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Fault-resilient sensing in wireless sensor networks

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Abstract

Research on wireless sensor networks (WSNs) has received tremendous attention in the past few years due to their potential applications and advances in the VLSI design. In WSNs with tiny sensors, mobility of a sink may provide an energy efficient way for data dissemination. Having a mobile sink in WSN, however, creates new challenges to routing and sensor distribution modeling in the network. In this paper, based on clustering and routing optimization algorithms, we propose a new scheme called K-means and TSP-based mobility (KAT mobility). After clustering the sensor nodes, the proposed method navigates the mobile sink to traverse through the cluster centers according to the trajectory of an optimized route. The mobile sink then collects the data from sensors at the visited clusters. Simulation results have demonstrated that the proposed scheme can provide not only better energy efficiency as compared to those obtained by conventional methods which assume random waypoint for the mobile sink, but also fault-resilience in case of malfunctions of some sensors due to attacks.

Keywords: Wireless sensor networks; Fault-resilient; Data collection; Mobility; Clustering

1. Introduction

A wireless sensor network consists of potentially thousands of tiny wireless devices capable of taking various environmental measurements, such as temperature, humidity, vibrations, and luminance. Such immensity of sensing has been promoting a plethora of emerging applications in areas ranging from homeland security, healthcare, to the military. Recent advances in MEMS (Micro-Electro-Mechanical Systems) and nanotechnology have fueled the development of super tiny wireless sensors such as "smart dust" devices [1,2] for sensing and collecting data. Networking and communications among these sensors in disseminating sensed data in an efficient, secured, and fault-tolerant manner is a major challenge. This is attributed to limited computational resources and power of the sensors, limited bandwidth and open channel communications within the network, and collaborative and distributive connectivity of a vast number of sensors. Power consumption is usually dominated by signed transmissions, and it is thus critical to design an energy efficient data collection scheme. In general, sensors with different capabilities are deployed to collect data in a hierarchical approach [3]. In particular, a data collection node referred to as a sink, which is connected to an existing wired network and/or is more resourceful, is used to collect/gather the measurements "sensed" by the sensors in a region. Sensors work together to disseminate data to a sink by forwarding/relaying each others data, more often, in a multi-hop fashion. Since this mode of operation imposes large communication load on sinks, sinks are provisioned with more resources, e.g., they are rechargeable and programmable. Mobile sinks are especially agile in gathering sensed data from sensors. Such a mobile sink is referred to as a "MULE (Mobile Ubiquitous LAN Extension)"; readers may refer to [4] for the basic concept of MULEs. Mobile sinks move randomly in the area of deployment of a sensor network; they pick up data from sensors only when they are within the closest

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range. The primary advantage of deploying mobile sinks is energy saving because mobile sinks are versatile and can communicate with sensors as often as only required.

Routing of mobile sinks plays a significant role in achieving the effectiveness of the data collection system. As it is pointed out in [5], if a sink is given many roles, it will become a very attractive target for attacks. Therefore, routine trajectories, which are following the same path with a fixed speed, should be avoided. Moreover, sensors may be compromised or sabotaged for various reasons. It remains a challenge to design the migration route of mobile sinks in a way not only to minimize the consumed energy on sensors but also to make them resilient to attacks, in particular those that annihilate sensors. This paper takes this challenge of determining the trajectories of mobile sinks in the wireless sensor network that is fault-resilient.

In this paper, we propose a mobility model of mobile sinks that can efficiently collect usable sensed data in a wireless sensor network, even if some sensors are compromised or annihilated. Our proposed scheme consists of two modules: the K-means clustering algorithm and the approximate solution for TSP (Traveling Salesman Problem). Sensors are first clustered by using the K-means clustering algorithm, from which the cluster centers are determined as anchor points. The migration route of mobile sinks is determined as an approximate solution of TSP. Accordingly, our new mobility is referred to as the **KAT** mobility (the **K**-means **a**nd **T**SP based mobility).

The remainder of this paper is organized as follows. Section 2 describes some related works. Section 3 presents the system model and an overview of the proposed algorithm. Simulation results are presented in Section 4. Finally, concluding remarks are given in Section 5.

2. Related works

Several data gathering schemes in WSNs have already been proposed [6–11], that can be categorized into flat and hierarchical topologies. In general, the hierarchical topology adopts clustering such as LEACH [12] and PEGASIS [13] to fulfill various functionalities of WSNs. For example, Ding et. al. applied the Ant Colony Optimization (ACO) [14,15] to determine low-cost chains from a sink to every sensor by optimizing the cluster centroids. In this paper, we focus on mobile sinks where sinks move around a monitoring area to collect data.

The three-tier architecture for deploying mobile sinks (MULEs) in a sparse sensor network was first reported in [4]. Fig. 1 denotes the abstraction of three-tier architecture. Sensors belong to the lower tier provide the sensed physical measurements. Access-points belong to the upper tier command the mobile sinks to start gathering information. They can be remotely controlled from a distant place with the Internet connectivity. Thus, mobile sinks belong to the middle-tier, and they relay the gathered data from the sensors to access-points by maneuvering through areas where sensors are scattered.

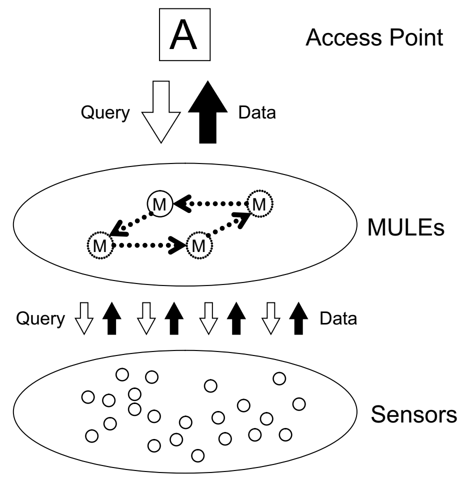

Fig. 1. Three-tier architecture.

