Coverage-Based Information Retrieval for Lifetime Maximization in Sensor Networks

Tong Zhao and Qing Zhao
Department of Electrical and Computer Engineering
University of California
Davis, CA 95616
{ttzhao, qzhao}@ece.ucdavis.edu

***Abstract*—We consider information retrieval in a wireless sensor network deployed to monitor a spatially correlated random field. We address sensor scheduling in each data collection under the performance measure of network lifetime. We formulate this problem as an energy constrained coverage problem and proposal a scheduling algorithm based on a greedy approach. In the proposed algorithm, we consider the impact of both the network geometry and the energy consumption by sensors to the network lifetime. Numerical examples are carried out to demonstrate the performance of the proposed algorithm.**

I. Introduction

In this paper we address the problem of lifetime maximization for quality-of-service (QoS) specific information retrieval for the reconstruction of a spatially correlated random signal field using a wireless sensor network. A wireless sensor network consists of low-cost, low-power, and energy-constrained sensors deployed for monitoring a physical phenomenon. Usually, it is undesirable or infeasible to replace or recharge sensors. Hence, the network lifetime becomes a critical issue when designing a wireless sensor network [1]. The goal of this paper is to design an optimal information retrieval scheme such that the signal field can be reconstructed from the collected information within a given QoS requirement while the network lifetime is maximized.

Measurements from proximate sensors are often correlated due to node redundancy and the spacial correlation of the underlying signal field. Hence, the basic idea of the proposed method is that during each information retrieval operation, we only select a subset of available sensor nodes to collect data; this subset is chosen to guarantee a QoS requirement. We optimally choose the subset for each data collection so that the network lifetime is maximized.

To solve this optimization problem, based on our assumptions on the random signal field, the QoS specification given as, for example, the maximum distortion for reconstructing the random field, and the signal field reconstruction approach, we first transform the problem into a coverage-related problem, i.e., we formulate the problem of maximizing the network lifetime for a given QoS into a problem of searching the maximum number of sets of sensor nodes that cover the whole monitored area. Each sensor node is associated with certain coverage range that is related to the QoS requirement. Hence, we can apply the methods based on the theory of coverage to solve the original problem. To solve this problem, we observe that there are two elements that have important influence on the network lifetime. One is the consumed energy by each sensor for data collection. This is due to the limited power supply of each sensor. The other is the network geometry information. Since we formulate the problem as a coverage problem, some sensors are critical to cover certain area. Hence, these sensors should be treated differently even if they have the same energy conditions as other sensors.

In the following, we first present the QoS specific information retrieval and transform it into a coverage-related problem with energy constraint. We then define the problem of maximizing the network lifetime for a given QoS, which is NP-complete. After that we propose a greedy search suboptimal method. In this approach we consider both the network geometry and the energy consumed by sensors in each information retrieval operation to prolong the network lifetime. We also derive an upper bound of the network lifetime, which provides a performance measure of the proposed algorithm. At last, we evaluate the performance of the proposed suboptimal approach using numerical examples and find that the performance of the proposed method approaches the lifetime upper bound.

A. Related Work

The problem of sensor node scheduling to maximize the lifetime of wireless sensor networks has been studied in [1] and [2], where distributed scheduling protocols are proposed that exploit both the channel state and the residual energy information. However, these results focus on the estimation of a parameter in stead of a random signal field. The problem of QoS specific information retrieval for a random signal field has been addressed in [3]. In that work, the QoS is specified by a maximum distortion and an outage probability, and the sensor network is partitioned into disjoint and equal-sized cells and only one sensor in each cell is enabled for transmission. This regular spatial sampling approach is more suitable for densely deployed networks or random field with strong spatial correlation.

The coverage problem has been study by many researchers (e.g., in [4]-[9], and their references). In [4] an upper bound of network lifetime to achieve α portion of the area coverage is derived. Their results are based on the assumption that the lifetime for each sensor is the same. Some methods for lifetime maximization while guaranteeing certain coverage are proposed in [5]-[9]. In [5], 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. However, as we show in the following, to maximize the network lifetime, it is not always optimal to minimize the number of sensors in each data collection. The methods in [6]-[8] focus on maximizing the number of disjoint cover sets, which are not optimal under our operation scenario, especially when the consumed energy for one data collection by each sensor is very different. A method for energy-efficient target coverage is proposed in [9] that allows sensors to participate in multiple cover sets. But this paper only addresses the problem of target coverage, not the area coverage that we are interested in. It also assumes that the consumed energy by each sensor is the same. In the propose method, we consider a more general case where the consumed energy by each sensor is different.

