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Data Collection Capacity of Random-Deployed Wireless Sensor Networks under Physical Models*

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Abstract: Data collection is one of the most important functions provided by wireless sensor networks. In this paper, we study the theoretical limitations of data collection in terms of capacity for a wireless sensor network where n sensors are randomly deployed. We first consider data collection under *physical model*. We show that the capacity of data collection is in order of $\Theta(W)$ where W is the fixed data-rate on individual links. Particularly, we give a simple collection method based on interference blocks and theoretically prove that the method can achieve the optimal capacity in order. If each sensor can aggregate its receiving packets into a single packet to send, the capacity of data collection increases to $\Theta\left(\frac{n}{\log n}W\right)$. We then derive a lower bound and an upper bound of data collection capacity under *generalized physical model* where the data rate depends on the signal to interference plus noise ratio.

Key words: data collection; capacity; physical model; wireless sensor networks

Introduction

The ultimate goal of wireless sensor networks is often to collect sensing data from all sensors to a sink node (or called a gateway) and then perform further analysis at the sink node. Such data collection service is one of the most common services used in a wide range of sensor network applications. In this paper, we study the fundamental capacity problem arising from data collection scenario in wireless sensor networks under different models of communications. For each setting, we derive the asymptotic upper bound of transport capacity and present algorithms to achieve or approximate such upper bound.

We consider a dense sensor network where n sensors are randomly deployed in a finite geographical region. Each sensor measures independent field values at regular time intervals and send these values to the sink. The union of all sensing values from n sensors at particular time is called *snapshot*. The task of data collection is to deliver these snapshots to the sink. Due to spatial separation, several sensors can successfully transmit at the same time if these transmissions do not cause any destructive wireless interferences. There are different communication models to capture such interference constraint, such as *protocol model*, *physical model*, and *generalized physical model*. In this paper, we focus on studying data collection capacity under physical model and generalized physical model, since they are more realistic than protocol model. In physical model, we assume that a successful transmission over a link has a fixed data-rate, W, while in generalized physical model, the data rate depends on the Signal to Interference plus Noise Ratio (SINR).

The performance of data collection in wireless sensor networks can be characterized by the rate at which sensing data can be collected and transmitted to the sink node. In particular, the theoretical measures that

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capture the possibilities and limitations of collection processing are delay and capacity for the many-to-one data collection. The *delay* of data collection is the time to transmit *one single snapshot* to the sink from the snapshot generated at sensors. Considering the size of data in the snapshot, we can define *delay rate* as the ratio between the data size and the delay. When multiple snapshots from sensors are generated continuously, data transport can be pipelined in the sense that further snapshot may begin to transport before the sink receiving the prior snapshot. The maximum data rate at the sink to continuously receive the snapshot data from sensors is defined as the *capacity* of data collection. Both *delay rate* and *capacity* reflect that how fast the sink can collect sensing data from all sensors. It is critical to understand the limitations of many-to-one information flows and devise efficient data collection algorithms to maximize performance of wireless sensor networks. In this paper, we are particularly interested in how delay rate and capacity of data collection vary as the number of sensors n increases.

Capacity under different communication scenarios in random wireless networks[1-7] has drawn much attention since the publication of the seminal paper by Gupta and Kumar[8]. Recently, capacity limits of data collection in random wireless sensor networks have been investigated in the literature[9-20]. In Refs. [9, 10], Duarte-Melo et al. first studied the many-to-one transport capacity in random sensor networks. Chen et al.[11,12] studied the capacity of data collection with multiple sinks and Liu et al.[13] studied the capacity of a general some-to-some communication paradigm in random networks. All these works are based on protocol model. El Gamal[14] studied the capacity of data collection subject to a total average transmitting power constraint where a node can receive data from multiple source nodes at a time. Barton and Zheng[15,16] then investigated data collection capacity under more complex physical layer models (non-cooperative SINR model and cooperative time reversal communication model). More details on related work of data collection capacity can be found in Section 4. In this paper, we study capacity of data collection under physical model or generalized physical model for random sensor networks with a single sink.

The major contributions of this paper are as follows. (1) For sensor networks without data aggregation, we propose a new data collection method whose delay rate and capacity under physical model are both $\Theta(W)$ which match the theoretical upper bounds in order. (2) By using data aggregation[21,22] where sensors can cooperate to aggregate information towards the sink, the communication overhead is reduced and the capacity is increased. We prove that the delay rate and the capacity of data aggregation under physical model are $\Theta(\sqrt{n\log n}W)$ and $\Theta\left(\frac{n}{\log n}W\right)$, respectively. For both cases, our proposed aggregation methods achieve the optimal orders (i.e., within a constant factor of upper bounds). (3) Considering data collection under a generalized physical model, in which data rate depends on the level of interference, we provide new upper bound $O((\log n)W)$ and lower bound $O((\log^{-\beta/2} n)W)$. Here $\beta>2$ is the path loss exponent.

A preliminary conference version of this paper appeared in Ref. [23]. This version contains a corrected analysis of interference under physical model, new bounds of data collection under generalized physical model, and a better overall presentation.

1 Preliminaries

1.1 Network and communication models

We assume a sensor network which includes n wireless sensor nodes $V = \{v_1, v_2, \cdots, v_n\}$ and a single sink node s. Here, we consider the *random extended network* model[24], where sensor nodes are uniformly deployed in a square region with side-length $a = \sqrt{n}$, by use of Poisson distribution with density 1. For the simplicity of analysis, we assume that the sink node s is in the upper right corner of the region (as shown in Fig. 1). Notice that if the sink is located at the center of the region or anyway in the region, it only adds a constant in the analysis. At regular time intervals, each sensor node measures the field value at its position and transmits the value to the sink node. We first adopt a fixed data-rate channel model in which each wireless node can transmit at W (bits/second) over a common wireless channel. Under such channel model, we assume that every node has a fixed transmission power. Then a fixed transmission range r can be defined such that a node v_i can successfully receive the signal sent by node v_j only if the distance between them is less or equal to r. We also assume that all packets have unit size b (bits). The time is slotted into time slots with $t = b/W$ (seconds). Thus, only one packet can be transmitted in a time slot between two neighboring nodes.

