Scalable and Energy Efficient Data Dissemination in Wireless Sensor Networks

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ABSTRACT

Data dissemination in wireless sensor networks is a key problem that acts as a bottleneck to its wide application in real world. In this paper, a novel data dissemination scheme − logarithmic spiral data dissemination (LSDD) − is proposed. In LSDD, data advertisements are disseminated following a parametric spiral-like path, which involves only a small fraction of nodes in a dense sensor network. By exploiting the nice feature of spiral, the scheme scales well for large sensor networks while saving much energy in the data dissemination process. By both numerical analysis and simulations, we show the distinct merits of LSDD as lower dissemination cost, better scalability, and better fault tolerance when compared to flooding-based schemes.

Categories and Subject Descriptors

C.2.2 [**Network Protocols**]: Routing protocol

General Terms

Algorithm, Design, Performance

Keywords

data dissemination, spiral, sensor network

1. INTRODUCTION

The advances of VLSI, MEMS, and wireless technology enable a wireless sensor network (WSN) [1], which consists of a large number of tiny and cheap sensor nodes [2], to be deployed in scenarios such as battle field surveillance, forest fire monitoring, natural habitat recording, etc. However, because of the limited energy and bandwidth owned by a sensor network, data dissemination becomes one of the bottlenecks that keep sensor networks from wide applications in practice. The data dissemination process includes two cases. One is that the *sink* nodes, which connect WSN with the outside network (e.g., Internet), spread its interests/queries over WSN; the other is that a sensor node reports interested phenomena around it to other sensor nodes or the sink nodes. Besides the energy and communication concerns, the data dissemination process also faces the challenge of fault tolerance due to the failure of sensor nodes in a volatile environment.

In the past decade, quite a few of data dissemination schemes have been proposed, which are summarized in [3]. However, flooding-based solutions lead to low energy efficiency and high channel congestion, which is not preferred in a resource-limited sensor network. In addition, most proposed schemes set up the dissemination path in a hop-by-hop manner and only local information is exploited at each hop. The resulting path, due to the ad-hoc nature of the sensor network, is usually suboptimal, unstable, and the energy consumed on path construction and maintenance is unpredictable as well.

In this paper, we propose a distributed, energy efficient, and scalable data dissemination scheme, logarithmic spiral data dissemination (LSDD), which is based on the logarithmic spiral geometrics as well as the local geographic information at each node. In LSDD, data advertisements are disseminated following a spiral-like path, which involves only a small fraction of nodes in a sensor network.

Compared with previous schemes, our solution provides a more predictable, stable network topology, and consequently reduces considerable traffic overhead on dissemination path construction and query/response process. Numerical analysis shows that the complexity of LSDD is only $O(\sqrt{n})$ for n nodes in coverage. It also shows that LSDD has effective control on the dissemination radius via its succinct parameters. Besides verifying the numerical analysis, our simulations show that LSDD outperforms flooding based schemes on both scalability and fault tolerance. The search cost of LSDD increases linearly as the source-sink distance increases rather than exponentially as in flooding based dissemination schemes. When there are multiple sink nodes, the search cost of LSDD is also linearly proportional to the number of sink nodes and at least one order of magnitude lower than SIDD and GBDD. On the other hand, LSDD is very robust against unreliable sensor nodes, which may fail in operation and change the topology of a WSN. In our simulation, even when 10 percent of nodes fail, LSDD achieves a success rate higher than 90 percent on average.

In this paper, we assume that all sensor nodes are uniformly and statically deployed on a flat plane, and all sensor nodes can learn their coordinates in the initial stage of

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deployment by reference nodes and location algorithms. To focus on the data dissemination issue, we assume that all messages have the same length, and the RF links between sensor nodes are symmetric, that is, a node can send a message to the node from which it can receive a message.

The rest of this paper is organized as follows. In Section II, we briefly review the main proposed data dissemination schemes and protocols. In Section III, we present LSDD in details. In Section IV, We provide both numerical analysis and simulation results. In Section V, we draw the conclusions.