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II. Problem Statement

Let $\mathcal{D}$ denote an area that is a set of points and $S(\mathcal{D})$ the random signal field. A network of sensor nodes is deployed to monitor this area. Our task is to reconstruct the signal field for a given QoS requirement using sensor measurements collected by an access point. We consider a general scenario that: based on the spacial correlation of the underlying signal field, the specified QoS, and the reconstruction method, if the access point receives a measurement from a sensor located at the point (x, y), it can reconstruct every point in a r-radius disk centered at (x, y) for a given QoS requirement. The radius r is related to the specified QoS. This scenario can be applied to a number of information retrieval applications in sensor networks. Two examples are presented as follows.

Example 1. The simplest case is that each sensor node in a sensor network has a sensing area of a r-radius disk centered at the position of itself. That is, each sensor node can measure every point of the signal field in this area within certain accuracy requirement.

Example 2. This scenario can also be applied to a more complex problem. Consider a spatially homogeneous random field, i.e., (i) $S(\mathcal{D})$ for all $(x, y) \in \mathcal{D}$ have common mean μ and variance σ^2; (ii) the correlation of two points in $\mathcal{D}$ is determined by the Euclidean distance between them

$$\begin{aligned} & R((x_1, y_1), (x_2, y_2)) \\ \triangleq\ & E[(S(x_1, y_1) - \mu)(S(x_2, y_2) - \mu)] \\ =\ & R(d); \end{aligned} \tag{1}$$

and (iii) $R(d)$ is continuous and monotonically decreasing. We assume a sensor located at (x, y) measures the value (one realization) of $S(x, y)$ and generates a packet containing its measurement to be transmitted to the access point.

Let $\mathcal{A}$ denote all the points whose measurements are collected during an information retrieval operation and $\bar{\mathcal{A}}$ the complement of $\mathcal{A}$ in $\mathcal{D}$. Then, we use the following rule to reconstruct the random field $S(\mathcal{D})$ from the measurements in $\mathcal{A}$. That is, we approximate the signal field in a point (x_0, y_0) in $\bar{\mathcal{A}}$ with the measurement of a point in $\mathcal{A}$ that is closest to (x, y). Hence, the estimate $\widehat{S}(x_0, y_0)$ of the signal field at (x_0, y_0) is given by

$$\widehat{S}(x_0, y_0) = S(x_1, y_1) \tag{2}$$

where

$$(x_1, y_1) = \arg \min_{(u,v)\in\mathcal{A}} d((x_0, y_0), (u, v)). \tag{3}$$

The QoS requirement is characterized by the maximum distortion D in terms of mean square error (MSE)

$$E\left[\left(\widehat{S}(x, y) - S(x, y)\right)^2\right] \le D \quad \forall (x, y) \in \mathcal{D}. \tag{4}$$

Since we have

$$E\left[\left(\widehat{S}(x, y) - S(x, y)\right)^2\right] = 2\sigma^2 - 2R\big(d((x, y), (u, v))\big), \tag{5}$$

where (u, v) is the point in $\mathcal{A}$ that is closest to (x, y), to ensure a maximum MSE of D as in (4), we need

$$R\big(d((x, y), (u, v))\big) \le \frac{2\sigma^2 - D}{2}. \tag{6}$$

If we define

$$r \triangleq \max\left(\left\{d : R(d) \le \frac{2\sigma^2 - D}{2}, \quad d \in [0, d_{\max}]\right\}\right), \tag{7}$$

it then follows that to estimate $S(x, y)$ with a maximum MSE of D, at least one sensor should be located at most r away from (x, y) and its measurement should be transmitted to the access point. Then, it is easy to verify that this problem belongs to the general scenario we present above.