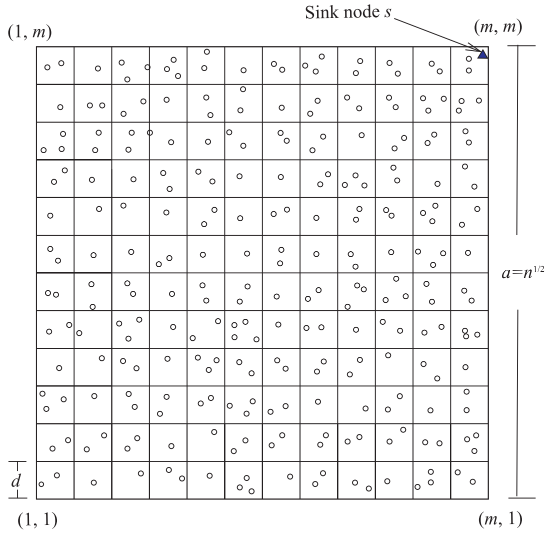


Fig. 1 Grid partition of the sensor network: m^2 cells with cell size of $d \times d$.

In the literature, there are three different communication models[25,26]: *protocol model*, *physical model*, and *generalized physical model*. In this paper, we focus on studying data collection capacity under the latter two models.

In *protocol model* (also called protocol interference model), all nodes are assumed to have uniform interference range R. When node v_i transmits to node v_j, node v_j can receive the signal successfully if no other node within a distance R of v_j is transmitting simultaneously. Usually, R/r is assumed as a constant larger than 1. Protocol model is the simplest communication model considering the interference among nodes, however, it is sometimes too simple to capture the complexity of interference.

In *physical model* (also called physical interference model), node v_j can correctly receive the signal from the sender v_i if and only if, given a constant $\eta > 0$, the SINR

$$\frac{P \cdot l(v_i, v_j)}{N_0 + \sum_{k \in I} P \cdot l(v_k, v_j)} \geqslant \eta.$$

Here $l(v_i, v_j)$ is the transmission loss between v_i and v_j, $N_0 > 0$ is the background Gaussian noise, I is the set of actively transmitting nodes when node v_i is the transmitting, and P is the transmission power (we assume that each sensor uses the same transmission power). In this paper, we consider the attenuation function $l(v_i, v_j) = \min\{1, ||v_i - v_j||^{-\beta}\}$ where $\beta > 2$ is the path loss exponent and $||v_i - v_j||$ is the Euclidean distance between v_i and v_j. Hereafter, we assume that all P, N_0, β, and η are fixed constants. Notice that values of P, N_0, η, and transmission range r should satisfy $\dfrac{P \cdot r^{-\beta}}{N_0} \geqslant \eta$. Thus, $r \leqslant (\dfrac{P}{N_0 \cdot \eta})^{1/\beta}$.

For both protocol model and physical model, as long as the value of a given conditional expression (such as transmission distance or SINR value) reaches some threshold, the sender can send data successfully to a receiver at a specific constant rate W due to the fixed rate channel model. However, fixed rate channel model may not capture the feature of wireless communication well. As a result, a more realistic model: *generalized physical model* (also called Gaussian channel model) is introduced. Such model determines the rate under which the sender can send its data to the receiver reliably, based on a continuous function of the receiver's SINR. Any two nodes v_i and v_j can establish a direct communication link $v_i v_j$, over a channel of bandwidth W, of rate

$$W_{ij} = W \log_2 \left(1 + \frac{P \cdot l(v_i, v_j)}{N_0 + \sum_{k \in I} P \cdot l(v_k, v_j)}\right).$$

This model assigns a more realistic transmission rate at large distance than the fixed rate channel models (protocol model and physical model).

1.2 Capacity and delay

We now formally define delay and capacity of data collection. Recall that each sensor at regular time intervals generates a field value with b (bits) and wants to transport it to the sink. We call the union of all values from all n sensors at particular sampling time a *snapshot* of the sensing data. The goal of data collection is to collect these snapshots from all sensors as quick as possible.

Definition 1 The *delay* of data collection, Δ, is the time transpired between the time a snapshot is taken by the sensors and the time the sink has all data of this snapshot.

Definition 2 The *delay rate* of data collection, Γ, is the ratio between the data size of one snapshot, $n \cdot b$, and the delay, Δ.

The data transport can be pipelined in the sense that further snapshots may begin to transport before the sink receives the prior snapshots. Therefore, we need to define a new data rate of data collection under pipelining.

Definition 3 The *usage rate* of data collection, U, is the number of time slots needed at the sink between completely receiving one snapshot and completely receiving next snapshot.

Thus, the time used by the sink to successfully receive a snapshot is $T = U \cdot t$. Due to pipelining, $T \leqslant \Delta$. Clearly, small usage rate and T are desired.

Definition 4 The *capacity* of data collection, C, is the ratio between the size of data in one snapshot and the time to receive such a snapshot (i.e., $\frac{nb}{T}$) at the sink.

Thus, the capacity, C, is the maximum data rate at the sink to continuously receive the snapshot data from sensors. Clearly, C is at least as large as the delay rate, Γ, and usually substantially larger. In this paper, we analyze both delay rate and capacity for data collection in random sensor networks.

2 Data Collection Capacity of Random Sensor Networks under Physical Model

In this section, we consider data collection with or without aggregation under physical model.

2.1 Data collection without aggregation

We first consider data collection without aggregation where each data packet generated from a sensor needs to individually reach the sink s. We will construct a data collection scheme whose delay rate is $\Omega(W)$, and then prove that it is order-optimal. Our data collection scheme is based on the following grid partition method and definition of interference blocks.