2. OVERVIEW OF DATA DISSEMINATION SCHEMES IN SENSOR NETWORK

In classical flooding schemes and its variants, flooding is the fundamental way for multi-hop routing, and the resulting traffic overhead leads to fast energy consumption and channel congestion. Some adjustment from the application layer can be used to alleviate those negative effects. For example, SPIN-1, SPIN-2 [4], and directed diffusion (DD) [5,6] are all scheme for content-based data dissemination, or the so-called *data-centric* routing. All of them associate the sensed data with a tag of brief description, and sensor nodes use such tags to establish dissemination path as well as aggregate data. However, as mentioned before, flooding is the underlying method for communications in both SPIN and DD. Moreover, multiple versions of data are rebroadcast to the network, which offsets the traffic reduction by data aggregation. In addition, there is no effective ways to manage the topology of the dissemination paths. As a result, those paths may be far from optimal in global view although it may be optimal at every hop.

As an alternative, gossiping [7] and rumor routing [8] proposed similar protocols to trim the full-flooding path: only part of neighbors of a node are selected to forward messages. Both query and data advertisements are forwarded in such random way until they are met. Though flooding is eliminated, the total cost to establish and maintain a dissemination path may still be high, due to the ad-hoc nature of a sensor network.

In [9], three heuristic algorithms are proposed to approximate a broadcasting tree in a static sensor network by which the broadcast energy is minimized. However, all three algorithms are centralized, therefore it is not very practical and efficient when the cost of required information exchange is considered. Y.Yu *et. al.* proposed GEAR (Geographical and Energy Aware Routing) in [10], which chooses routes based on the local knowledge of neighbors' energy and geographies. Traffic overhead is lowered by limiting the flooding in a specific destination region, as each node is assumed to be location-aware. However, a pre-assumption of GEAR is that the destination must be known *apriori*. However, in most applications, there is no way for sink node to know this in advance.

The recently proposed Trajectory Based Forwarding (TBF) [11] is closely related to our work. In [11], TBF is described as a general framework that combines source routing and Cartesian geographic forwarding. However, the authors did neither develop any specific scheme based on a particular trajectory nor adequate numerical empirical results to support the advantages of TBF. In our work, we show advantages of LSDD by both numerical analysis and simulation.

3. LOGARITHMIC SPIRAL DATA DISSEMINATION SCHEME

In a two-dimension plane under polar coordinates, a logarithmic spiral [12, 13] is defined as a curve such that:

$$r = ae^{b(\theta-\theta_0)}, \tag{1}$$

where the radius r is the distance from origin to the point with angle θ, a and b are arbitrary positive constants, and θ_0 is the initial spiral angle. Under the Cartesian coordinates, (1) converts to:

$$\begin{cases} x = a\cos(b\theta)e^{b(\theta-\theta_0)} \\ y = a\sin(b\theta)e^{b(\theta-\theta_0)} \end{cases} \tag{2}$$

The expression of a reversed logarithmic spiral is identical with (1) except that a minus is put before b

$$r = ae^{-b(\theta-\theta_0)}. \tag{3}$$

In LSDD, both query messages from a sink node and data advertisement messages from sensor nodes are forwarded along paths approximating a logarithmic spiral curve, but in opposite directions, respectively. The parameters of the spiral can be broadcast or preprogrammed to all sensor nodes in advance. When a sensor node detects something interesting that needs to be disseminated, it initiates a spiral dissemination. It first runs the spiral path search algorithm (SPSA) to choose the next-hop neighbor node that fits the intended spiral path best, then sends an advertisement message to the chosen sensor node. An advertisement message includes the signature of the interested phenomenon, the location of the source node, the id of the previous hop node, the spiral angle of the previous hop node, and other parameters like TTL (Time-To-Live) of the advertisement and the maximum hop number of the dissemination path, etc.

When a sensor node receives an advertisement packet, it first makes a local copy of this advertisement, then uses the same SPSA to choose one neighbor as the next hop, and forwards the advertisement message. In this way, the advertisement is forwarded hop by hop in the sensor network following a spiral-like track. Considering the sink nodes are located near the boundary in most cases, the SPSA has implemented an option to circle the boundary of a WSN. If the boundary circling option is off, then the SPSA will stop when it reaches the boundary or the limit on hop number.