Several applications of mobile sinks have already been reported. For example, in ZebraNet [16], sensors, acting as mobile sinks, are attached to animals (zebras), which gather the sensed physical data by exploiting the natural motion of the animals. Owing to the unpredictable movements of the animals, it is difficult to control its motion as a mobile sink. Wang et.al. [17] attempted to predict movements of a sink by integer linear programming which, however, incurs a tremendous computational overhead. Such method is suitable for applications which can afford off-line computation, such as initiating the route of a sink. It is, however, too computational intensive for re-routing a sink in real-time. The use of multiple controlled mobile sinks was investigated in [18], wherein the proposed load balancing technique indicates the potential of power saving. Our work focuses on exploiting mobility to achieving graceful performance resilient and tolerant to faulty and sabotaged sensors.

Reference [19] provides a survey on exploiting mobility in ad-hoc networks, and more recently, advanced research works have been reported in [20–23]. However, in the context of sensor networks, if sinks are mobile, no immediate end-to-end connection between two communicating nodes can be established. Consequently, it is difficult to apply these results on ad-hoc networks directly to sensor networks. According to some basic experiments by changing mobile sink parameters (e.g. arrival rate), reported in [4,24], the random walk mobility and other existing mobility models achieved almost the same performance in terms of the data collecting rate and latency. Yet, several open issues regarding the mobility of the energy efficient data collection remain.

In [25], performance of the data mobile sink model using Mica2 Motes with the TinyOS system in urban environments was investigated, but this work mainly studied the mobile sinks speed. The contributions of our proposed work are two-folded: (1) a new migration routing of mobile sinks is proposed to enhance the fault-resilient ability and the efficiency of the wireless sensor network in data collection, in which a new performance metric has been introduced to quantify the efficiency of the system; (2) to delineate the performance differences of mobility models through extensive and detailed simulations of the sensor network equipped with sensor-specified protocol and battery consumption model.

3. Data collection

We assume that an administrator distributes sensors to monitor the targeted area, and sensors are scattered at random positions and do not move afterwards. The administrator is assumed to be able to localize the actual coordinates of scattered sensors, which acquire the monitored data at their own positions. The amount of data which they can acquire per unit time is fixed, and buffers in which data can be stored temporarily are equipped. The model of data collection follows those surveyed in the "Query Processing System" [26], which also includes Directed Diffusion [27], the most popular protocol stack used in sensor networks [8,28]. We adopt the One Phase Pull model [29] because it is the simplest scheme among the versions of Directed Diffusion. For illustrative purposes, consider the sensor network consisting of one sink and six sources (seven nodes in total), as shown in Fig. 2. In this example, the sink node collects the data monitored at a certain source node, labeled "source". The other five sensors function as relay nodes in this case. Each sensor maintains a symmetric connectivity with his neighbors, as shown in Fig. 2(a). At first, the sink sends a query, referred to as an interest message, to the network. These interest messages are flooded through the network (Fig. 2(b)). That is, the sensors act as relays forwarding the interest message towards the source node. In reply to the interest message, the source node sends a data message which is composed of the buffered data.

Data messages are sent only through the route(s) in which the interest message traversed (Fig. 2(c)). As a result, sensors "construct" their networks by themselves, and the sink is able to collect the monitored data. Fig. 2(d) shows an example of the path, but this is the shortest case, since we can consider the many paths by using Directed Diffusion. Even though the sensed data may be out of the radio range of the sink, they can be relayed to the sink in the multi-hop fashion as described in Fig. 2.

3.1. Mobile sink

In some strategic scenarios such as a battlefield, only mobile sinks are allowed to identify and revoke compromised sensors, and to collect data from sensors [5]. Since a sink possesses this kind of privilege, it is essential to safeguard the sink from attacks. One of the realistic solutions is by means of random trajectories [30]. By moving randomly within a monitoring area and obtaining the data from sources at random locations, it is possible to reduce the threat of attacks. However, random mobility may compromise the efficiency of data collection. Therefore, we need to devise the migration trajectories for sinks with efficiency yet preserving their random behavior. This means that the mobile sinks have random speed so that the arrival timing at each centroid can not be easily inferred by attackers. Meanwhile, the change of trajectories depends on the sensors that survived the attack. Furthermore, sensors located in combat areas may be destroyed or malfunction. In these scenarios, mobile sinks should be adopt to the environment, and reprogram their trajectories accordingly.

3.2. Conventional mobility models

For illustrative purposes, we make the following assumptions:

- The monitoring area is $5 \times 5\ \text{km}^2$.
- The number of sensors is 200.
- The positions of mobile sinks are initialized at $(0,0)$, as shown, for example, in Fig. 3(a).

In the event of an attack, the geographical area affected by the attack is a square in which x is between 0 and 1.5 km, and y is between 1.5 and 3.0 km, as shown by the box of red lines in Fig. 3(b).

In this paper, we examine the following two conventional mobility models: the random waypoint mobility which is described in the following, and the deterministic mobility which can be considered as the simplest mobility model. These mobility models are specified by three parameters: *minspeed*, *maxspeed* and *pausetime*.

3.2.1. Random waypoint mobility

The random waypoint mobility [31] is a widely used mobility model [19], in which a mobile sink chooses a

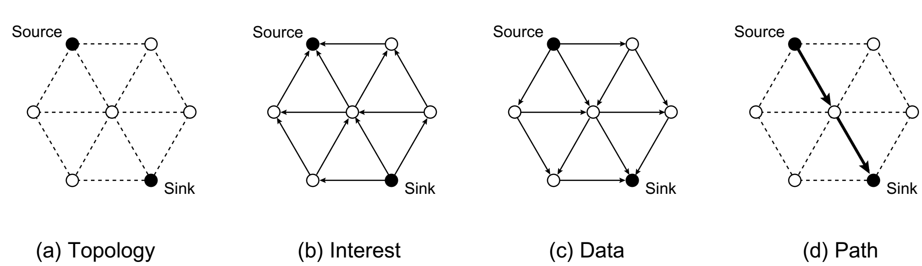

Fig. 2. Directed Diffusion (one phase pull) [27].