2.1.1 Partition method

We first introduce a grid partition method which is essential for our data collection methods and their theoretical analysis. As shown in Fig. 1, the network (e.g., the $a \times a$ square) is divided into m^2 micro cells of the size $d \times d$. Here $m = a/d$. We assign each cell a coordinate (i, j), where i and j are between 1 and m, to indicate its position at j-th row and i-th column.

The following lemma gives a guidance of the cell size.

Lemma 1[27] Given n random nodes in a $\sqrt{n} \times \sqrt{n}$ square, dividing the square into micro cells of the size $\sqrt{3\log n} \times \sqrt{3\log n}$, every micro cell is occupied with probability at least $1 - \frac{1}{n^2}$.

Therefore, if we set $d = \sqrt{3\log n}$ (i.e., $m = \sqrt{\frac{n}{3\log n}}$), every micro cell has at least one node with high probability (the probability converges to one as $n \longrightarrow \infty$).

We then derive the upper bound of the number of nodes inside a single cell.

Lemma 2 Given n random nodes in a $\sqrt{n} \times \sqrt{n}$ square, dividing the square into micro cells of the size $\sqrt{3\log n} \times \sqrt{3\log n}$, the maximum number of nodes in any cell is $O(\log n)$ with probability at least $1 - \frac{3\log n}{n}$.

Proof The proof is straightforward from results of the *balls into bins problem*[28] and thus ignored here. ■

In order to make the whole network connected, the transmission range r needs to be equal or larger than $\sqrt{5}d$ so that any two nodes from two neighboring cells are inside each other's transmission range. Hereafter, we set $r = \sqrt{5}d = \sqrt{15\log n}$.

2.1.2 Interference blocks under physical model

For our collection scheme, we first divide the field into big blocks with size $L \times L$ as shown in Fig. 2. We call these blocks *interference blocks* and L *interference distance*. Thus, the number of interference blocks is $\left\lceil \frac{a^2}{L^2} \right\rceil$. We label each block with (i, j) where i and j are the indexes of the block as in Fig. 2. In our collection scheme, we schedule data transmission in parallel at all blocks but make sure that there is only one sensor in each interference block transferring at any time. To avoid interference from senders in other interference blocks, we need interference distance L larger than certain value.

Next, we derive the lower bound of interference distance such that all simultaneous transmissions as shown in Fig. 2 can be successfully received. Here, we consider the SINR at the receiver in interference block [0, 0] (which is in the center of the field) since it has the minimum SINR among all receivers. Similar to the technique used in Ref. [29], we now label all simultaneous transmissions by layers from block [0, 0],

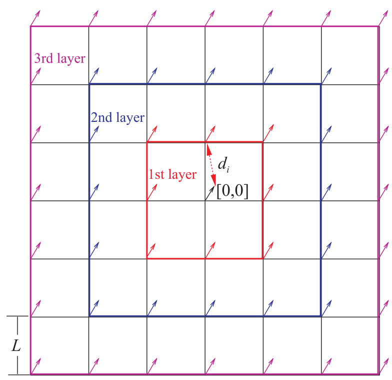


Fig. 2 Grid partition of interference blocks with size of $L \times L$ and simultaneous transmissions around the center block [0,0] by layers.

as shown in Fig. 2. Based on physical interference model, its SINR is at least

$$\frac{P \cdot r^{-\beta}}{N_0 + \sum_{\text{All layers } i \geqslant 1} c_i P \cdot (d_i)^{-\beta}}.$$

Here, d_i is the minimum distance from a transmitter on i-th layer to the receiver in block $[0,0]$ and c_i is the number of transmitters on i-th layer. Therefore, we need to derive L such that SINR $\geqslant \eta$, i.e.,

$$\sum_{\text{All layers } i \geqslant 1} c_i (d_i)^{-\beta} \leqslant \frac{r^{-\beta}}{\eta} - \frac{N_0}{P}.$$

Notice that $d_i \geqslant iL - 2d$ and $c_i = 8i$. For example, there are 8 transmitters at the first layer with distance at least $L - 2d$ and 16 transmitters at the second layer with distance at least $2L - 2d$, and so on. Thus,

$$\sum_{i \geqslant 1} c_i (d_i)^{-\beta} \leqslant \sum_{i \geqslant 1} 8i(iL - 2d)^{-\beta} \leqslant$$
$$\sum_{i \geqslant 1} 8i(iL - 2id)^{-\beta} =$$
$$8(L - 2d)^{-\beta} \sum_{i \geqslant 1} i^{-(\beta-1)}.$$

Since $\beta > 2$, $\sum_{i \geqslant 1} i^{-(\beta-1)}$ converges to a constant, let it be denoted by ϕ. Then we only need

$$8\phi(L - 2d)^{-\beta} \leqslant \frac{r^{-\beta}}{\eta} - \frac{N_0}{P},$$

to guarantee that the SINR at the receiver in the center is at least η. This can be satisfied by setting

$$L \geqslant \left(\frac{1}{8\phi} \cdot \left(\frac{r^{-\beta}}{\eta} - \frac{N_0}{P}\right)\right)^{-\frac{1}{\beta}} + 2d.$$

Remember $r \leqslant \left(\frac{P}{N_0 \cdot \eta}\right)^{1/\beta}$, this makes sure we can find such suitable L. We can further select $L = \left(\frac{1}{8\phi} \cdot \left(\frac{r^{-\beta}}{\eta} - \frac{N_0}{P}\right)\right)^{-\frac{1}{\beta}} + 2d$. Since $r = \sqrt{5}d$,

$$\frac{L}{d} = \left(\frac{1}{8\phi} \cdot \left(\frac{(\sqrt{5}d)^{-\beta}}{\eta d^{-\beta}} - \frac{N_0}{P d^{-\beta}}\right)\right)^{-\frac{1}{\beta}} + 2 =$$
$$\left(\frac{1}{8\phi} \cdot \left(\frac{5^{-\beta/2}}{\eta} - \frac{N_0 d^{\beta}}{P}\right)\right)^{-\frac{1}{\beta}} + 2.$$

When $n \to \infty$, this ratio goes to a constant, denoted by α.