The query procedure is similar to the dissemination procedure but in a reverse direction. A sink node initiates a query, and the query follows the reverse spiral path until it meets the dissemination spiral, or the termination condition is satisfied, for example, the maximum hop number is reached, boundary is reached or there is no node to choose. Before forwarding the query to the next-hop, the sensor node will also broadcast a message to its neighborhood to see if it meets the dissemination path of the desired knowledge.

The source node may periodically update the information along the spiral path, or work in a spontaneous mode that launch the spiral dissemination whenever the interested phenomenon is detected. To avoid redundant traffic, all sensor nodes will drop an advertisement or query packet unless it is newer than their local copy.

We developed SPSA to address the problem how every sensor node in the dissemination path selects the next hop so that the whole path approaches a spiral curve, assuming each nodes know the parameters of the spiral and the coordinates of the original node and all its one-hop neighbor nodes. An illustration of this problem is shown in Figure 1.

r_i: radius of the ith node
θ: spiral angle increment
d_i: distance between the hop node and the ideal spiral
h_i: hop from the ith node to the $(i+1)$th node
S: spiral path

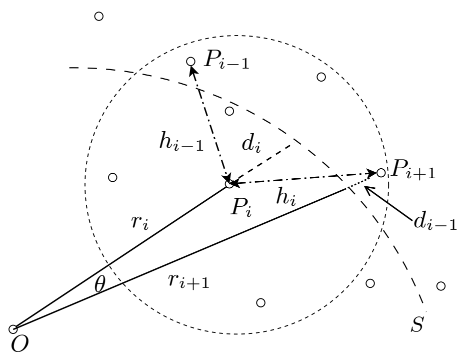


Figure 1: Spiral Dissemination Path Estimation

Let P_i denote the sensor node for the ith hop in a spiral dissemination path, O denote the original node which initiates the spiral, and $P_i^{(j)}$ denote the jth one-hop neighbor node, $j = 1, 2 \ldots, N$.

Let $\mathcal{D}(P_i)$, $\mathcal{A}(P_i)$, and $\mathcal{R}(P_i)$ denote the actual radius, the spiral angle of P_i, and the supposed spiral radius of P_i. Let $\mathcal{L}(P_i)$ denote the distance from P_i to its next hop on a ideal spiral, respectively. Note that the $\mathcal{R}(P_i)$ can be derived by (1) given $\mathcal{A}(P_i)$, and

$$\mathcal{L}(P_i) = \|\mathcal{R}(P_i) - \mathcal{D}(P_i)\|$$

. Let K_a denote the weight on the spiral angle and K_d denote the weight on the distance, where both K_a and K_d are constants.

This path search problem can be formulated to an linear programming (LP1) as follows:

$$\text{Max } \sum_{i=1}^{N} x_i (k_a \mathcal{A}(P_i) + \frac{k_d}{\mathcal{L}(P_i)})$$

subject to

$$\textstyle\sum_{i=1}^{N} x_i = 1 \qquad (a)$$

$$x_i = \begin{cases} 1 & \text{if } P_i \text{ is chosen} \\ 0 & \text{else} \end{cases} \quad i = 1, 2, \ldots, N. \quad (b)$$

$$x_i \leq I(\mathcal{A}(P_i) > \mathcal{A}(P_0)), \quad (c)$$
where $I(\cdot)$ is the indicator function

Instead of using the weighted sum of the interval spiral angle and the distance to the ideal spiral as the cost function, another linear programming (LP2) can be formulated by changing the cost function to the ratio of the above two terms. That is, LP2 can be written as

$$\text{Max } \sum_{i=1}^{N} x_i (\frac{\mathcal{A}(P_i)}{\mathcal{L}(P_i)})$$

subject to

$$\textstyle\sum_{i=1}^{N} x_i = 1 \quad (a)$$

$$x_i = \begin{cases} 1 & \text{if } P_i \text{ is chosen} \\ 0 & \text{else} \end{cases} \quad i = 1, 2, \ldots, N. \quad (b)$$

$$x_i \leq I(\mathcal{A}(P_i) > \mathcal{A}(P_0)),$$
where $I(\cdot)$ is the indicator function $\quad (c)$

