Power-Efficient Real-Time Data Collection using Mobile Robots*

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Abstract

Wireless sensor networks (WSNs) have been exploited widely in many applications (such as military surveillance, habitat and volcano monitoring). However, considering the limited energy budget in sensor nodes, power management has become an important issue in WSNs to increase their operation times. In this paper, we present our research on power efficient real-time data collection *in WSN using a* mobile robot*. The mobile robot roams in the deployment area, collects data from* static *sensors deployed in the field and conveys the data to a base station. Targeting at minimizing the energy consumption on the static sensors, we study power efficient path planning schemes for the mobile robot, which also has limited energy but can be recharged at the base station, to collect the data from all sensors within a given time interval periodically. We propose clustering based approach and minimum spanning tree based approach for the problem.Preliminary simulation results and the experiment setup with LEGO robots and Tmote Sky sensors are also presented.*

1 Introduction

With the mass production of inexpensive embedded devices with wireless networking and sensing capabilities, it is possible to exploit them for many applications. In general, wireless sensor networks (WSNs) consist of potentially hundreds of sensor nodes, which are deployed in an ad hoc manner to collect data from a region of interest over a period of time [1, 6]. In the recent past, WSNs has received a lot of attention due to the large number of applications that can potentially benefit from their deployments. For example, successful large-scale deployments of WSNs include ecology monitoring [13] and habitat monitoring [9].

In conventional WSN deployments, the data collection is normally achieved by using a multihop data forwarding mechanism toward a *static base-station*, which has the computational power to store and process all the collected data. A major shortcoming of this traditional approach is that it neglects the spatiotemporal nature of data generation. Typical data generation rates are local both in time and space as has been observed in several WSN deployments. For instance, investigations of natural phenomena in forest environments have validated spatiotemporal distribution of solar illumination, temperature, and humidity [3, 13, 16].

Mobile elements have been utilized to address the limitations of static base-stations and to facilitate the data collection by moving around the deployed field and conveying data to the base-station [11, 18]. However, the employment of mobile elements introduces many new challenges (such as *how to move* and *when to move the base-station*, as well as *what to do with obstacles on the path*). To effectively serve the varying data-rates in sensor networks, mobile element scheduling considers the problem of controlling the mobility of mobile elements to reduce latency for data collection or to collect data from static sensors before the buffer is full [11, 12, 18]. In [11], *data mules* exploit *random* movement of mobile base-station to opportunistically collect data from a sparse sensor network. Here, the static sensor nodes buffer the sensor data locally, and upload the data only when the mobile base-station is within its direct communication distance. For a sparse sensor network where all nodes have certain mobility, *message ferry* approach utilizes special mobile nodes as ferries to provide communication services [18].

It has been shown that the general problem of path planning for the mobile base-station to visit sensor nodes before their buffers overflow is NP-complete. Some heuristic based solutions have been proposed to address this problem [7, 12, 17]. In one recent work, the mobile base-station (i.e., *data salmon*) periodically moves to a global optimal

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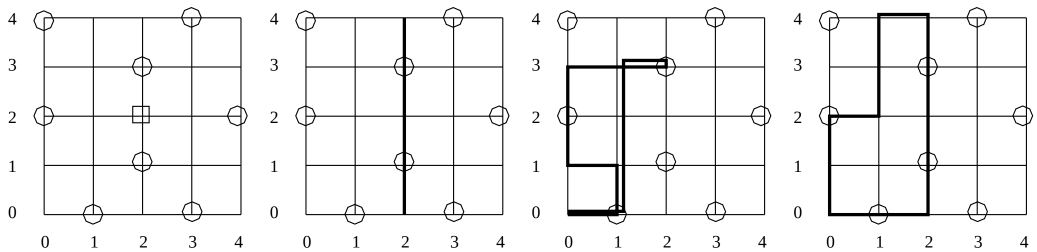

(a) Static Base Station (b) Data Mule (c) Clustering (d) MST

Figure 1. An Example with Paths of Different Approaches

location by adapting to the changes in the system and data flows from remote static nodes towards the data salmon [5]. However, data salmon does not move towards individual remote sensor nodes. Imouse [14] mobile robots use a Stargate processing board to connect various devices such as webcam, mote, wireless LAN card for surveillance applications, without considering timing constraints. More recently, one hybrid approach that combines multihop data forwarding and mobile elements is studied in [15].