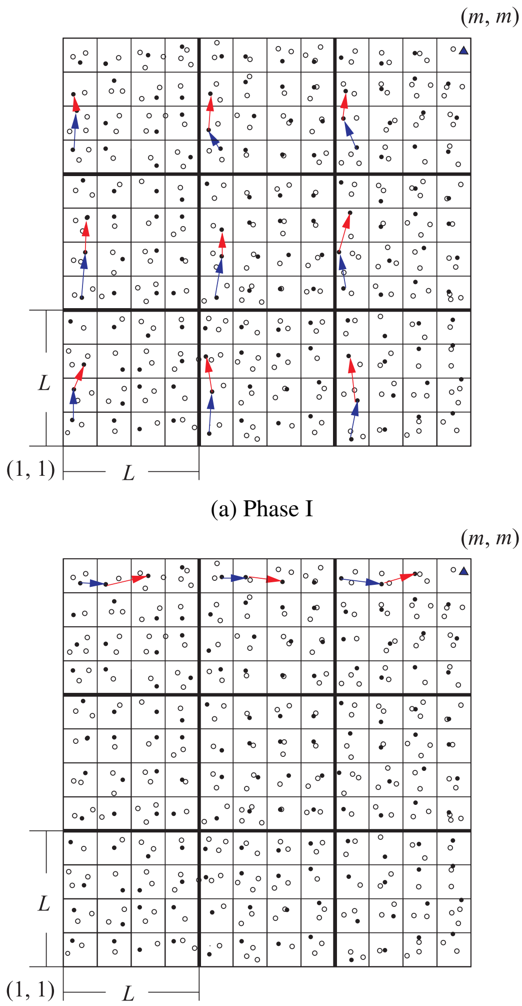
2.1.3 Data collection scheme

After having interference blocks, we can now present our collection algorithm. It has two phases. In Phase I, every sensor sends its data up to the highest cell in its column (in the a-th row) as shown in Fig. 3a, and in Phase II, all data is sent via cells in the a-th row to the sink as shown in Fig. 3b. In each phase, the data transmissions in all interference blocks are performed in parallel. Notice that similar interference-aware scheduling (taking turn among interference blocks) has been used in both Refs. [29] and [30] for unicast or broadcast under physical model and in Refs. [11, 12] for data collection under protocol model.

2.1.4 Analysis of delay rate

Now we analyze the delay rate of our data collection scheme above. We define the time needed for the two phases as T_1 and T_2, respectively.

By Lemma 2, the number of nodes in each cell is at most $O(\log n)$. Every node needs one time-slot t to send one packet to its neighbor in the next cell. To avoid



(a) Phase I

(b) Phase II

Fig. 3 Our collection method: Phase I: each node sends its data to its upper cell; Phase II: each node in the top row sends its data to its right cell.

interference, every interference block can only have one node to send a packet to its upper neighbor in every time slot t during Phase I. In Fig. 3, bold lines show the interference blocks. Remember that $\frac{L}{d}$ is a constant α, thus the number of cells in the interference block is $\left(\frac{L}{d}\right)^2 = \alpha^2$. And the packet in the lowest row (i.e., cell $(1,k)$) has to walk m cells to reach nodes in the highest cell in the rectangle. Hence,

$$T_1 \leqslant \left(\frac{L}{d}\right)^2 \cdot t \cdot O(\log n) \cdot m \leqslant O(t\log n)m = O(t\log n)\sqrt{\frac{n}{3\log n}} = O(t\sqrt{n\log n}).$$

At the beginning of Phase II, all data are already at cells of the top row. The sink s lies on the same row with these cells. We now estimate T_2 needed for sending all data to s. Each cell in the top row has at most $mO(\log n)$ nodes' data and the number of cells in each interference block is $\frac{L}{d}$. Similarly, we can get

$$T_2 \leqslant \frac{L}{d} \cdot t \cdot mO(\log n) \cdot m \leqslant m^2 O(t\log n) = O(nt).$$

Therefore, the total time needed to collect b-bit information from every sensor in the field to the sink is $T_1 + T_2 = O(nt)$. Thus, the total delay $\Delta_{\rm col}$ for the sink to receive a complete snapshot is at most $O(nt)$. Consequently, the total delay rate of this collection scheme is

$$\Gamma_{\rm col} = \frac{nb}{\Delta_{\rm col}} = \Omega\left(\frac{nb}{nt}\right) = \Omega(W).$$

It has been proved that the upper bound of delay rate or capacity of data collection is W[9,10]. It is obvious that the sink cannot receive at rate faster than W since W is the fixed transmission rate of individual link. Therefore, the delay rate of our collection scheme achieves the order of the upper bound, and the delay rate of data collection is $\Theta(W)$. Notice that for each individual sensor, the lowest achievable delay rate of our method is $\Theta(W/n)$ which also meets the upper bound.

2.1.5 Capacity of data collection

Next, we consider the situation with pipelining. It is clear the upper bound of capacity is still W. Since our above scheme already reaches the upper bound, the pipelining operation can only improve the capacity within a constant factor.