In both LP1 and LP2, constraint (c) filters out all the neighbor nodes with spiral angle less than the current node, while constraint (a) and (b) limit that only one node can be chosen. In the cost function, we make a trade-off between the path advance and the spiral approximation. This trade-off is adjustable in LP1 by changing the values of K_a and K_d. Simulation shows that both LP1 and LP2 work very well. Thus, when evaluating other performances by simulation, we choose LP1 for SPSA and fix the weight values as $K_a = 1$ and $K_d = 2$. Figure 2 shows an sample path with boundary found by SPSA in a limited area. Note that when the path reaches itself in the boundary case, the forwarding action will stop, and a closed circle will be formed.

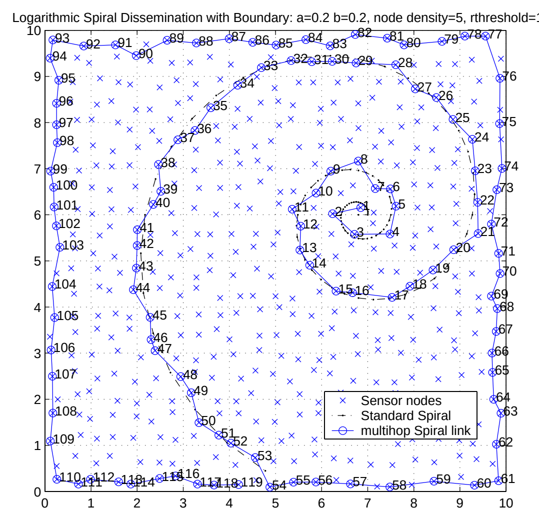


Figure 2: Spiral Dissemination Path with boundaries

As mentioned before, query messages are forwarded in the reversed spiral path, which employs the same SPSA algorithm except that the sign of b changes. Such setting guarantees that the intersection of the query path and the dissemination path. After receiving a query message, a sensor node will check the query with its local cache and its one-hop neighbors. If there is no match by timeout, the sensor node makes a local copy of the query and forwards the query to the next hop. Otherwise, the data and the location of the answering node are forwarded back to the sink node by greedy geographical forwarding.

The spiral dissemination achieves high energy efficiency and low traffic overhead at the price of relatively long delay and blind area inside the spiral path. Therefore, LSDD is not suitable for time-urgent applications. However, LSDD is versatile in that: 1)by adjusting b, the percentage of blind area is under control. Two extreme cases are a straight line ($b \to \infty$) and full blooding ($b \to 0$); 2)by incrementing θ_0 in successive disseminations, a spiral path can sweep the whole coverage over a controllable period and leave no blind area.

4. NUMERICAL ANALYSIS

Let l denote the arc length of a spiral path defined by 1. To simplify the expression, we set $\theta_0 = 0$ in the rest of this section. Thus

$$l = \frac{ae^{b\theta}\sqrt{1+b^2}}{b}. \tag{4}$$

Its coverage area S can be derived as

$$S = \int_{\theta \ominus 2\pi}^{\theta} \int r dr d\theta = \frac{a^2}{4b} e^{2b\theta}(1 - e^{-4b\pi}), \tag{5}$$

where

$$(\alpha \ominus \beta) = \begin{cases} \alpha, \text{ if } \alpha < \beta \\ \alpha - \beta, \text{ if } \alpha \geq \beta \end{cases}$$

Suppose that the node density is K nodes per unit area. Let N_c denote the number of sensor nodes in an area covered by a spiral path, and N_c can be estimated based on (5) as

$$N_c = KS = \frac{Ka^2}{4b} e^{2b\theta}(1 - e^{-4b\pi}). \tag{6}$$

Let N_s denote the number of sensor nodes used to construct a spiral, and N_s can be estimated based on (4) as

$$N_s = l\sqrt{K} = \frac{\sqrt{K}ae^{b\theta}\sqrt{1+b^2}}{b}. \tag{7}$$

Suppose that n nodes are covered by a spiral path. Let $N_c = n$, and substitute (6) into (7), we have

$$\begin{aligned} N_s &= l\sqrt{\frac{N_c}{S}} \\ &= \sqrt{\frac{1+b^2}{b(1-e^{-4\pi b})}} \cdot \sqrt{n} \\ &= c\sqrt{n} \end{aligned} \tag{8}$$

When b is fixed, c becomes a constant, thus $N_s \sim O(\sqrt{n})$. Therefore, the number of sensor nodes involved by LSDD is only as $O(\sqrt{n}$ on average, while full flooding involves every node.

