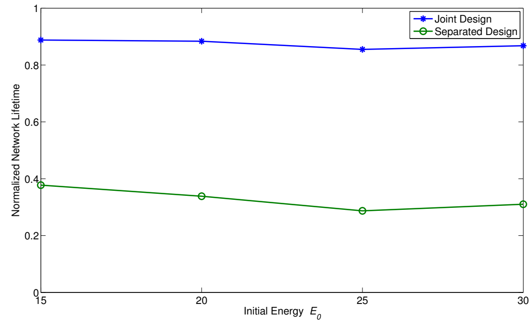

Figure 4. Normalized network lifetime vs. initial energy

bound obtained by MTE is 1.6 times of the proposed upper bound. This is because in MTE, we consider only the minimum energy consumed by a single sensor; however, in the proposed method, we consider the minimum energy consumed by all the sensors covering the subregion for data transmission.

In the second set of examples, we study the performance of the proposed suboptimal method to maximize the network lifetime. We compare the obtained network lifetime using the proposed joint design method with the lifetime upper bound. We also compare the performance of the proposed method with a separate design method. In the separate design method, we separate the design of the sensor scheduling and information routing to maximize the network lifetime. For the sensor scheduling, we use the method in Ref. 5 to select the sensors into the cover set. For the routing, we find the minimum energy path[15] to send the measured data from the sensors to the sink. We first compare the obtained lifetime with the upper bound with respect to the initial energy of the sensor. The results are shown in Figure 3 and 4. Here, we set the coverage range to be 4 and the number of sensors to be 100. We observe that the lifetime achieved by the proposed joint design method is close to the upper bound. For example, when the initial energy is 20, the obtained network lifetime can achieve 89% of the upper bound. When the initial energy increases, the performance decrease slightly. We also observe that the proposed joint design has substantial performance improvement comparing with the separate design method, which can achieve below 40% of the upper bound. The same observation can be found when we compare the performance with respect to the coverage range and the number of sensors. The comparison results are shown in Figure 5 and 6. We also observe that some other parameters also have effects on the performance of the method. For example, when we increase the path loss factor, the performance becomes a little worse.

6. CONCLUSIONS

In this paper we addressed the problem of joint design of sensor scheduling and information routing to optimize the network lifetime in wireless sensor networks. We first transformed the problem of maximizing the network lifetime into the maximization of the number of the weighted communication graphs; each graph corresponds to a data collection operation. As a result, we formulated the lifetime maximization problem into an integer programming which is NP-hard. We then proposed a method to derive the upper bound of the network lifetime under the scenario that the communication range is no less than twice the coverage range, which guarantees that the coverage implies the connectivity. After that, we derived a suboptimal method to maximize the network lifetime by jointly designing the sensor scheduling and routing. The numerical examples demonstrated that the obtained network lifetime using the proposed method is close to the upper bound and is substantially larger than the separate design methods. In the future work, we will consider the effect of the transmission channel fading on the network lifetime. Under that case, the transmission energy by each sensor is a random variable. We will study other random field models and the corresponding network lifetime maximization methods. The method we consider here is a centralized approach. We will also consider developing a distributed implementation.

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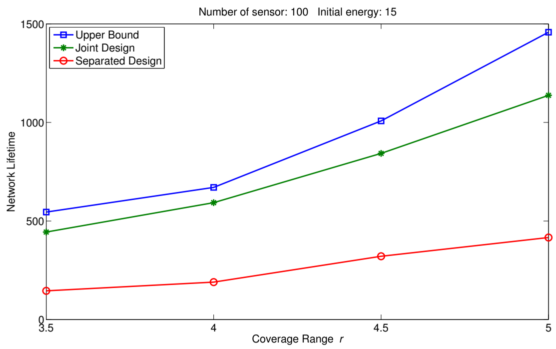

Figure 5. Network lifetime vs. coverage range

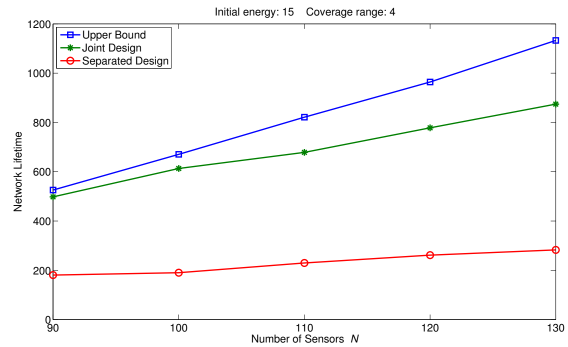

Figure 6. Network lifetime vs. number of sensors

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