With pipelining, in Phase I, the sensor can begin to transfer the data to its up-cell from next snapshot after sensors in its interference block finish their transmission of previous snapshot. Whenever the cells in the top row receive $m \cdot b$ data (every cell in the top row receives a data from its lower cell), Phase II can begin at the top row. We consider the improvements of pipelining on both phases. With the pipelining, the time T_1' for the highest cell to receive a new set of $m \cdot b$ data in Phase I is

$$T_1' \leqslant \left(\frac{L}{d}\right)^2 \cdot t \cdot O(\log n) = O(t\log n).$$

And the time T_2' for the sink to receive a new set of $a \cdot b$ data in Phase II is

$$T_2' \leqslant \frac{L}{d} \cdot t \cdot m = O\left(t\sqrt{\frac{n}{\log n}}\right).$$

Therefore, the total time for sink to receive $m \cdot b$ data is $T_1' + T_2' = O\left(t\sqrt{\frac{n}{\log n}}\right)$. Thus, the capacity of our method with pipelining is still

$$C_{\rm col} = \frac{m \cdot b}{T_1' + T_2'} = \Omega(W).$$

This also meets the upper bound W in order.

In summary, we have the following theorem:

Theorem 1 Under physical model, the delay rate and the capacity of data collection in random sensor networks with a single sink are both $\Theta(W)$.

2.2 Data collection with aggregation

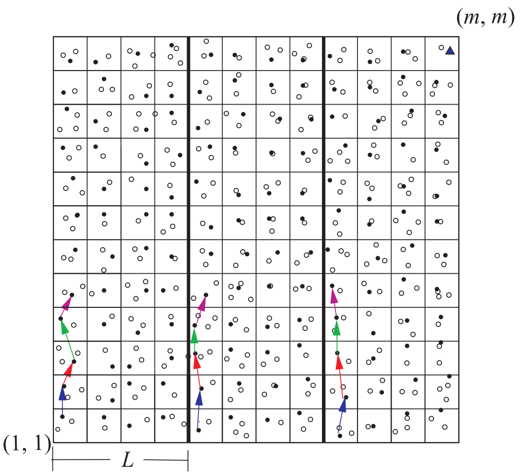
We now consider data collection with aggregation, where each sensor can aggregate its received data (multiple packets) into a single packet. The definitions of delay rate and capacity under this model are similar to those of data collection in Section 1. Notice that when the sink receives the aggregated value (just b bits) of a snapshot of the field (n sensors), we still count the size of all values from that snapshot as the size of the received data. Thus, the delay rate is $\frac{nb}{\Delta}$ and the capacity is $\frac{nb}{T}$. The methods we used here are the same with those from our previous results[11,12] for protocol model. The only difference is that now the interference block is with size of L instead of $R + r$. Since L is in the same order of r as R in protocol model, all methods and analysis in Refs. [11,12] can stay the same. For the completeness of this paper, we briefly describe them in the following.

2.2.1 Analysis of delay rate

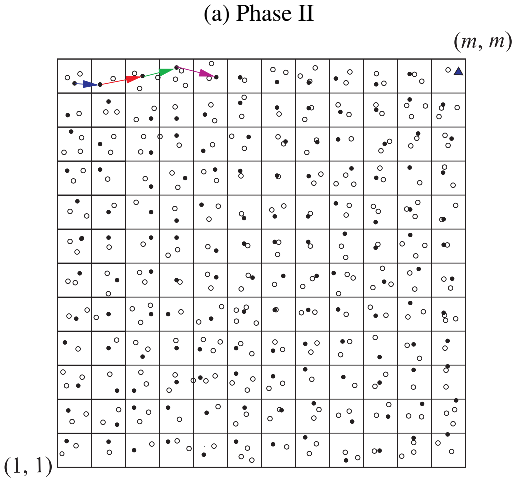
Our aggregation scheme has three phases and uses the same partition method in Section 2.1.1.

First, each micro cell chooses a sensor which collects data from all the other sensors in the same micro cell and aggregates into one packet. Based on Lemma 2, each micro cell has at most $O(\log n)$ nodes. Assume that T_1'' is the time needed to collect data inside each cell. Because of the interference distance L, T_1'' is at most $\left(\frac{L}{d}\right)^2 \cdot O(\log n) \cdot t$.

Second, every selected node waits for all data in the same snapshot from cells, which are below its own cell and within the same column, and then aggregates them with its value into a single packet and sends it to its upper cell. See Fig. 4a. At the end of this phase, all values have been aggregated at the top row where the sink sits. The time needed for this phase T_2'' is bounded from above by $m \cdot t \cdot \left(\frac{L}{d}\right) = \Theta\left(\sqrt{\frac{n}{\log n}} t\right)$, since in every $\frac{L}{d}$ columns only one node can transmit due to interference, as shown in Fig. 4a.



(a) Phase II



(b) Phase III

Fig. 4 Our aggregation method. Phase II: each selected node aggregates data to its upper cell; Phase III: each selected node in the top row aggregates data to its right cell.

Third, as shown in Fig. 4b, the information is aggregated via cells one by one in the top row. The time needed T_3'' is at most $m \times t = \Theta\left(\sqrt{\frac{n}{\log n}} t\right)$.

Therefore, the total delay $\Delta_{\text{agg}} \leqslant T_1'' + T_2'' + T_3'' = O\left(\sqrt{\frac{n}{\log n}} t\right)$. The delay rate is

$$\Gamma_{\text{agg}} = \frac{nb}{\Delta_{\text{agg}}} = \Omega(\sqrt{n \log n} \cdot W).$$

Next, we prove that this delay rate is order-optimal. Notice that for one snapshot the data aggregation is completed when the sink has the aggregated value of all data in the snapshot. Let T_{complete} denote the time that all data of one snapshot are aggregated in the sink and T_{farthest} be the time needed for the value of the farthest node reaching the sink. Since to compute the aggregated value, all values from the snapshot are needed, $T_{\text{farthest}} \leqslant T_{\text{complete}}$. Based on the network model, the farthest node from the sink locates on one corner of the field. We denote the distance between the farthest node and the sink as R. It is easy to show that the minimum value of X is $\frac{\sqrt{2}a}{2}$ (when the sink is in the center of the field), i.e., $X \geqslant \frac{\sqrt{2n}}{2}$. The data in the farthest node needs at least $\frac{X}{r}$ time slots to reach the sink, for the transmission range is r. Hence,

$$T_{\text{farthest}} \geqslant \frac{X}{r} \cdot t = \frac{X}{r} \cdot \frac{b}{W} \geqslant \frac{\frac{\sqrt{2n}}{2}}{r} \cdot \frac{b}{W} = \sqrt{\frac{n}{30 \log n}} \cdot \frac{b}{W}.$$