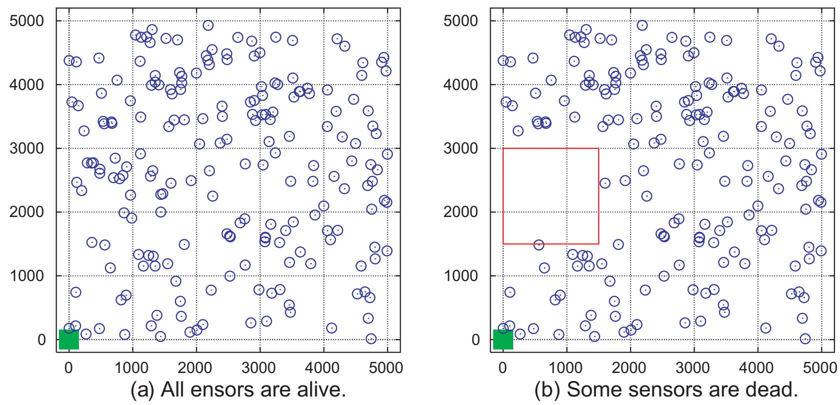

Fig. 3. Sensor placements.

random destination in the monitoring area, and moves from one waypoint to the next until it reaches the chosen destination. The speed of the mobile sink from one waypoint to another is selected each time uniformly between [*minspeed*, *maxspeed*]. Fig. 4(a) shows an example of the random waypoint mobility. Note that the random walk mobility, which used in prior work [4,24], is similar to the random waypoint mobility especially when the pausetime is zero [19].

3.2.2. Deterministic mobility

Deterministic mobility refers to the fact that the trajectories are deterministically selected. For example, as shown in Fig. 4(b), the four deterministic destinations of a mobile sink are set at the four corners of a monitoring area. The sink chooses the speed in the same way as that of the random waypoint mobility; i.e. the mobile sink travels from one destination to another at a speed selected from a uniformly distributed random number. As reported in [5], we can think of various types of trajectory (e.g., triangle, ellipse, etc.) as the deterministic mobility. Here, we simply adopt the square trajectory in proportion to the monitoring area.

3.3. Proposed KAT mobility

The trajectories of a mobile sink across the whole range of the monitoring area shown in Fig. 4 by using the two models described in Section 3.2. However, sensors are randomly scattered with different densities; some areas are sparse, some are dense as shown in Fig. 3(a). In addition to the underlying nature of scattered sensors, when the events of compromised sensors are invoked artificially, the sensors are distributed disproportionately. From the point of view of energy efficiency, if the administrator can control mobile sinks like a pilotless drone plane, the trajectory of mobile sinks can be optimized with relation to the distribution dynamically. Consequently, we propose the KAT mobility for a mobile sink, which is based on the clustering algorithm [32] and the route optimization [33]. Denote $\boldsymbol{x}$ as a sensor, represented by a p-dimensional vector (i.e. location of the sensor), and $\boldsymbol{y_i}$ ($i = 1,\ldots,K$) the i-th sink (in the context of clustering, the i-th cluster).

3.3.1. Clustering algorithm

Clustering is a procedure to divide the set U of sensors into the K clusters $C_1,\ldots,C_K$. Let total number of sensors be $N = |U|$; in general $N \gg K$. With respect to clustering, a sink is in rough proximity of a group of sensors [34], and thus the cost of clustering can be evaluated as an approximation error $d(\boldsymbol{x},\boldsymbol{y_i})$ between a sink and sensors. While dividing the set U into the K clusters, the affiliation of sensor $\boldsymbol{x}$ with the i-th cluster C_i is represented by

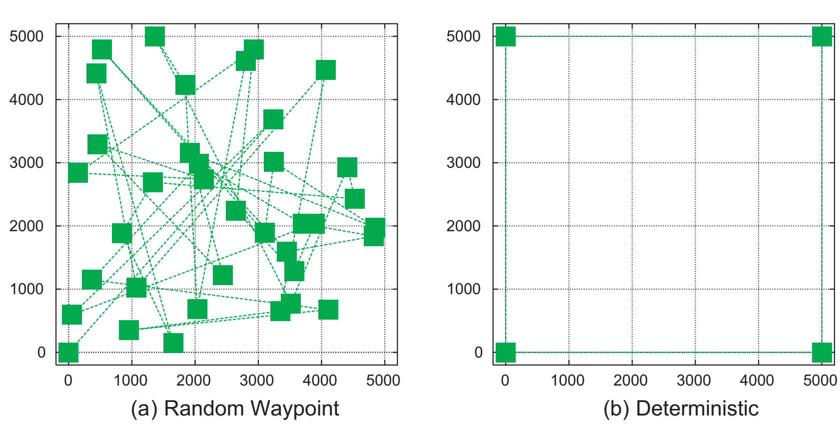

Fig. 4. Conventional mobility models.

$$v_{x,i} = \begin{cases} 1 & x \in C_i \\ 0 & x \notin C_i \end{cases}. \tag{1}$$

The sum of approximation errors is

$$D = \sum_{x} \sum_{i=1}^{K} \{v_{x,i} \cdot d(x, y_i)\}. \tag{2}$$

The final target is to configure C_i such that D is minimized. In this paper, we set $p = 2$ because the coverage area is 2-dimensional, and position of each sensor as well as the sink is represented by X–Y coordinate.

In K-means method [35], the cost can be evaluated as the Euclidian-distance between the sensor x and the i-th sink y_i.

$$d(x, y_i) = \|x - y_i\|^2. \tag{3}$$

We propose to minimize the energy of the actual communications by clustering to decrease the consumption of each sensor's battery, which is proportional to $d(x,y_i)$ [12].