2 Problem Statement

In this work, we consider power efficient real-time data collection in a WSN using a mobile robot. The mobile robot (i.e., *mobile sensor element*), which is also battery powered, moves in the deployment area for data collection and periodically returns to the base station to convey the collected data and to recharge. Given the restricted travel time because of limited energy budget, the mobile robot may not be able to reach the location of *each* and *every* sensor node to minimize the power consumption of the sensor nodes in the deployed area and to maximize their lifetimes.

Therefore, in this paper, for a given WSN with multiple sensor nodes, we will study energy efficient path planning schemes for the mobile robot to minimize the total energy consumption by all the sensor nodes.

For the system considered, we assume that:

- N sensors denoted by $S_i, 1 \leq i \leq N$ are placed on a rectangular area;
- Mobile robot moves at a constant speed s;
- Mobile robot can travel without recharge for at most T time units, during which it needs to collect data from all sensor nodes in the field;
- The power level for sensor nodes, with the distance d, to transmit/receive data is βd^θ, where β and θ are system dependent parameters;
- Each sensor communicates with the mobile robot when the distance between them is minimal.

From the assumptions, we can get that the length of the travel path P of the mobile robot is limited by $L = T \cdot s$. Suppose that $d(S_i, P)$ denotes the shortest distance between the sensor node S_i and the travel path P of the mobile robot. The problem considered in this paper can be formally defined as, finding the travel path P to:

$$Minimize: \ \sum_{i=1}^{N} \beta d(S_i, P)^\theta \cdot t$$

$$Subject\ to: \ \ |P| \leq L$$

where $|P|$ denotes the length of the path P and t is the communication time needed for each sensor node to transmit its data to the mobile robot.

3 Proposed Schemes

As an example, we consider 8 sensors on a 5×5 grid as shown in Figure 1, where the circles represent static sensors and the rectangle represents the base station. Suppose that the battery energy on the mobile robot can only support the robot moving for 12 units of distance. Without utilizing the mobile element, in the conventional approach, a static base-station can be put in the center of the field as shown in Figure 1a. In the data mule approach [11], without considering the location of individual sensor nodes, the mobile element will simply move along the central vertical line as illustrate in Figure 1b, where the mobile element only travels for 8 units of distance.

For better usage of the mobile element and minimizing the energy consumption of sensor nodes, the travel path of the mobile element should visit as many sensor nodes as possible provided that the path length is within the limit. Note that, the problem is similar to the *travel salesman problem (TSP)* and is expected to be NP-hard. For the initial step of the work, we focus on two two different heuristic approaches: the *clustering based scheme* and the *minimum spanning tree (MST) based scheme*.

- *Clustering based Scheme:* N sensors are divided into k clusters using k-means clustering algorithm [8]. First, the center of the cluster is moved to the nearest intersection. Next the Minimum Spanning Tree route building recursion builds a viable path using the centers of the clusters versus the sensors themselves. The number of clusters is specified at input time and does not decrease during the program run. The algorithm uses the Minimum Spanning Tree to shrink the centroids location until an optimal path is reached using the virtual sensors as the data needed for the k-means algorithm. determining the value of k determines the efficiency of the algorithm. Too low a value and a less than optimal path is located. Too great a value and the virtual sensor position will be moved greater than necessary.

- *Minimim-spanning-tree (MST) based Scheme:* Once a Minimum Spanning Tree has been built a leaf is located on the graph. Once the leaf is located a queue is formed of vertices and using a recursive function the order of vertices can thus be determined. Once the order of intersections is determined the points are extended to traverse the grid by moving across the x-axis then the y-axis versus a direct route so that each point traverses all the intersections between the two points. If a solution does not satisfy the constraint on the maximum edges the shrinking function is called. The shrinking function creates a set of virtual sensors that correspond to the actual sensor positions. The virtual sensors are moved, first on the x-axis and second on the y-axis starting with the least moved sensor. Each call to the shrink method moves a single sensor across one axis. The movement is always towards the previous sensors location thus shrinking the edge distance. The process of building a Minimum Spanning Tree and shrinking is repeated until a valid path is found.

Suppose that the mobile robot is placed on $(0, 0)$, where a base station is located. The robot will move along the lines of the grid to collect data and returns to $(0, 0)$ for conveying the data to a basestation and recharging its battery. Figures 1cd show the generated paths for the mobile robot under the clustering based scheme and MST based scheme, respectively. Here, we can see that, the paths for both schemes have the length of 12 units, which is within the limit.