Consequently, we have

$$T_{\text{complete}} \geqslant T_{\text{farthest}} \geqslant \sqrt{\frac{n}{30 \log n}} \cdot \frac{b}{W}.$$

Therefore, the delay rate of data aggregation is at most

$$\frac{nb}{T_{\text{complete}}} \leqslant \frac{nb}{\sqrt{\frac{n}{30 \log n}} \cdot \frac{b}{W}} = \Theta(\sqrt{n \log n} \cdot W).$$

In summary, our data aggregation algorithm can achieve the upper bound of delay rate $\Theta(\sqrt{n \log n} \cdot W)$.

2.2.2 Data collection capacity with aggregation

In the above aggregation algorithm, until the sink receives the aggregated value for all data in the previous snapshot, sensors begin to send data in the next snapshot. However, with pipelining, a sensor can start sending (or aggregating) data in the next snapshot before the aggregated value of the previous snapshot reaches the sink. Actually, it can initiate sending if the aggregated data of the previous snapshot are far away enough. Thus, all three phases in the algorithm can perform in pipelining.

At the beginning of each snapshot, each micro cell will choose a node to collect data from all the other nodes in the same micro cell and aggregates into one packet. The time required is $\left(\frac{L}{d}\right)^2 \cdot O(\log n) \cdot t = O(t \log n)$.

For Phase II and Phase III, if the aggregated values in previous snapshot are one interference block ahead (above or right in Fig. 4), the values from next snapshot can be sent or aggregated. The time difference between such two snapshots is bounded by $\left(\frac{L}{d}\right)^2 \cdot t$. This is much smaller than the time used for aggregation of data in a cell ($O(t \log n)$). Thus, in a cell, when the aggregation of data from one snapshot finishes, the aggregation values of previous snapshot are already far away from this cell and cannot cause any interference with current transmissions originated from this cell.

Therefore, within every $O(t \log n)$ seconds the sink can collect one snapshot data with pipelining. Then the capacity of our data aggregation method is $\frac{nb}{O(t \log n)} = \Omega\left(\frac{n}{\log n} W\right)$.

Next, we prove that the upper bound of data aggregation with pipelining is $O\left(\frac{n}{\log n} W\right)$. In other words, our scheme achieves the order of the optimal. Because n sensors are randomly distributed in the $\sqrt{n} \times \sqrt{n}$ square, if we divide the region into disks with radius $\frac{L}{2} = \alpha\sqrt{3 \log n}/2$, every such disk has average $\frac{3\pi\alpha^2 \log n}{4}$ sensors. Due to Pigeonhole principle, there exist some disks that have $\Theta(\log n)$ sensors. Now let D be such a disk. When one sensor in D sends its data packet to a destination, all of the other $\Theta(\log n)$ sensors cannot send their data. The aggregation of these $\Theta(\log n)$ sensors will cost at least $\Theta(\log nt)$, i.e., $T_{\text{agg}} \geqslant \Theta(\log nt)$. Thus, the capacity C_{agg} is less than or equal to $O\left(\frac{n}{\log n} W\right)$ for sure.

In summary, we have the following theorem for data collection with aggregation.

Theorem 2 Under physical model, the delay rate and the capacity of data collection with aggregation in random sensor networks with a single sink are $\Theta(\sqrt{n \log n} W)$ and $\Theta\left(\frac{n}{\log n} W\right)$, respectively.

Notice that the delay rate and the capacity are in the same order for data collection (Theorem 1), i.e., the pipelining can only improve constant factor of the data rate. However, for data aggregation, it is very interesting to see that pipelining can increase the data rate in order of $\Theta\left(\sqrt{\frac{n}{\log^3 n}}\right)$.

3 Data Collection Capacity of Random Networks under Generalized Physical Model

Physical model assumes a threshold-based channel, where the signal can be decoded at a fixed constant rate W only if the SINR is greater than some threshold. If the SINR is below the threshold, no throughput is received at all. However, in practical, the throughput is usually a function of the SINR at the receiver. Thus, generalized physical model is more realistic communication model than protocol model and physical model, especially under random extended networks[24]. Therefore, in this section, we also study the theoretical bounds of data collection capacity under generalized physical model. Notice that since the data rate now is related to SINR and interference, the capacity analysis becomes much complex and challenging.

3.1 Upper bound of data collection capacity

First, we give a lemma to derive an upper bound of data collection capacity under generalized physical model.

Lemma 3 Under generalized physical model, the capacity of data collection in random sensor networks is at most $O((\log n)W)$.

Proof We first order all the incoming links of sink s according to their length as follows: $||v_1 - s|| \leqslant ||v_2 - s|| \leqslant \cdots \leqslant ||v_{n'} - s||$. Here n' is the number of incoming links at sink s who transmit simultaneously to s, clearly $n' \leqslant n$. Next, we try to bound the SINR of the sink node s. For any link $v_i s$ ($i \neq 1$), its SINR,

$$\text{SINR}_{is} \leqslant \frac{P \cdot l(v_i, s)}{N_0 + \sum_{k=1}^{i-1} P \cdot l(v_k, s)} \leqslant \frac{P \cdot l(v_i, s)}{N_0 + \sum_{k=1}^{i-1} P \cdot l(v_i, s)} < \frac{1}{i-1}.$$

Therefore, for $i \neq 1$,

$$W_{is} = W \log_2(1 + \text{SINR}_{is}) < W \log_2\left(\frac{i}{i-1}\right).$$