Considering the node redundancy and the spacial correlation of the signal field, to prolong the network lifetime, during each information retrieval operation, we only select a subset of available sensor nodes to collect data. This set of sensors is chosen to guarantee certain QoS requirement. Therefore, our goal is to solve the problem of how to optimally schedule the sensor nodes for each data collection such that the signal field is reconstructed within a given QoS and the network lifetime is maximized.

III. Coverage-Based Information Retrieval for Lifetime Maximization

In this section, we study the QoS specific information retrieval for network lifetime maximization. Here we define the network lifetime as the time interval from the instant of the sensor network deployment to the instant that the signal field $S(\mathcal{D})$ cannot be reconstructed for a given QoS requirement from the current live sensors. We first show that the lifetime maximization can be formulated as a coverage-related problem. We then apply the approach based on the theory of coverage to solve it.

A. Problem Formulation

Based on the discussion in Section II, our QoS specific information retrieval can be formulated as a coverage problem. That is, we assume each sensor has a coverage area that is a disk with radius r; then, if we can find a set of sensors such that the union of the coverage areas of these sensors covers the whole region being monitored, the field $S(\mathcal{D})$ can be reconstructed within a given QoS requirement. Hence, the network lifetime can be redefined as the time interval from the instant of the network deployment to the instant when we cannot find a set of live sensors that covers the whole area. Therefore, maximizing the network lifetime is equivalent to searching for the maximum number of cover sets with the energy restriction. Each cover set corresponds to the set of sensors scheduled to collect the data during each information retrieval operation. Here, the cover set means a set of live sensors that covers the monitoring area, and we denote r the coverage range that is related to a specific QoS requirement.

Let us assume N sensors $\{s_1, \ldots, s_N\}$ are randomly deployed to cover the area $\mathcal{D}$. Each sensor has an initial energy E_0 and a r-radius disk coverage area. We denote $\{C_j, j = 1, \ldots, K\}$ a sequence of cover sets. That is, the sensor nodes s_i's in the cover set C_j satisfy

$$\bigcup_{s_i\in C_j} A(s_i) \supset \mathcal{D} \quad \text{for} \quad j = 1, \ldots, K, \tag{8}$$

where s_i denotes a live senor, and $A(s_i)$ represents the coverage area of s_i. In the j-th data collection, measurements from the sensor nodes in C_j are collected. Then, the problem of maximizing the network lifetime for a given QoS can be described as follows. Here we assume that a sensor is dead only because it is out of energy.

Given an area $\mathcal{D}$ and a set of sensors $\{s_1, \ldots, s_N\}$, find a sequence of cover sets $\{C_1, \ldots, C_K\}$ such that

(i) K is maximized,

(ii) for each sensor appearing in the cover sets $\{C_1, \ldots, C_K\}$, the total consumed energy is no larger than the initial energy E_0.

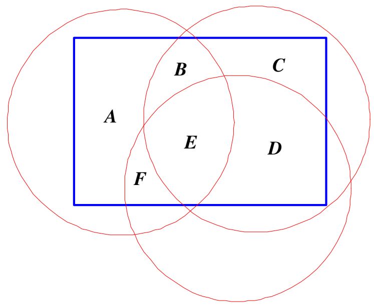

Fig. 1. A rectangular area is divided by three sensors into six subregions.

We define a boolean variable b_{ij} for $i = 1, \ldots, N$ and $j = 1, \ldots, K$, such that

$$b_{ij} = \begin{cases} 1, & s_i \in C_j \\ 0, & s_i \notin C_j \end{cases} . \tag{9}$$

We assume single hop communications between sensors nodes and the access point. In each information retrieval operation, the i-th sensor consumes energy $E_c^{(i)}$ if it is scheduled for transmission. Clearly, E_c^i depends on the distance from the i-th sensor to the access point. Then, the above optimization problem can be formulated as:

$$\begin{array}{ll} \text{Maximize} & K \\ \text{subject to} & \bigcup_{\{i|b_{ij}=1\}} A(s_i) \supset \mathcal{D}, \text{ for } j = 1, \ldots, K, \\ & \text{and} \\ & \sum_{j=1}^{K} b_{ij} E_c^{(i)} \leq E_0, \text{ for } i = 1, \ldots, N, \\ \text{where} & b_{ij} \in \{0, 1\}. \end{array}$$

The first condition represents that each set C_j is a cover set, and the second condition represents the energy constraint of each sensor. This problem is NP-complete [10]. In the following we propose a sub-optimal method using greedy techniques to solve this problem.