Algorithm	*Power consumption*
Static base station	$(2 + 8 + 15 + 8)\beta t = 33\beta t$
Data Mule	$(2 + 3 + 12)\beta t = 15\beta t$
Clustering scheme	$(2 + 2 + 4 + 5)\beta t = 12\beta t$
MST	$(3 + 4)\beta t = 7\beta t$

Figure 2. Energy consumption of sensors

Assuming $\theta = 2$, Figure 2 shows the calculated total energy consumption of all sensors in one round of data collection for all the schemes in Figure 1. Here, t is the time required to transmit data in a sensor node to the mobile element. The communication energy consumption for the sensor nodes that are on the path of the mobile element is assumed to be negligible. We can see that, compared to the previous schemes, both the newly proposed clustering-based and MST-based schemes perform much better, in terms of minimizing energy consumption of the sensors.

4 Simulations and Experiments

To systematically evaluate the performance of the proposed schemes, in this section, we present our initial simulation results as well as the experimental setup. We use Glomosim [2] simulator to emulate large deployment of sensor nodes. Using a network simulator allows us to include the cost of all the communication operations and allows us the option to study the effects of different sensor distributions and network protocols. Built in power model of Glomosim is used for the experiments as well.

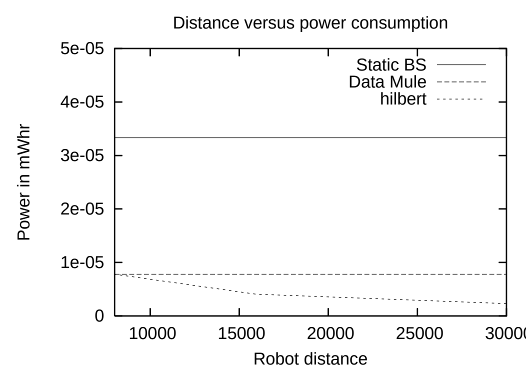

Figure 3. Simulation Results

Simulation results for 100 sensors deployed in a 1000x1000 field is given in figure 3. With limited moving ability, data mule moves along a single axis and provides limited energy savings [11]. Hilbert curve is a improved version of data mule and moves along hilbert curve to collect the data. As shown in the figure mobility based approaches significantly outperform the static basestation approach. WE are working on implementing the clustering and MST based schemes.

Experimental Setup To verify the performance of the proposed schemes experimentally, we are working on an experiment testbed consisting of Tmote Sky sensors [10] and LEGO robots. Equipped with MIT Handy Board controllers [4], the functionality of the LEGO robot can be easily extended considering the simple interface of the Handy

Board with other digital/analog I/O devices. For instance, we have successfully designed the interface between Handy Board and Tmote Sky sensor and developed corresponding communication library. That is, together with a Tmote Sky sensor, the LEGO/Handy Board robot will be used as the mobile sensor element, which can accept instructions *wirelessly* from a base station (e.g., a host machine) and collect data automatically following a planned path.

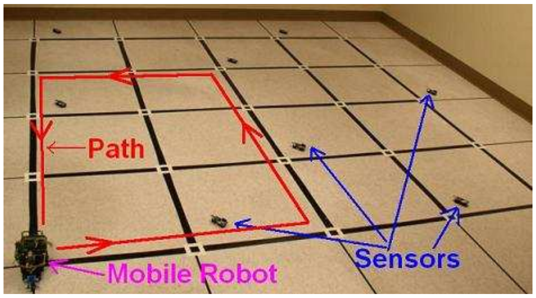

Figure 4. Experimental tested

The experimental testbed with a few sensor nodes and one mobile LEGO robot is shown in Figure 4. Here, LEGO light sensors and electrical tape with different colors are used for the mobile robot to locate itself. From the initial experiments, the mobile robot takes around 4.5 seconds to travel a 2 feet grid, 1.4 seconds to make a turn (left or right), and 30 milliseconds to collect a randomly generated number from the static sensor node that is on the path.

5 Conclusion and Future Work

Wireless sensor networks (WSNs) have received a lot of attention recently. As the precious system resource in sensor nodes, power needs to be managed carefully in WSNs. In this paper, we use a mobile robot for power efficient data collection with the goal of saving energy at sensor nodes. We propose two heuristic schemes for the problem. Clustering based scheme groups nodes into clusters and the mobile robot will visit the center of each cluster for data collection. For the minimum spanning tree (MST) based scheme, it starts with a MST with locations of all sensor nodes and removes edges to meet the path length constraint. We illustrate the effectiveness of the new schemes and describe an experimental testbed that will be used to validate the simulation results. Future work includes extensive simulation of proposed schemes as well as physical experiments that will complement the simulations. In addition, multiple mobile robots will be exploited for better schemes.

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