So the maximum rate at sink s is at most

$$W_{1s} + \sum_{i=2}^{n'} W \log_2\left(\frac{i}{i-1}\right) =$$
$$W_{1s} + W \log_2\left(\prod_{i=2}^{n'} \frac{i}{i-1}\right) \leqslant$$
$$\max_i(W_{is}) + W \cdot \log_2(n') \leqslant \max_i(W_{is}) + W \cdot \log_2(n).$$

The first part of this upper bound depends on the rate of the shortest incoming link at sink, while the second part depends on the total number of nodes. Notice that $\max_i(W_{is}) \leqslant W \log_2\left(1 + \frac{P}{N_0}\right)$. Thus, which part in the bound playing an important role depends on the relationship between n and $1 + \frac{P}{N_0}$. If P and N_0 are constants as we assumed, $\max_i(W_{is}) \leqslant O(W)$. Then, the upper bound of capacity can be written as $O((\log n)W)$. ■

3.2 Lower bound of data collection capacity

We now can introduce our data collection algorithm, which uses the same partition method and scheduling algorithm as those for physical model in Section 2. The only difference is the size of interference block.

We now divide the field into big interference blocks with certain size $L(d) \times L(d)$ as shown in Fig. 2. Thus, the number of interference blocks is $\left\lceil \frac{a^2}{L(d)^2} \right\rceil$. In our collection scheme, we will schedule data transmission in parallel at all blocks but make sure that there is only one sensor in each interference block transferring at any time.

We now prove that the transmission rate of each transmitting sensor node in such data collection scheme is at least $\Omega(d^{-\beta}W)$, if $L(d) = \kappa d$ and $\kappa > 2$ is a constant.

Lemma 4 In each interference block with size of $\kappa d \times \kappa d$, there exists a node that can transmit at rate $\Omega(d^{-\beta}W)$ to any destination in its adjacent cell.

Proof Let us focus on one given sensor node v_i which transmits to a destination v_j in v_i's adjacent cell. Its transmission rate is

$$W_{ij} = W \log_2\left(1 + \frac{P \cdot l(v_i, v_j)}{N_0 + \sum_{k \in I} P \cdot l(v_k, v_j)}\right).$$

Since the distance between v_i and v_j is at most $\sqrt{5}d$, $P \cdot l(v_i, v_j) \geqslant P \cdot (\sqrt{5}d)^{-\beta} = \Omega(d^{-\beta})$.

We then need to find the upper bound of the interference at the receiver v_j from simultaneous transmitters. Using the same technique in Section 2, we consider layers of simultaneous transmissions in surrounding interference blocks as shown in Fig. 2. Once again assume that $d_i \geqslant iL(d) - 2d$ is the minimum distance from an i-th layer transmitter to v_j and $c_i = 8i$ is the number of transmitters on i-th layer. Therefore,

$$\sum_{k \in I} P \cdot l(v_k, v_j) \leqslant \sum_{i=1}^{\infty} 8iP(iL(d) - 2d)^{-\beta} \leqslant$$
$$\sum_{i=1}^{\infty} 8iP(i\kappa - 2)^{-\beta} d^{-\beta} \leqslant$$
$$8P \cdot d^{-\beta} \cdot \sum_{i=1}^{\infty} i(i\kappa - 2)^{-\beta}.$$

Since $\beta > 2$, the summation $\sum_{i=1}^{\infty} i(i\kappa - 2)^{-\beta}$ converges to a constant ρ. Therefore,

$$\sum_{k \in I} P \cdot l(v_k, v_j) \leqslant 8P\rho \cdot d^{-\beta} = O(d^{-\beta}).$$

When $n \to \infty$, $d \to \infty$, hence, the SINR

$$\frac{P \cdot l(v_i, v_j)}{N_0 + \sum_{k \in I} P \cdot l(v_k, v_j)} = \Omega(d^{-\beta}).$$

Therefore, the transmission rate from v_i to v_j,

$$W_{ij} = \Omega(d^{-\beta}W).$$ ■

We use the same data collection scheme in Section 2. The total time we need to collect all the n packets is

$$T \leqslant \left[\left(\frac{\kappa d}{d}\right)^2 O(\log n)m + \left(\frac{\kappa d}{d}\right) O(\log n)m^2\right] \cdot$$
$$\frac{b}{\Omega(W \cdot d^{-\beta})} \leqslant O(\log nm^2) \cdot \frac{b}{W\Omega(d^{-\beta})} =$$
$$\frac{O(n)}{\Omega(d^{-\beta})} \cdot t \leqslant O(n(\log^{\frac{\beta}{2}} n)) \cdot t.$$

Thus, the achieved capacity of data collection under generalized physical model is $\Omega((\log^{-\frac{\beta}{2}} n)W)$.

In summary, the bounds of data collection capacity can be summarized as follows.

Theorem 3 Under generalized physical model, the capacity of data collection in random sensor networks is between $\Omega((\log^{-\frac{\beta}{2}} n)W)$ and $O((\log n)W)$.

4 Related Works

Gupta and Kumar initiated the research on capacity of wireless ad hoc networks by studying the fundamental capacity limits in the seminal paper[8] under both protocol model and physical model. A number of following papers studied capacity under different communication scenarios in wireless networks: unicast[1,2], multicast[3-5], and broadcast capacity[6,7].