B. Lifetime Upper Bound

We first derive an upper bound for the network lifetime to achieve full area coverage for the case that the lifetime for each sensor is different. It is an extension of the result in [4]. This upper bound provides a measure for the performance of the following proposed suboptimal method. It also represents some critical elements we should consider when designing the algorithm.

To derive the upper bound, we first define a concept of subregion as follows.

Definition: *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.*

An example that a rectangular area is divided by three sensors into six subregions is shown in Figure 1.

According to the definition of the subregion, we can divide the whole monitored area into a set of disjoint subregions $\{\mathcal{F}_1, \ldots, \mathcal{F}_L\}$ such that

$$\bigcup_{l=1}^{L} \mathcal{F}_l = \mathcal{D} \quad \text{and} \quad \mathcal{F}_i \cap \mathcal{F}_j = \emptyset \quad \text{for} \quad i \neq j. \tag{10}$$

Based on the relationship between subregions and sensor nodes, we associate each subregion with a subset F_l of all sensor nodes that cover the subregion. That it, $F_l = \{s_{n_1}, \ldots, s_{n_l}\}$ where

$$\mathcal{F}_l \subset A(s_i) \quad \text{for} \quad i = n_1, \ldots, n_l. \tag{11}$$

We observe that for each subregion $\mathcal{F}_l$, $l = 1, \ldots, L$, during each data collection, at lease one sensor s_{n_i} in the subset F_l should be selected to transmit its measurements. For sensor node s_{n_i}, its lifetime is define as

$$\left\lfloor \frac{E_0}{E_c^{(n_i)}} \right\rfloor \tag{12}$$

which is equal to the number of data collection that can be provided by this sensor. Therefore, to cover the subregion F_l, at most M_l times of data collection can be contributed by all the sensors covering that subregion, where

$$M_l = \sum_{s_{n_i} \in F_l} \left\lfloor \frac{E_0}{E_c^{(n_i)}} \right\rfloor . \tag{13}$$

Since we want to cover all the subregions, the network lifetime is upper bounded by

$$\min_{F_l} \sum_{s_{n_i} \in F_l} \left\lfloor \frac{E_0}{E_c^{(n_i)}} \right\rfloor . \tag{14}$$

If the consumed energy by each sensor is the same, the lifetime of each sensor is also the same. Under this case, the above lifetime upper bound is the same as the result obtained in [4].

From the above equation of the lifetime upper bound, we observe that the subregions that are most sparsely covered by the sensors play an important role to prolong the network lifetime. Here, the subregions that are most sparsely covered are the subregions that are covered by the least number of the sum of the lifetime of all the sensors that cover the subregion. From this observation, we implement the following ideas into the proposed method. We identify the sparsely covered subregions in the area and cover them first. By doing this, we choose the most potential sensor nodes to cover the critical subregions. We also try to prevent the redundant coverage of the sparsely covered subregions in one cover set.

C. A Greedy Approach for Lifetime Maximization

According to the above discussion, in this section, we propose a greedy approach to solve the problem of maximizing the number of cover sets. The basic procedure of the proposed method is: we identify a critical subregion that is the subregion of most sparsely covered, and then select a sensor to cover it first. Among all the sensors that cover the critical subregion, we choose a sensor into the cover set according to the sensor's residual energy, consumed energy, and the redundance coverage. Applying this method, we take into account both the network geometry information and energy consumed by sensors in one data collection to design our sensor node scheduling scheme. The greedy approach is presented as follows.

Step 1: Subregion creation.

- Based on the position of live sensors and their coverage range r, the whole area is divided into a series of disjoint subregions $\{\mathcal{F}_1, \ldots, \mathcal{F}_L\}$.
- Each subregion $\mathcal{F}_l$ is associated with a subset of all the sensors that cover the subregion $\mathcal{F}_l$: $F_l = \{s_{n_1}, \ldots, s_{n_l}\}$ such that

$$\mathcal{F}_l \subset A(s_i) \quad \text{for} \quad i = n_1, \ldots, n_l. \tag{15}$$

And each sensor s_i is associated with a subset of subregions that are covered by the sensor s_i: $S_i = \{\mathcal{F}_{n_1}, \ldots, \mathcal{F}_{n_i}\}$ such that

$$\bigcup_{n=n_1}^{n_i} \mathcal{F}_n = A(s_i). \tag{16}$$

Step 2: Cover set searching.
The following two substeps are repeated until all the subregions are covered. The output is a cover set C_j for the j-th information retrieval operation.