Let S_f denote the coverage area of full flooding under a dense and uniform node distribution. S_f can be estimated as

$$S_f = N_c/K \tag{9}$$

The maximum radius of the flooding can be approximated by

$$R_f = \sqrt{\frac{S_f}{\pi}} = \sqrt{\frac{N_c}{K\pi}}. \tag{10}$$

Let γ denote the ratio of the flooding dissemination radius to the spiral dissemination radius, and γ can be estimated as

$$\gamma = \frac{R_f}{R_{sp}} = \frac{\sqrt{\frac{N_c}{K\pi}}}{ae^{b\theta}}. \tag{11}$$

Substituting (6) into (11),

$$\gamma = \sqrt{\frac{1-e^{-4\pi b}}{4\pi b}}. \tag{12}$$

For the convenience of readers, variables used in section III and IV are summarized in table 1.

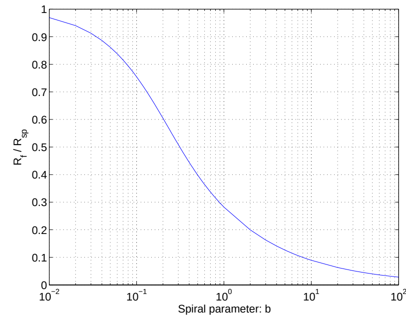


Figure 3: Ratio of the estimated dissemination radius between spiral and flooding

Table 1: Variables used in Section III and IV

P_i	the ith hop in a spiral dissemination path
$\mathcal{D}(P_i)$	actual radius of P_i
$\mathcal{A}(P_i)$	spiral angle of P_i
$\mathcal{R}(P_i)$	supposed spiral radius of P_i
$\mathcal{L}(P_i)$	ideal distance from P_i to its next hop
K_a	weight on angle
K_d	weight on distance
l	denote the arc length of a spiral path
K	node density
N_c	number of sensor nodes covered by a spiral path
N_s	number of sensor nodes in a spiral
S_f	coverage area of full flooding
R_f	The maximum radius of the flooding
γ	ratio of R_f to spiral dissemination radius

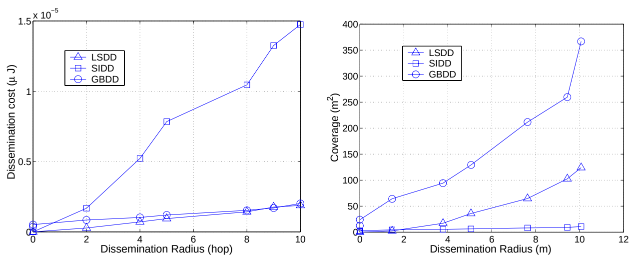
5. PERFORMANCE EVALUATION

All simulation tests are developed and carried out in MATLAB. In our simulation, the working field is a rectangular area divided into $L \times L$ unit square cells. The side length of each cell is d, which is normalized to 1 m in our simulation. Sensor nodes are uniformly distributed in each cell. Following the previous denotation, the node density is K nodes per unit cell. The spiral parameters are empirically set as $a = 0.1$, $b = 0.2$, and $\theta_0 = 0$. The effective radio range, R_t, is set equal to d. A Berkeley mote [14] is used as the prototype for the physical layer modeling of a sensor node. Therefore, the energy consumption in our simulation is measured as the current drawn from the battery. The current values in our results are converted to the fraction of the capacity of a battery, which is assumed 3000 mA. For the conversion between the current drawn rate and power, please reference to [15]. We assume that CSMA/CA is the MAC layer protocol and UDP is the transport layer protocol. Besides LSDD, two other data dissemination schemes are implemented as the control samples: sink initiated data dissemination (SIDD) and gossiping based data dissemination (GBDD). In SIDD, the sink node flood query messages and sensor nodes wait for query passively; sensor nodes forward the data back by greedy geographic forwarding if there is a matched query. In GBDD, both sink node and sensor node use gossiping routing to forward the query and sensed data.

