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Analysis of Cluster Lifetime with Rate Allocation in Wireless Networks Subtitleasneeded (papersubtitle)

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Abstract: ***We consider the rate allocation problem for data aggregation in wireless sensor networks with two objectives: 1) maximizing the lifetime of a local aggregation cluster and, 2) achieving fairness among all data sources. The two objectives are generally correlated with each other and usually they cannot be maximized simultaneously. We adopt a lexicographic method to solve this multi-objective programming problem. First, we recursively induce the maximum lifetime for the local aggregation cluster. Under the given maximum lifetime, we then formulate the problem of maximizing fairness as a convex optimization problem, and derive the optimal rate allocation strategy. We also present low-complexity algorithms that a local aggregation cluster can use to determine the optimal rate allocation. Our simulation results validate our analytical results and illustrate the effectiveness of the approach.***

Keywords: ANT, 802.15.4, BLE, WSN, MAC protocol

1. Introduction

We consider a wireless sensor network that is deployed in astrategic location for surveillance — e.g., tracking intrudingtargets [5]. Some nodes in the network generate physicalmeasurements of an intruding target after sensing the presence of a target. A common operation on such tracking applications is data aggregation [9]. During aggregation, sensed data isgathered from different sensor nodes (i.e., source nodes) andis combined at a local cluster head. Source nodes may transmitsensed data via either one hop or multi-hop towards the cluster head. Generally, sensor nodes are battery-powered and consumeenergy in sensing, transmitting, and receiving data. The limitedsize of sensor nodes only allows for very limited energystorage and in most applications such as tracking, it is infeasibleto recharge the node batteries. Although substantial Improvements have been achieved in chip design for energyconservation, energy-efficient battery designs still lag behind.

Thus, one of the fundamental challenges in sensor networks is their energy efficient operation, and significant research effortsare focusing on this problem.An important approach for achieving energy efficiency is tocontrol the data rates in the network- or upper layers. Thereare several reasons for doing so. For example, by controllingthe data rates, network congestion can be controlled or eveneliminated [4]. Congestion, if not controlled can impede theperformance of applications with delay constraints, besideswasting transmission energy and radio resources due to retransmissions.Further, by controlling the data rates, the network's energyconsumption can be balanced, and thereby the network lifetimecan be maximized [16], [10]. For example, nodes with highremaining energy can be allowed to transmit more data,while those with low energy can be allowed to transmit less.Without such balanced energy consumption, some nodes mayquickly exhaust their power, causing network partitions ormalfunctions.

The requirement, from many data aggregation applications,is to achieve fairness [3], [4] among source rates.Typically, applications can achieve better performance when data gathered from different source nodes are identical in termsof data rate. For instance, equal amount of data from somevideo sensor nodes can help the cluster head build a whole sceneimage or video. To achieve fairness, it is important tohave data rates among all source nodes as equal as possible.In most cases, an optimized rate allocation that simultaneouslymaximizes the network lifetime and fairness is difficultas the two objectives are correlated with each other. For maximizingthe network lifetime, it is better to bias the rate allocationfor nodes with different remaining energy/transmissioncost, as this will balance the energy consumption. However, formaximizing fairness, it is better to average the data rate of allnodes as much as possible. There is an inherent trade-off [17],[11] between biased rate allocation (lifetime maximization)and even rate allocation (fairness). Thus, find a rate allocationstrategy to achieve such trade-off is a challenge.In this paper, we formulate the above challenge as a multiobjectiveprogramming problem and adopt a lexicographicmethod [15] to solve the problem. First, we recursively inducethe maximum possible lifetime in a local aggregation tree.Under the given maximum lifetime, we then formulate theproblem of maximizing fairness as a convex optimizationproblem, and derive the optimal rate allocation strategy. Wealso present a low-complexity algorithm to compute the maximumnetwork lifetime and the optimal rate allocation forfairness. To the best of our knowledge, this is the first resulton rate allocation in sensor networks that simultaneouslymaximizes network lifetime and fairness in data aggregationusing a lexicographic method.The rest of the paper is organized as follows: In Section II,we overview the related work in rate allocation for sensornetworks. In Section III, we present the network topology,transmission power model, and our problem formulation. InSection IV, we mathematically analyze the problem model andpresent our lexicographic solution. Section V describes ouralgorithms. We report our experimental results in Section VI, and conclude in Section VII.

2. Related Work

The problem of rate control and energy management inwireless sensor networks has been extensively studied. Tomaximize the network lifetime, Bhardwaj et al. [1] presenta network lifetime upper bound for energy-efficient collaborativedata gathering with optimal role assignments. Xueetal. [16] adopt a dual decomposition method to determine theoptimal network lifetime for data aggregation in which sourcenodes have multiple routing paths to the sink node. In [13], Sankar et.al present a distributed algorithm with guaranteedapproximation error for flow routing. In [7], Hou et al. studythe max-min rate allocation among all nodes with a systemlifetime requirement.