3.3.2. Route optimization

The route optimization of mobile sinks is analogous to the TSP (Traveling Salesman Problem). If the sink is mapped to the traveling salesman, and each sensor to a city, the route optimization of the mobile sink to visiting every sensor once and just once is equivalent to finding the shortest trip of the traveling salesman to visiting every city once. Ultimately, when the number of sensors equals to the number of clusters, a mobile sink(x) will visits all sensors(y_i), in which case the distance $\forall i\ d(x,y_i)$ becomes zero. However, the TSP is NP-hard [36] so that finding the optimal tour is computationally infeasible. Fortunately for sensor networks, sensors can communicate with each other, and mobile sinks do not need to visit all sensors. After clustering the sensors as described in Section 3.3.1, we need only to optimize the routes among cluster centroids. Using the same expression formula discussed in [37], our goal is to find the ordering π of the centroids that minimizes the tour lengths

$$\sum_{i=0}^{K-1} d(y_{\pi(i)}, y_{\pi(i+1)}) + d(y_{\pi(K)}, y_{\pi(0)}), \tag{4}$$

where the initial position of each mobile sink is y_0. We implemented a simple local search algorithms called 2-Opt and *Or*-Opt, which is based on the heuristics modification of a current solution to TSP. Readers are referred to the references [37,33] for details.

3.3.3. Proposed procedure

Our proposed KAT mobility scheme consisting of two modules are overviewed in Fig. 5. Determination of the trajectory of a mobile sink can be summarized as follows:

Step 1. Initialize the position y_i randomly, $t = 0$.

Step 2. Define the threshold "Thr", as the stopping criterion, for the following iterative process.

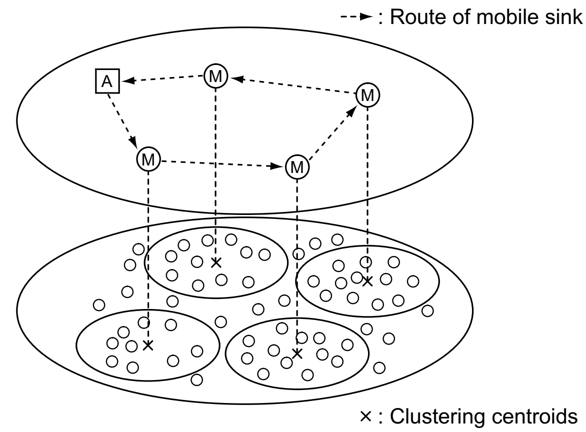

Fig. 5. Overview of proposed modules.

(1) When $d^{(t)}(x,y_i) < d^{(t)}(x,y_j)$, $\forall j \neq i$, assign a sensor $x \in C_i^{(t)}$.

(2) Set sinks position to the center of each cluster.

$$y_i^{(t+1)} = \sum_{x \in C_i^{(t)}} x$$

(3) Calculate the sum of errors $D^{(t+1)}$ at time $t + 1$, and if

$$\frac{|D^{(t+1)} - D^{(t)}|}{D^{(t)}} > \mathrm{Thr}$$

is true, we can update t and continue this iteration. Otherwise, the final centroid is set to $y_i^{(t+1)}$ and break this iteration.

Step 3. Minimize the tour length by using the 2-Opt and *Or*-Opt algorithm, and find that the local optimal TSP solution which is the ordering π of the centroids.

Consequently, mobile sinks trace the trajectory of the local optimal TSP solution. Our proposed method assumes that each mobile sink knows *a priori* the positions of its member sensor nodes. The mobile sink may lose communications with its faulty or sabotaged member sensors, in which case the sink can stay at the centroid point of its cluster and discover broken sensors by applying the statistical anomaly detection [38,39]. The trajectory of the sink can then be recalculated/updated as soon as the sink reaches the access point. Fig. 6(a) shows an example of the migration route of a mobile sink. With compromised sensors, the route of the sink obtained (optimized) by the proposed procedure is shown in Fig. 6(b).

4. Evaluation

We have used the Qualnet simulator (Ver. 3.9.5) and its extension [40,41] to study and demonstrate the effectiveness of KAT mobility for data collection in a wireless sensor network.

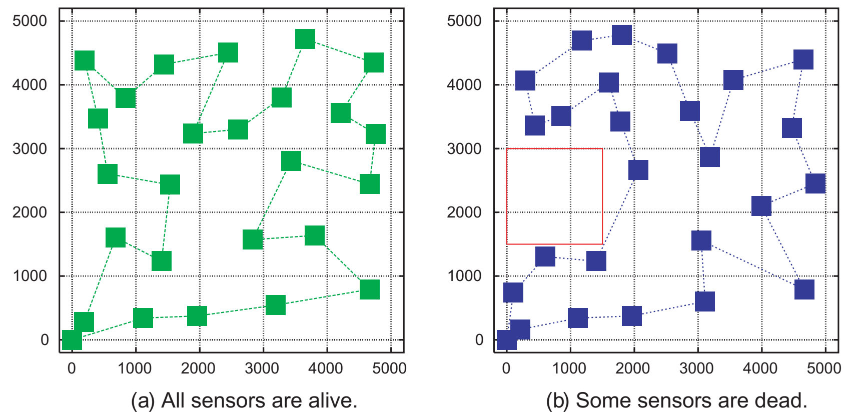

Fig. 6. KAT mobility.

4.1. Simulation setup

Fig. 7 shows an overview of the sensor and mobile sink architecture. A sensor node functions as a source, and a mobile node functions as a sink. Both the sensor node and the mobile sink node perform according to a sensor-specified network protocol. The energy consumption of a sensor node uses the LCP-based battery model, and the mobile sink node travels using the three mobility models described in previous section.

4.1.1. Network model

We adopt a layered architecture similar to that of the TCP/IP protocol stack. The application and the network layer are described in Section 3. The link layer and the physical layer meet the global standard IEEE 802.11b in wireless networks. The transmission rate is 11 Mbps and the corresponding range is about 272 m, which is computed by the formula of the free space propagation loss from receive sensitivity and transmission power.