The above settings make it convenient to scale our simulation to practical scenarios by choosing appropriate L, d, K

and R_t. For example, when $L = 20$, $R_t = d = 100$ m, $k = 5$, our simulation is equivalent to a sensor network 2000 sensor nodes uniformly deployed within a 4 km^2 square area. We only count the energy consumption and traffic overhead for data dissemination and query, and omit those for other purposes like neighborhood detection or sensed data transmission. All simulation results are averaged over 10 runs on different network topologies.

First, we compare the energy consumption of three schemes under the dissemination radius constraints. The simulation settings are $L = W = 10$, $K = 5$, $d = R_t = 1$. As shown in Figure 4(a), all three schemes consume more energy given longer radius. However, when the radius is larger than 1, SIDD consumes more than LSDD and GBDD, the difference increases fast at energy increases, and LSDD consume less energy than GBDD almost all the time. Also, Figure 4(b) shows that the LSDD expands much faster than both SIDD and GBDD such that it always covers the largest area for any given radius.



(a) Transmitted Messages v.s. Dissemination Radius (b) Coverage v.s. Dissemination Radius

Figure 4: Energy efficiency tests

Next, we compare the search costs between LSDD, SIDD, and GBDD. Here the search refers to as the energy consumed in path setup for either dissemination or query. After a path is constructed, the traffic incurred by data transmission will not be counted. The simulation settings for these tests are the same as previous. Figure 5 shows the relationship between average search costs and the source-sink distance for all three schemes. SIDD and GBDD exhibit similar performance, and GBDD costs a little less at large distances. When the distance is smaller than 4, both the SIDD and GBDD cost less than LSDD. When the distance is larger than 4, the search costs of both grow much faster than that of LSDD, which suggests that LSDD fits better in large-scale WSNs. For example, the search costs of SIDD and GBDD are both about six times higher than that of LSDD when the distance is larger than 15.

We evaluate the scalability of LSDD, SIDD, and GBDD by applying them to WSNs with different sizes and node densities. As summarized in the legend of Figure 6, there are 3 settings for each scheme. Several interesting facts are illustrated in this figure: 1)the search cost of LSDD is one or two order of magnitude lower than that of SIDD or GBDD in all settings; 2)SIDD and GBDD work out the similar results; 3)the effects of network size and node density on LSDD are much less than those on SIDD or GBDD—all curves of LSDD are very close while there are huge differences between the curves of SIDD(or GBDD) for different settings. All the above indicates the advantage of LSDD over the other two schemes on scalability. Figure 7 compares the total search