1) *Critical subregions.* We select the critical subregion as

$$F_c = \arg\min_{F_l} \sum_{s_i \in F_l} \left\lfloor \frac{E_r^{(i)}}{E_c^{(i)}} \right\rfloor \tag{17}$$

where $E_r^{(i)}$ is the residual energy of the i-th sensor before the current data collection.

2) *Sensor node selection.*
   - In order to decrease the redundant coverage of the sparsely covered subregions, we define a redundance value v_i for the i-th sensor node

$$v_i = \text{the number of } \mathcal{F}_c | \mathcal{F}_c \in S_i. \tag{18}$$

     That is, v_i is the number of the selected critical subregions that are covered by the i-th sensor.
   - For the sensors covering the current critical subregion, we first choose the sensors satisfying $v_i = v_{\min}$, where $v_{\min} = \min\{v_i, i = 1, \ldots, N\}$.
   - Among the selected sensors, we calculate a value of a utility function $g(\cdot)$ based on the sensor's residual energy and the consumed energy. The sensor with the greatest value is chosen into the current cover set.
   - The subregions covered by the selected sensors are removed from the previous set of uncovered subregions.

Step 3: Residual energy update.
- For all the sensors in the current cover set, we update their residual energy $E_r^{(i)}$ by deducting the energy $E_c^{(i)}$ consumed at the current information retrieval operation from the previous residual energy

$$E_r^{(i)} := E_r^{(i)} - E_c^{(i)}. \tag{19}$$

- If the residual energy of a sensor is less than the required energy for an information retrieval operation, this sensor is considered dead and removed from the set of live sensors.
- If any sensors are removed from the set of live sensors, the subregions and their associated relationship with sensors in (15) and (16) are updated.

The above steps are repeated until $\mathcal{D}$ is no longer fully covered by live sensors. This instant is the end of the network lifetime.

Discussion: In the above approach, in the *sensor node selection* step, we only consider the sensors with the minimum value of v_i. This will decrease the redundant coverage of the sparsely covered subregions. The reason is that, among all the sensors that cover the current critical subregion, if there are sensors that do not cover any previous selected critical subregions, $v_{\min}$ will be zero. Then, we will choose a sensor from these nodes into the cover set. If all the sensors cover the previous critical subregions, then we will select the node that cover the least number of the previous critical subregions into the cover set.

We create the utility function $g(\cdot)$ using the residual energy and the consumed energy. The possible choices for the $g(\cdot)$ can be

$$g(s_i) = E_r^{(i)}/E_c^{(i)}, \tag{20}$$
$$g(s_i) = E_r^{(i)} - E_c^{(i)}, \tag{21}$$
$$g(s_i) = E_r^{(i)}. \tag{22}$$

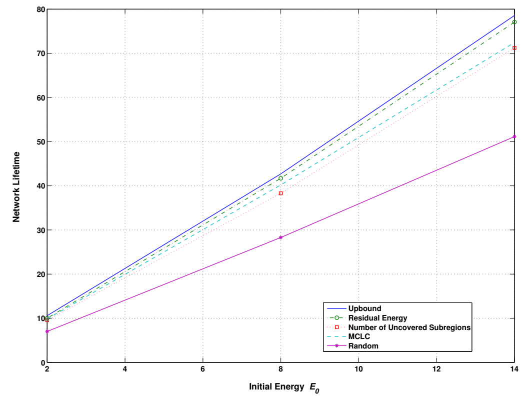

Fig. 2. Lifetime vs. Initial Energy for the case the consumed energy by each sensor is the same.

In the following we use the numerical examples to compare these three functions, and we show that the ratio between the residual energy and the consumed energy provides the best performance.