The problem of achieving fairness in rate allocation hasalso been well studied. For instance, achieving MAC-layer fairness among one-hop flows within a neighborhood is studiedin [8]. In [14], the fair data collection problem with the NUM framework is studied. In [2], Chen et al. determinethe maximum rate at which individual sensors can producedata without causing congestion in the network and unfairnessamong peer nodes.Some previous efforts also consider both network lifetimemaximization and fair rate allocation. In [11], Nama et al.present a general cross-layer framework that takes into accountradio resource allocation, routing, and rate allocationfor achieving trade-off between lifetime maximization andfairness. The authors solve the tradeoff problem via a dualdecomposition method. In [17], the similar problem is addressedat the transport layer. The method in this work isto construct a new optimization function by linearly addingup the two objective functions (i.e., lifetime and the objectivefunction presenting fairness) and derive an optimal solutionfor maximizing the newly constructed function.The differences between our work and the above two worksare: 1) we study the tradeoff problem in a local cluster whichhas a tree-like network topology that is more suitable for data aggregation . 2) We adopt a lexicographic method in which weprefer network lifetime maximization to fairness comparingwith no preference in the existed works. This is becausenetwork lifetime is strongly correlated to energy consumptionwhich is one of the most performance-critical aspect of sensor networks.

3. Network Topology and Problem Model

3.1 Network Topology

The network topology for data aggregation is a tree structure(aggregation tree). We have three types of sensor nodes in the network: source nodes, relay nodes, and the cluster head (i.e.,root node in the aggregation tree).The source nodes are leaf nodes which generate sensor data.

The function of a source node is simple: once triggered by anevent, it starts to capture live information about the target,which is then directly sent to the local cluster head within onehop or multiple hops. Only source nodes can generate data inour system. A relay node does not generate data. Its functionsinclude: 1) receiving data from its children nodes which canbe relay nodes or source nodes, and 2) forwarding the receiveddata to the next hop toward the cluster head (root node). Thecluster head is the aggregation end point.For this network topology for data aggregation, we make thefollowing assumptions: (1) All sensor nodes and the clusterhead are time-synchronized; (2) Any sensor nodes at most hasone parent in the aggregation tree; (3) Each sensor node canmeasure its transmission energy per byte and the remainingbattery capacity; and (4) Within each cluster, the source nodescan sense events (targets) and transmit the sensed data to thecluster head simultaneously.We also assume that interference and hidden terminal problemat relay nodes/cluster head can be avoided by virtualcarrier sensing via RTS/CTS mechanism in IEEE 802.15.4CSMA/CA protocol which is widely adopted by the MACprotocol (i.e, S-MAC or B-MAC) for sensor networks. And inthe rest of the paper, for convenience, we will use the termsleaf node and source node interchangeably, and the terms rootnode and cluster head interchangeably.

3.2 Power Dissipation Model

For a sensor node, the power consumption due to data communication (i.e., receiving and transmitting) is the dominantfactor. Suppose there are *N* sensor nodes in a cluster. Eachnode is denoted as ni(i · N). We denote gias the bit ratefrom node nito its next hop node, and ci as the transmissionpower cost over the radio link.

3.3 Motivation

Radio communication quality between low power sensor devices is affected by spatial and temporal factors. The spatial factors include the surrounding environment, such as terrain and the distance between the transmitter and the receiver. Temporal factors include surrounding environmental changes in general, such as weather conditions. In this section, we present experimental results for investigation of these impacts.

We note that previous empirical studies on communication reality [3] [4] [5] [10] [12] [2] suggest that for a specified transmission power, fixed communication distance, and antenna direction, the received signal power and the link quality vary. But they do not focus on a systematic study of the radio and link dynamics when different transmission powers are considered. We conducted these measurements, and we are the first to study systematically the spatial and temporal impacts on the correlation between transmission power and Received Signal Strength Indicator (RSSI)/ Link Quality Indicator (LQI) [15]. Both RSSI and LQI are useful link metrics provided by CC2420 [7]. RSSI is a measurement of signal power which is averaged over 8 symbol periods of each incoming packet.

4. Link Quality Threshold

Wireless link quality refers to the radio channel communication performance between a pair of nodes. PRR (packet reception ratio) is the most direct metric for link quality. However, the PRR value can only be obtained statistically over a long period of time. Our experiments indicate that both RSSI and LQI can be used effectively as binary link quality metrics for transmission power control. Guided by the observations obtained from empirical experiments, in this section, we propose our Adaptive

Transmission Power Control (ATPC) design. The objectives of ATPC are to make every node in a sensor network find the minimum transmission power levels that can provide good link qualities for its neighboring nodes, to address the spatial impact to dynamically change the pair wise transmission power level over time, to address the temporal impact.

5. Algorithms

Based on the problem formulation and the lexicographical solution, we present an algorithm to compute the lifetime and the fair rate allocation. The algorithms containboth distributed part and centralized part. The intermediate roots of different subtrees will distributively calculate BitCapacity and Fair Bit Bound for their leaf children. But thefinal maximum lifetime and optimal rate vector is calculatedby the Cluster Head, in a centralized way.Algorithm 1 shows the operation for all source nodes. It hasthe lowest computational complexity.