Capacity of data collection in random wireless sensor networks was studied in Refs. [9-20]. In Refs. [9, 10], Duarte-Melo et al. first studied the many-to-one transport capacity in random sensor networks under protocol model and gave the result of overall capacity of data collection as $\Theta(W)$. They also showed that compressing data are inefficient to improve the capacity when the density of the sensor network increases to infinity in Ref. [10]. El Gamal[14] studied data collection capacity subject to a total average transmitting power constraint. They relaxed the assumption that every node can only receive a packet from one source node at a time. It was shown that the capacity of random networks scales as $\Theta(\log nW)$ when n goes to infinity and the total average power remains fixed. Their method uses antenna sharing and channel coding. Barton and Zheng[15] also investigated data collection capacity under more complex physical models (non-cooperative SINR model and Cooperative Time Reversal communication (CTR) model). They first demonstrated that $\Theta(\log nW)$ is optimal and achievable by using CTR for a regular grid network[16], then showed that the capacities of $\Theta(\log nW)$ and $\Theta(W)$ are optimal and achievable by CTR when operating in fading environments with power path-loss exponents that satisfy $2 < \beta < 4$ and $\beta \geqslant 4$ for random networks[15]. Chen et al.[11,12] studied capacity of data collection with multiple sinks in random networks under protocol model. They showed with multiple sinks (either grid or random deployment of k sinks), the capacity of data collection increases from that of the single sink case. When the capacity is constrained by the number of sinks (i.e., $k = O\left(\frac{n}{\log n}\right)$), it is beneficial to add more sinks. However, when the capacity is constrained by the interference among sinks (i.e., $k = \omega\left(\frac{n}{\log n}\right)$), adding more sinks has no substantial capacity improvement. Liu et al.[13] recently introduced the capacity of a more general some-to-some communication paradigm in random networks where there are $s(n)$ randomly selected sources and $d(n)$ randomly selected destinations. They derived the upper and lower bounds for such a problem. Note that data collection is a special case for their problem when $s(n) = n$ and $d(n) = 1$. Most recently, Ji et al.[17-20] also studied data collection methods in random wireless sensor networks under different communication models. In Ref. [17], an order-optimal continuous data collection method was proposed for single-radio multi-channel wireless sensor networks under protocol model and a pipeline scheduling algorithm for data collection was proposed for dual-radio multi-channel networks under protocol model. In Ref. [18], a cell-based path scheduling algorithm was proposed for data collection under physical model which can achieve $\Theta(W)$ of capacity, then a segment-based pipeline scheduling algorithm using compressive data gathering technique to further improve the collection capacity was presented. In Ref. [19], Ji and Cai investigated the achievable data collection capacity for asynchronous wireless sensor networks under generalized physical model by giving a scalable distributed data collection algorithm with $\Theta(W)$ of achievable capacity. In Ref. [20], Ji et al. considered data collection capacity under a probabilistic network model where the successful transmission over a link is a random variable related to the SINR. They proposed two scheduling algorithms (a cell-based multipath algorithm and a zone-based pipeline algorithm) for such a model. All research above (including this paper itself) shares the standard assumption where large number of sensor nodes are randomly and uniformly distributed in a plane. Such an assumption is useful for simplifying the analysis and deriving nice theoretical limitations, but may be invalid in some practical sensor applications. Chen et al.[31,32] recently studied the data collection capacity under protocol model or physical model for arbitrarily-deployed wireless sensor networks.

For capacity of data collection with aggregation, there are also several studies. Giridhar and Kumar[21] investigated a general aggregation problem in random sensor network where a symmetric function of the sensor measurements is used for data aggregation. It was shown that for random planar network, the maximum rate for computing divisible functions (a subset of symmetric functions) is $\Theta\left(\frac{W}{\log n}\right)$. In addition, using a technique called block-coding, they further showed that type-threshold functions can be computed at a rate of $\Theta\left(\frac{W}{\log\log n}\right)$ in the physical model. Moscibroda[22] further studied the aggregation capacity for arbitrarily deployed networks (named as *worst-case capacity*) under both protocol and physical models. He showed that the worst-case capacities of data aggregation are $\Theta\left(\frac{W}{n}\right)$ under protocol model and $\Omega\left(\frac{W}{\log^2 n}\right)$ under physical model respectively. Notice that the worst-case capacity definition in his paper was in terms of the union of all arbitrary networks instead of any fixed arbitrary network. In Refs. [11, 12], Chen et al. considered the data aggregation capacity under protocol model for random sensor networks. Finally, there are also some results[33-35] on how to schedule data aggregation in sensor network such that the delay or latency is minimized. In Ref. [33], Huang et al. developed an algorithm which had the latency bound $23R + \Delta - 18$, where Δ is the maximum node degree and R is the network radius. In Ref. [34], the minimum data aggregation time problem was proved NP-hard and aggregation schedules of latency at most $(\Delta - 1)R$ was proposed. In Ref. [35], the authors proposed a new tree based approximation algorithm to guarantee performance ratio $\frac{7\Delta}{\log_2|S|} + c$, where S is the set of sensors containing data and c is a constant.

5 Conclusions

In this paper, we study the theoretical limitations of data collection in terms of achievable capacity for random sensor networks under physical models. Under physical model, we propose simple collection methods to achieve the asymptotical upper bound of capacity in order for data collection tasks with or without aggregation. Under generalized physical model, we derive an upper bound of data collection capacity and give an achievable lower bound by analyzing a simple collection method. These results and previous results on protocol model are summarized in Table 1. These theoretical results can lead to better network planning and performance for data collection in wireless sensor network applications. For future work, we will try to close the gap in capacity bounds under generalized physical model by giving more-efficient data collection methods and tight upper bound analysis. In addition, it is interesting to study how to schedule the data collection or aggregation when multiple sinks are used under physical model or generalized physical model.

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Table 1 Summary of data collection capacity in random sensor networks

Communication scenario	Communication model	Capacity
Data collection	Protocol model	$C = \Theta(W)$
Data collection with aggregation	Protocol model	$C = \Theta\left(\frac{n}{\log n}W\right)$
Data collection	Physical model	$C = \Theta(W)$
Data collection with aggregation	Physical model	$C = \Theta\left(\frac{n}{\log n}W\right)$
Data collection	Generalized physical model	$O((\log n)W) \geqslant C \geqslant \Omega\left((\log n)^{-\frac{\beta}{2}}W\right)$

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