4.1.2. Battery model

In this paper we use the analytical high-level battery model proposed in [42,43], which is widely used in sensor network simulations [44–46]. This model assumes that the LCP (load current profile) is approximated by an N-step staircase function. Here, t is the time that the battery has been discharged for, and the battery charge consumption $p(t)$ is described by

$$p(t) = \sum_{k=0}^{N-1} I_k \cdot F(t, s_k, s_k + \delta_k, \beta) \tag{5}$$

where I_k is the k-th LCP, and s_k and δ_k denote the start time and the duration of the k-th step in LCP, respectively. Further, β is a constant and F is the non-linear function defined as:

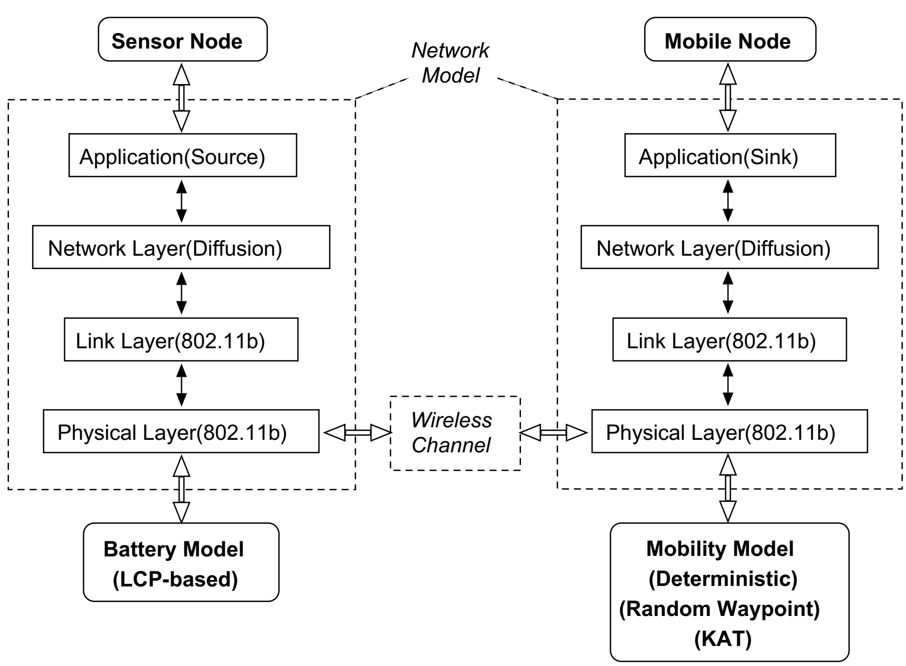

Fig. 7. Sensor node and mobile sink node architecture.

$$F(x,y,z,\beta) = z - y + 2\sum_{m=1}^{M} \frac{\exp\{-\beta^2 m^2 (x-z)\} - \exp\{-\beta^2 m^2 (x-y)\}}{\beta^2 m^2} \quad (6)$$

where M is the censored order. If the capacity of the battery is α, then the remaining energy is $\alpha - p(t)$. Following [47], the two constant parameters are as follows:

$\alpha = 40,375, \quad \beta = 0.273.$

We have simulated the Compaq Itsy Pocket Computer [48,49], equipped with an Orinoco wireless card. This card consumes 805 mW in the listening mode, 950 mW in the receiving mode, and 1,600 mW in the transmitting mode; these parameters are the same as used in [50].

4.2. Parameter settings

The simulation time is fixed to 30 min and the area is the 5×5 km^2 square field. In this area sensors are randomly placed and then remain fixed in their respective positions. Mobile sinks are first placed in zero point and moved according to the sensor mobility. The mobility schemes are described in Sections 3.2 and 3.3. The mobile sinks velocity varies from 10 m/s to 30 m/s randomly, and the pause time is 20 s. Each sensor is equipped with a buffer of 10 MB, and can generate a constant rate of data of 512 B/s. When a mobile sink transmits the interest message and once a sensor receives it, then the sensor immediately transmits the data message, which is held in its buffer. The results presented were averaged over ten random simulations with different seeds.

4.3. Performance metrics

We are concerned with how much data the system can collect. The average received bytes R of the data collection system per device (sensor, mobile sink) is defined by

$$R\ [\mathrm{KB}] = \frac{(\text{Received Bytes by all mobile sinks})}{N \times M}, \quad (7)$$

where N is the number of all sensors, and M is the number of mobile sinks. R means the volume of traffic per device. Another relevant parameter is the consumed energy of the system. The average consumed energy C of the data collection system normalized by the number of mobile sinks is defined as

$$C\ [\mathrm{mWhr}] = \frac{(\text{Consumed Energy by all sensors})}{M}. \quad (8)$$

Note that only a mobile sink can send a query request to sensors. Finally, we introduce the following metric E to quantify the efficiency of the system:

$$E\ [\mathrm{KB/mWhr}] = \frac{R}{C} = \frac{(\text{Received Bytes by all mobile sinks})}{(\text{Consumed Energy by all sensors}) \times N}. \quad (9)$$

That is, this metric indicates the amount of data collected from one sensor per unit energy. Besides, since the number of mobile sinks M has no direct effect on E, this becomes significantly useful for the evaluation of the data collection system, in case of wireless sensor network.

4.4. Experimental results

Fig. 8 shows the performance comparisons among the three mobility models, when the number of mobile sink is 1 ($M = 1$) and the number of clusters is 10 ($K = 10$). In the deterministic mobility, the average efficiency increases in proportion to the number of sensors. This is because more data could be collected through easily constructed relayed paths, due to the increase in number of sensors. In the random waypoint mobility, the average efficiency also increases proportionally. Positioning of more mobile sinks close to sensors in the sensing area produces considerable improvement. The KAT mobility takes into account the closest position to sensors. From Fig. 8 we can see that when the

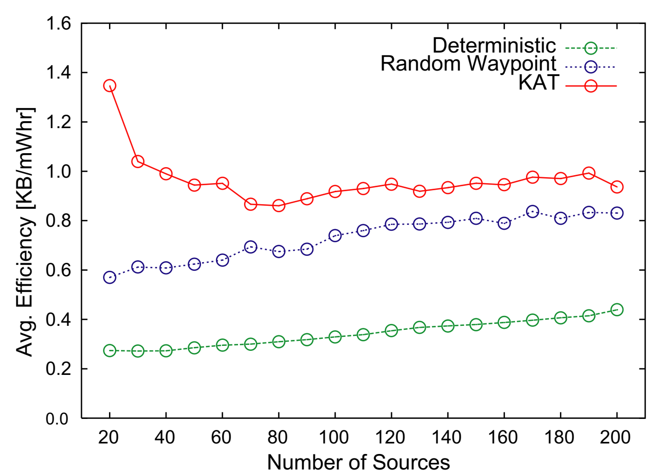

Fig. 8. Performance comparisons among the three mobility models.