IV. Performance Evaluation

In this section we use numerical examples to evaluate the performance of the proposed greedy approach for maximizing the network lifetime. In these examples sensor nodes are randomly deployed in a 20×20 area; each sensor has a disk coverage area with range r; and the initial energy for each sensor is the same. We consider two scenarios to evaluate the performance: in one scenario, we let the consume energy for one data collection by each sensor is the same; and in anther scenario, we consider a more general situation where the consume energy is different.

In the first case, the scenario is equivalent to the situation that the lifetime of each sensor is the same. We compare the performance of the proposed method with the lifetime upper bound and three other lifetime maximization methods: (i) we choose the utility function to be the number of the uncovered subregions covered by the sensor (this method provides us a smaller number of sensors in a cover set); (ii) most constrained least constraining (MCLC) method in [8], which maximize the number of disjoint cover sets; (iii) we choose the sensor from the sensor nodes that cover the critical subregion into the cover set randomly. In the proposed method, we use the residual energy as the utility function. We deploy $N = 100$ sensor nodes into the area and the coverage range $r = 5$. We vary the initial energy E_0, and the result is shown in Figure 2.

We observe that the performance of the proposed method approaches the lifetime upper bound which demonstrates the near optimal performance of the proposed method. Its performance is better than MCLC and the method when we use the number of the uncovered subregions as the utility function. And the method with the randomly selected cover set has the worst performance. Since the method of selecting the sensor node that covers the largest number of uncovered subregions into the cover set provides us the cover set with smaller number of sensors, we draw the conclusion that for maximizing the network lifetime, it is not always optimal to minimize the number of sensors in each cover set. This observation agrees with the result in [6].

In the second case, the lifetime for each sensor is different. We also compare the performance of the proposed method with the lifetime upper bound and three other methods: (i) we choose the

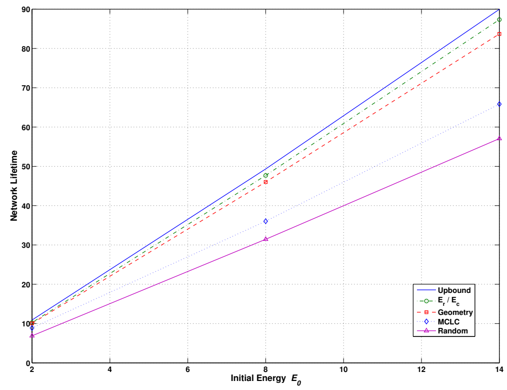

Fig. 3. Lifetime vs. Initial Energy for the case the consumed energy by each sensor is different.

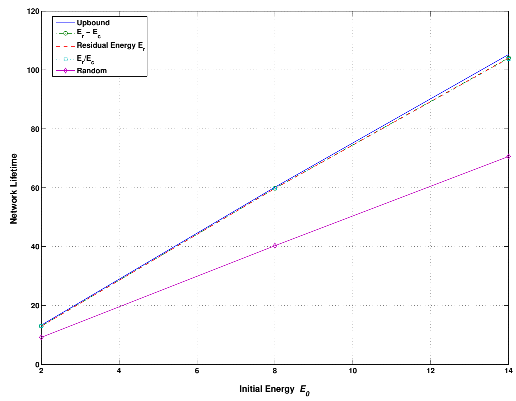

Fig. 4. Lifetime vs. Initial Energy for the case the consumed energy by each is different.

critical subregion as the subregion that is covered by the least number of sensors and the utility function is the number of the uncovered subregions covered by a sensor (the property of this method is that it uses only the network geometry information to schedule the sensors); (ii) MCLC method; (iii) we choose the sensor from the sensor nodes that cover the critical subregion into the cover set randomly. In the proposed method, we use the utility function $g(s_i) = E_r^{(i)}/E_c^{(i)}$. We also fix the number of sensors and the coverage range and vary the initial energy. The result is shown in Figure 3.

From the result, we also find that the proposed method has the near optimal performance and is better than the other three methods. Especially, we observe that comparing with the MCLC algorithm, the performance of the proposed method has more substantial improvement than in the case that the lifetime of each sensor is the same. The reason is that, in MCLC method, the sensors are divided into mutually exclusive cover sets, and these cover sets are activated successfully. In the case that the lifetime of each sensor is different, the functional time of each cover set is determined by the sensor with the minimum lifetime in that set. Therefore, the total network lifetime is much smaller than the optimal value.