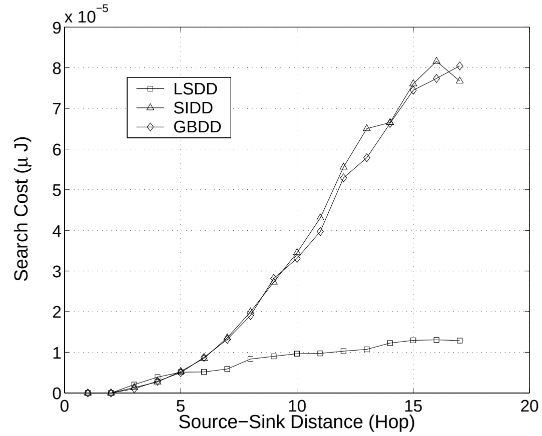


Figure 5: Average Search Cost Comparison

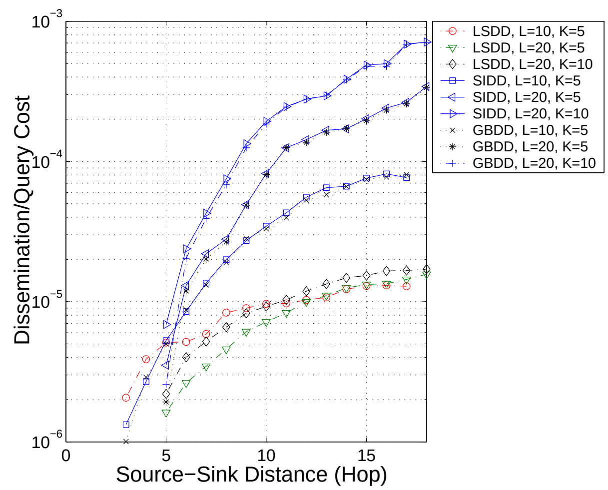


Figure 6: Scalability Comparison for single sink node case

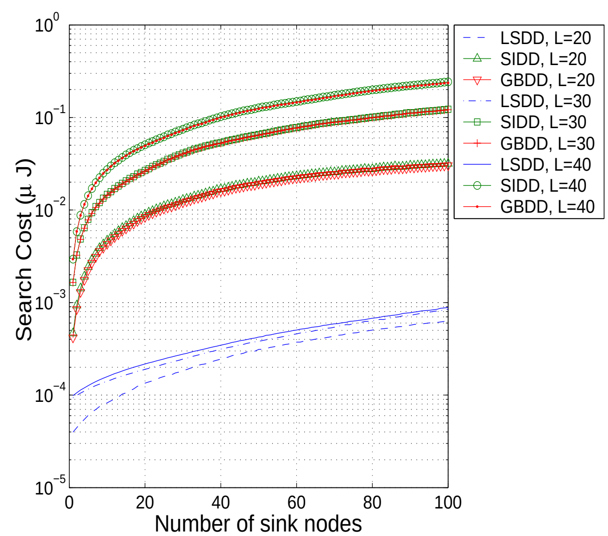


Figure 7: Search cost comparison with multiple sink nodes

costs of LSDD, SIDD, and GBDD with multiple sink nodes, which can be regarded as an extended test for the scalability of LSDD. The simulation settings are the same as the single case but with more than one sink nodes placed in the working field. It is clear that again LSDD is the most efficient among all three alternatives, which further confirms that LSDD is more suitable for large-scale WSNs or WSNs with high node density. To examine the performance of LSDD

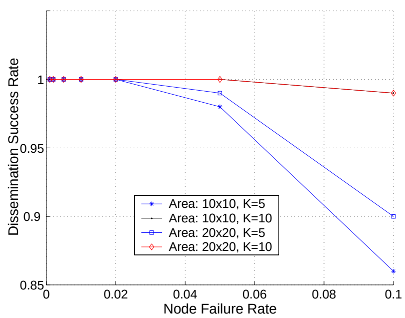


Figure 8: Fault tolerance test

in a faulty WSN, the node failure rate is added as a new parameter. First, a data dissemination is performed when all nodes are turned on. The last hop along the dissemination path (usually on the boundary) is regarded as the target node. Then some nodes are drawn uniformly as failure nodes and are turned off. Another data dissemination is performed to see if the target node can be reached. For each node failure rate, the success percentage is calculated over 100 tests. As shown in Figure 8, this test is performed under 4 different network settings. As expected, the success percentage is negatively proportional to the node failure rate, and positively proportional to the node density. When the node failure rate is lower than 0.1, the success percentage is higher than 85 percents in all settings. It indicates that LSDD is very robust to the node failures, and the negative effect of failure nodes on LSDD decreases as a WSN becomes larger and/or denser.

6. CONCLUSION

In this paper, we proposed a novel data dissemination scheme logarithmic spiral data dissemination (LSDD). By imitating a natural evolution of the spiral to facilitate the data dissemination and data query in WSNs, LSDD improves the performance-resource ratio in stable structure and achieves high energy efficiency, low traffic overhead, and flexible scalability. As shown in our simulation, LSDD performs much better than flooding-based schemes with regard to energy efficiency, scalability, workload capacity, and fault tolerance. Our current work shows that LSDD, even though still in a developing stage, stands for a promising way of data dissemination as a geographic-based routing protocol enhanced by spiral trajectory as global knowledge,

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