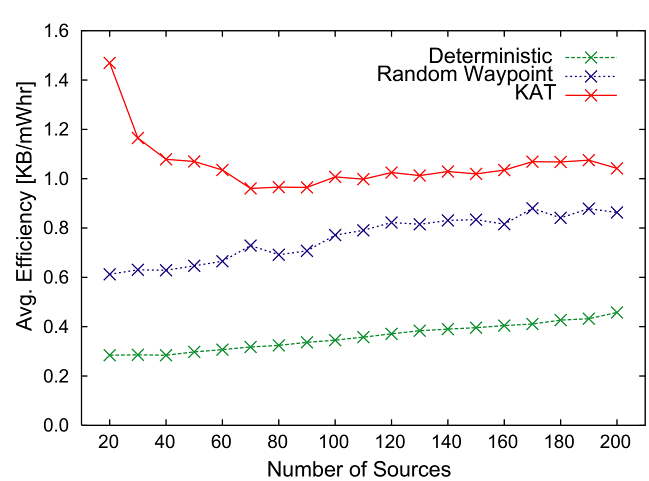

Fig. 9. Performance comparisons among the three mobility models when sensors in the given area are dead.

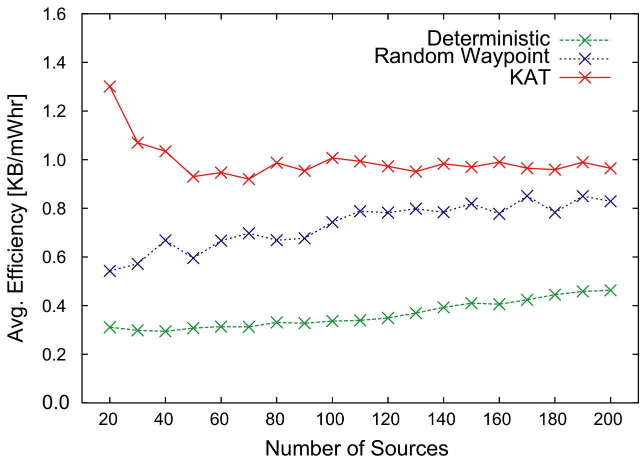

Fig. 10. Performance comparison with dead sensors (1% dead).

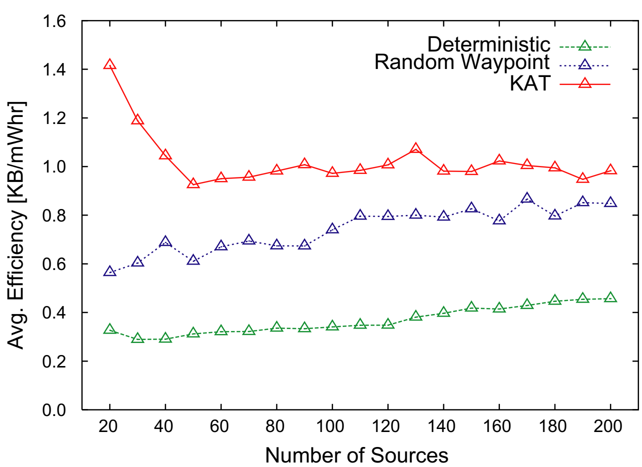

Fig. 11. Performance comparison with dead sensors (5% dead).

number of sources are small (e.g., from 20 to 60), KAT mobility provides greater efficiency compared to the deterministic mobility and the random waypoint mobility. This is because the sensors are distributed sparsely. In these cases, the conventional mobility models have difficulty in finding sensor nodes for path connectivity and therefore, KAT mobility performs the best among the three mobility schemes.

When some sensors are dead in a certain area, due to fault devices or attacks, the trajectory of the KAT mobility dynamically changes, as mentioned in Section 3.3. The trajectories obtained by the conventional methods remain the same. Fig. 9 shows the performance comparisons among three mobility models with dead sensors. Again, as expected, the proposed scheme is significantly more efficient than the conventional methods.

Next, we assumed when some sensors are dead randomly in the sensing area. This for example could be the case when some sensor nodes have insufficient resources or affected by attacks. It is proved again that the trajectory of the KAT mobility changes dynamically. Figs. 10–12 show the average efficiency when the percentage of sabotage sensors are 1%, 5% and 10%, respectively. The performance differences between our proposed and the conventional methods are significant. These simulations have been demonstrated the robustness of KAT mobility against faulty sensors.

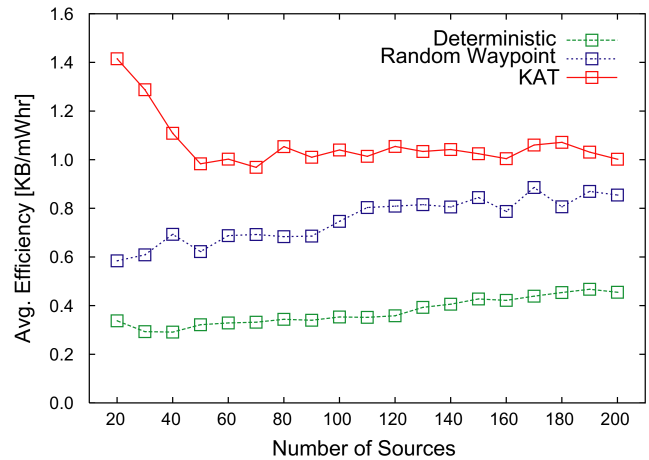

Fig. 12. Performance comparison with dead sensors (10% dead).