In the next example, we also consider that case that the lifetime of each sensor is different. We compare the performance of the proposed method with three utility functions, as shown in Equations (20)-(22). The results are shown in Figures 4-5. We first use the network lifetime

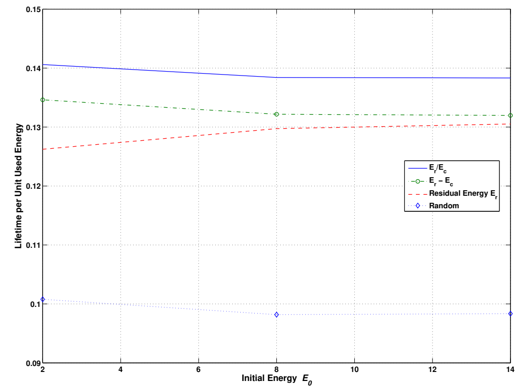

Fig. 5. Lifetime per Unit Energy vs. Initial Energy for the case the consumed energy by each is different.

as a measure to compare these three functions, and we find that the performance of all these three functions is very close to the lifetime upper bound, and the difference among themselves is very small. When we enlarge the figure, we can still find that the performance when we use utility function $E_r^{(i)}/E_c^{(i)}$ is better than $E_r^{(i)} - E_c^{(i)}$, which is better than $E_r^{(i)}$. This observation agrees with our previous results in [2]. When we increase the number of deployed sensor nodes and the coverage range, the difference among them is more obvious.

We also use another measure, the network lifetime divided by the total consumed energy by all sensors, to compare the performance of these three utility functions. That is, we use the network lifetime achieved by a unit energy as a measure. The utility function $E_r^{(i)}/E_c^{(i)}$ has the best performance, and the performance of $E_r^{(i)} - E_c^{(i)}$ is better than only using the residual energy. This observation represents that the method of using $E_r^{(i)}/E_c^{(i)}$ as a utility function is more energy efficient.

In the last example, we study the performance of the following three strategies to choose the critical subregion:

$$F_c = \arg\min_{F_l} \sum_{s_i \in F_l} \left\lfloor \frac{E_r^{(i)}}{E_c^{(i)}} \right\rfloor, \tag{23}$$

$$F_c = \arg\min_{F_l} \sum_{s_i \in F_l} E_r^{(i)}, \tag{24}$$

$$F_c = \arg\min_{F_l} \sum_{s_i \in F_l} 1. \tag{25}$$

The strategy in (23) is what we use in the proposed method. The result is shown in Figure 6. The performance of the strategy in (23) is better than the others. This can be explained as this strategy uses the sensor residual energy, consumed energy, and the network geometry information, while the other two strategies use only parts of these elements.

V. Conclusions

We studied the problem of network lifetime maximization for QoS specific information retrieval for the reconstruction of a spatially correlated signal field in a wireless sensor network. We transformed the problem into a coverage-related problem and formulated the lifetime maximization into an optimization problem of searching for the maximum number of cover sets with an energy constraint, which is NP-complete. We proposed a greedy approach to solve this problem. We evaluated the performance of the proposed approach

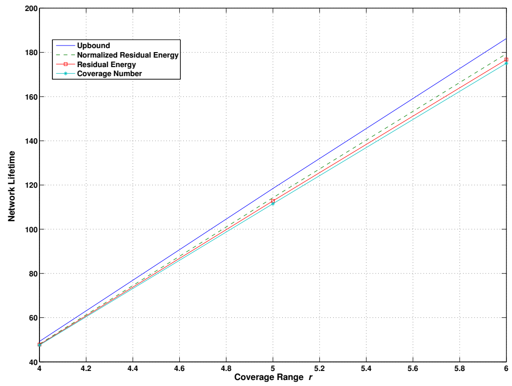

Fig. 6. Lifetime vs. Coverage Range for the case the consumed energy by each is different.

and showed that the network lifetime obtained using this approach was close to its upper bound. In our future work, we will study other selection of contribution functions. We will consider the effect of the transmission channel fading state on the network lifetime. We will also extend our work and consider the multi-hop transmission between each sensor and the access point.

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