Algorithm 1: Operations in Leaf Node (Source Node) *ni*:
1: Initialization:
2: *Ei*= getInitialEnergy(*ni*);
3: *ci* = getPowDispPara(*ni*);
Bi = *FB*(*i*) = *Ei*
ci
4: ;
5: Report *fBi; fFB*(*i*)*gg*to its parent node;
On receiving multicasted rate allocation vector *g* = *fgsk*6: *g*
If *sk*= *i*, set *gi*= *gsk*7: .

Algorithm 2: Operations in Relay Node *ni*:
1: Initialization:
2: Set value for *Ei*, *ci* and *Bi*;
On Receiving Reports
©
Bdk;fFB(*s j*)*jsj2 Sdkgjdk2 Di*
a
3: :
Bi = *minfBi;*
P
sk2Si
*Bsk*4: *g*;
Sort the members in
©
fFB(*sj*)*jsj2 Sdkgjdk2 Di*
a
5: ;
6: *fFB*(*j*)*g* = The sorted set in which *Bj*¡1 · *Bj*;
7: *sum* = 0;
8: for *k* = 1 to *jSij*do
FB(*k*) = *minfFB*(*k*)*; Bi¡sum*
*jSij*9: *g*;
10: *sum* = *sum* + *FB*(*k*);
11: Report *fBi; fFB*(*sk*)*gg*to the parent node;
12: On receiving multicasted rate vector *g*:
13: Forward the information to all subtrees via multicast;

6. Experimental Results

We evaluated the effectiveness of our algorithms throughsimulation-based experiments. We first randomly generated anaggregation tree with a topology as illustrated in Figure. 3. Thenumber of children of non-leaf nodes was randomly distributed

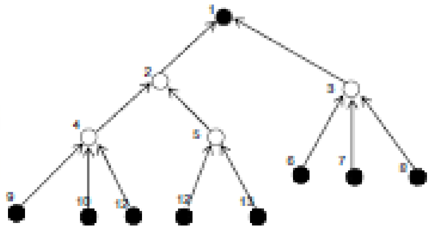

Figure 1: Topology in Experiments

The distance between one node to its next hop node was alsorandomly generated between [15*;* 30] (m). In our experiments,we set ® = 50*nJ*=*b*, ¯ = 0*:*0013*pJ*=*b*=*m*4, and *m* = 4 for thepower consumption model. The initial energy reserve of each sensor node was defined using a normal distribution with meanand variance of (25*J;* 16*J*2). The shared channel capacity(IEEE 802.15.4) is set to 128*Kb*=*s* in our experiment.

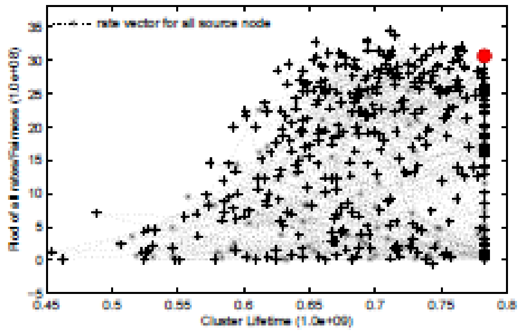

Figure 2: Topology in Experiments and Solution Space for All Rate Vectors

To illustrate our solution strategy for the multi-objectiveprogramming problem, we show the entire solution space inFigure. 4. Each data point in the figure corresponds to one rate Vector (for all source nodes). The value of network lifetime and the product of all source data rates were calculated foreach vector.

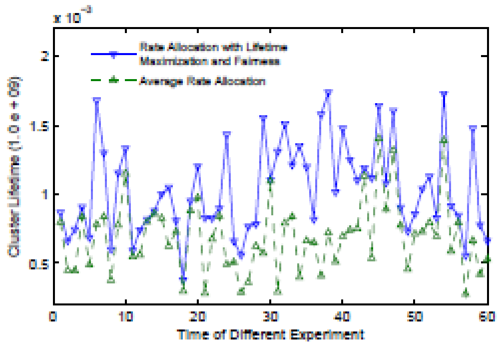

Figure 3: Network Lifetime in Different Experiments

Figure 3 shows the lifetime of the same cluster when we change the node configuration with different remaining energy and transmission distance. The remaining energy and transmission distance of each node in different experiments hasa normal distribution.We repeated the experiment for 60 times,and drew the maximum network lifetime in each time for ourrate allocation strategy and the average rate allocation strategy.From the figure, we observe that the maximum lifetime alsohas a normal distribution. In addition, our rate allocationstrategy always achieves better performance than the averagerate allocation strategy.

7. Conclusions

This paper studies how to maximize the cluster lifetimeand to achieve fairness with rate control for data aggregationapplications on sensor networks. To solve the multi-objectiveprogramming problem, we adopt a lexicographic method byfirst determining the solution space of lifetime maximization and then deriving the optimal rate allocation strategy for fairnessunder that solution space. We also present low-complexityalgorithms to compute the maximum lifetime and the optimalrate vector for fairness. The simulation results illustrate theeffectiveness of the approach.Several directions exist for further study, including rateallocation with multi-target tracking and multi-path routingfor lifetime maximization and fairness.

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