5. Conclusion

In this paper, a new data collection scheme for wireless sensor networks has been proposed. In this scheme, in addition to normal sensor nodes, some mobile sinks are also assumed. Mobile sinks use a certain mobility pattern in the sensing area. The novelty of the proposed scheme in comparison with the conventional schemes is that in the proposed scheme the mobile sinks could be considered as independent sensors from regular sensor nodes, and therefore they can be recharged and reprogrammed to acquiesce to the updated trajectory. The trajectory of the migration of a sink is assumed random in order to mitigate malicious attacks. Realizing the fact that the conventional random waypoint mobility would not necessarily be energy efficient, in the proposed KAT mobility scheme we use the K-means clustering algorithm and the TSP-derived migration route for the mobile sinks. The tradeoff between the throughput and energy consumption is considered as the efficiency metric in our evaluation. Meanwhile, the proposed KAT mobility can calculate the optimal route for the sink to circumvent the damaged area or malfunctioned sensors caused by attacks while still preserving its random behavior, i.e., the mobile sinks move at random speeds so that the arrival timing at each centroid cannot be easily inferred by attackers. Simulation results demonstrated that the proposed scheme can provide better energy efficiency and fault-resilience compared with conventional methods that assume random waypoint model for the mobile sink. Proper distribution of sensors may further improve the proposed scheme by assigning the appropriate number of clusters and number of mobile sinks needed. In addition, self-regulating technique [51] for assuring service level can also be combined with the proposed method to provide a better and practical solution. These are left as our future research endeavor.

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References

[1] V. Hsu, J. Kahn, K. Pister, Wireless communications for smart dust, in: UC Berkely Electronics Research Laboratory Memorandum M98/2, 1998, pp. 168–171.

[2] J. Kahn, R. Katz, K. Pister, Next century challenges: mobile networking for smart dust, in: Proc. of ACM Int'l. Conf. on Mobile Computing and Networking (MOBICOM 1999), 1999, pp. 271–278.

[3] I. Stojmenovic, Handbook of Sensor Networks Algorithms and Architectures, Willy InterScience, 2005.

[4] R. Shah, S. Roy, S. Jain, W. Brunette, Data mules: modeling and analysis of a three-tier architecture for sparse sensor networks, Ad Hoc Networks 1 (2–3) (2003) 215–233.

[5] W. Zhang, H. Song, S. Zhu, G. Cao, Least privilege and privilege deprivation: towards tolerating mobile sink compromises in wireless sensor networks. in: Proc. of the Sixth ACM Int'l. Symp.Mobile Ad hoc Netw. Comput.(MobiHoc 2005), 2005, pp. 378–389.

[6] I. Akyildiz, S. Weilian, Y. Sankarasubramaniam, E. Cayirci, A survey on sensor networks, IEEE Commun. Mag. 40 (8) (2002) 102–114.

[7] I. Akyildiz, S. Weilian, Y. Sankarasubramaniam, E. Cayirci, Wireless sensor networks: a survey, Comput. Netw. 38 (4) (2002) 393–422.

[8] J. Al-Karaki, A. Kamal, Routing techniques in wireless sensor networks: a survey, IEEE Trans. Wirel. Commun. 11 (6) (2004) 6–28.

[9] K. Akkaya, M. Younis, A survey on routing protocols for wireless sensor networks, Ad Hoc Netw. 3 (3) (2005) 325–349.

[10] I. Stojmenovic, Handbook of Sensor Networks Algorithms and Architectures, John Wiley & Sons, 2005.

[11] R. Rajagopalan, P. Varshney, Data-aggregation techniques in sensor networks: a survey, IEEE Commun. Survey Tutorial 8 (4) (2006) 48–63.

[12] W. Heinzelman, A. Chandrakasan, H. Balakrishnan, An application-specific protocol architecture for wireless microsensor networks, IEEE Trans. Wirel. Commun. 1 (4) (2002) 660–670.

[13] S. Lindsey, C. Raghavendra, K. Sivalingam, Data gathering algorithms in sensor networks using energy metrics, IEEE Trans. Parallel Distrib. Syst. 13 (9) (2002) 924–935.

[14] M. Dorigo, C. Blum, Ant colony optimization theory: a survey, Theor. Comput. Sci. 344 (2–3) (2005) 243–278.

[15] O. Cordon, F. Herrera, T. Stutzle, A review on the ant colony optimization metaheuristic: basis, models and new trends, Mathware & Soft Computing 9 (2–3) (2002) 141–175.

[16] P. Juang, H. Oki, Y. Wang, M. Martonosi, L. Peh, D. Rubenstein, Energy-efficient computing for wildlife tracking: design tradeoffs and early experiences with zebranet, in: Proc. of the Tenth International Conference on Architectural Support for Programming Languages and Operating systems (ASPLOS), 2002, pp. 96–107.

[17] Z. Wang, S. Basagni, E. Melachrinoudis, Exploiting sink mobility for maximizing sensor networks lifetime, in: Proc. of the 38th Hawaii Int'l. Conf. Syst. Sci., 2005, p. 287.

[18] D. Jea, A. Somasundara, M. Srivastava, Multiple controlled mobile elements (data mules) for data collection in sensor networks, in: Proc. Distributed Comput. Sensor Syst. (DCOSS 2005), 2005, pp. 244–257.

[19] T. Camp, J. Boleng, V. Davies, A survey of mobility models for ad hoc network research, Wirel. Commun. Mobile Comput. 2 (5) (2002) 483–502.

[20] W. Ye, J. Heidemann, D. Estrin, Performance of mobile ad hoc networking routing protocols in large scale scenarios, Proc. IEEE Military Commun. Conf. (MILCOM 2004) 1 (2004) 21–27.

[21] M. Grossglauser, D. Tse, Mobility increases the capacity of ad hoc wireless networks, IEEE Network 10 (4) (2002) 477–486.

[22] I. Chatzigiannakis, S. Nikoletseas, P. Spirakis, An efficient communication strategy for ad-hoc mobile networks, in: Proc. of the 15th Int'l. Conf. on Distributed Computing (DISC 2001), 2001, pp. 285–299.

[23] Q. Li, D. Rus, Sending messages to mobile users in disconnected ad-hoc wireless networks, in: Proc. of the Sixth Annual International Conference on Mobile Computing and Networking (MobiCom 2000), 2000, pp. 44–55.

[24] S. Jain, R. Shah, W. Brunette, G. Borriello, S. Roy, Exploiting mobility for energy efficient data collection in wireless sensor networks, Mobile Netw. Appl. 11 (3) (2006) 327–339.

[25] G. Anastasi, M. Conti, E. Gregori, C. Spagoni, G. Valente, Motes sensor networks in dynamic scenarios: an experimental study for pervasive applications in urban environments, in: Int'l. J. Ubiquitous Comput. Intell. 1 (1).

[26] A. Woo, S. Madden, R. Govindan, Networking support for query processing in sensor networks, Commun. ACM 47 (6) (2004) 47–52.

[27] C. Intanagonwiwat, R. Govindan, D. Estrin, J. Heidemann, F. Silva, Directed diffusion for wireless sensor networking, IEEE Netw. 11 (1) (2003) 2–16.

[28] C.-K. Toh, Ad hoc Mobile Wirel. Netw. – Protocol Syst., Pearson Education, 2002.

[29] B. Krishnamachari, J. Heidemann, Application-specific modeling of information routing in sensor networks, in: Proc. 2004 IEEE Int'l. Conf. Performance, Comput. Commun. (IPCCC 2004), 2004, pp. 717–722.

[30] M. Laibowitz, J. Paradiso, Parasitic mobility for pervasive sensor networks, in: Proc. of Third Int'l. Conf. on Pervasive Comput.(PERVASIVE 2005), 2005, pp. 255–278.

[31] D. Johnson, D. Malt, Dynamic source routing in ad hoc wireless networks, IEEE Trans. Mobile Comput. 2 (1996) 153–181.

[32] R. Duda, P. Hart, D. Stork, Pattern Classification, 2nd ed., John Wiley & Sons, 2000.

[33] N. Ansari, E. Hou, Computational Intelligence for optimization, Springer, 1997.

[34] R. Johnson, D. Wichern, Applied Multivariate Statistical Analysis, second ed., Prentice-Hall, 1988.

[35] K. Fukunaga, Statistical Pattern Recognition, second ed., Academic Press, New York, NY, 1990.

[36] M. Garey, D. Johnson, Computers and Intractability: A Guide to the theory of NP-Completeness, W.H. Freeman and Company, New York, 1979.

[37] D. Johnson, L. McGeoch, The Traveling Salesman Problem: A Case Study in Local Optimization, John Wiley & Sons, 1997.

[38] S. Kurosawa, H. Nakayama, N. Kato, Y. Nemoto, A. Jamalipour, A self-adaptive intrusion detection method for aodv-based mobile ad hoc networks, in: Proc. of the Second IEEE Int'l. Conf. Mobile Ad-hoc and Sensor Syst. (MASS 2005), 2005, pp. 8B–4.

[39] S. Kurosawa, H. Nakayama, N. Kato, Y. Nemoto, A. Jamalipour, Detecting blackhole attack on aodv-based mobile ad hoc networks by dynamic learning method, Int'l. J. Netw. Security 5 (3) (2007) 338–346.

[40] QualNet – Scalable Network Technologies Website. Available from <http://www.scalable-networks.com//>.

[41] B. Vasu, M. Varshney, R. Rengaswamy, M. Marina, A. Dixit, P. Aghera, M. Srivastava, R. Bagrodia, Squalnet – a scalable simulation framework for sensor networks, in: Proc. Third Int'l Conf. Embedded Netw. Sensor Syst.(SenSys 2005), 2005, pp. 322–322.

[42] D. Rakhmatov, S. Vrudhula, An analytical high-level battery model for use in energy management of portable electronic systems, in: Proc. 2001 IEEE/ACM Int'l. Conf. Computer-aided Design (ICCAD 2001), 2001 pp. 488–493.

[43] D. Rakhmatov, S. Vrudhula, Energy management for battery-powered embedded systems, Trans. Embedded Comput. Sys. 2 (3) (2003) 277–324.

[44] A. Savvides, S. Park, M. Srivastava, On modeling networks of wireless microsensors, in: Proc. the 2001 ACM SIGMETRICS Int'l. Conf. Measur. Model. Comput. Syst. (SIGMETRICS 2001), 2001, pp. 318–319.

[45] M. Handy, D. Timmermann, Simulation of mobile wireless networks with accurate modeling of non-linear battery effects, in: Proc. Int'l. Conf. Appl. Simulation Model., 2003, pp. 532–537.
[46] M. Varshney, R. Bagrodia, Detailed models for sensor network simulations and their impact on network performance, in: Proc. Seventh ACM Int'l. Symp. Model. Anal. Simulation Wirel. Mobile Syst. (MSWiM 2004), 2004, pp. 70–77.
[47] D. Rakhmatov, S. Vrudhula, D. Wallach, A model for battery lifetime analysis for organizing applications on a pocket computer, IEEE Trans. VLSI Syst. 11 (6) (2003) 1019–1030.
[48] M. Viredaz, D. Wallach, Power evaluation of a handheld computer, IEEE Micro. 23 (1) (2003) 66–74.
[49] R. Rao, S. Vrudhula, D. Rakhmatov, Battery modeling for energy-aware system design, Computer 36 (12) (2003) 77–87.
[50] M. Wolenetz, R. Kumar, J. Shin, U. Ramachandran, A simulation-based study of wireless sensor network middleware, Int'l. J. Netw. Management 15 (4) (2005) 255–267.
[51] S. Ci, M. Guizani, H. Chen, H. Sharif, Network utilization in mobile ad-hoc wireless networks, IEEE Trans. Vehicular Technol. 55 (4) (2006) 1302–1310.

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