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An Efficient Method for Improving Data Collection Precision in Lifetime-adaptive Wireless Sensor Networks

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***Abstract*—Two important factors that affect the performance of wireless sensor networks (WSNs) are data quality and network lifetime. This paper exploits the tradeoff between data quality and network lifetime to improve data collection precision while the network lifetime is adapted. The problem is to minimize the total error bound for approximate data aggregation in both single-hop and multi-hop WSNs to achieve the adaptive network lifetime. This problem is formulated as an optimization problem by combining the changing pattern of sensor readings, the residual energy of sensor nodes, and the communication cost from the sensor node to the base station. Our method is theoretically analyzed and further evaluated by conducting simulation experiments. To the best of our knowledge, this is the first study on minimizing the total error bound while achieving the adaptive network lifetime.**

I. Introduction

Wireless sensor networks (WSNs) have been widely deployed for a number of applications, such as ecosystem monitoring, surveillance, national security, and wild-fire prevention; thus attracting increasing attention in both academia and industry. The Sonoma Redwoods sensor network project [22], which consists of 72 Mica2dot motes placed through two giant redwood trees in a grove in Sonoma Country, CA, USA, is such a representative deployment. The biologists at UC Berkeley are now able to access some data, such as temperature, humidity, and Photo-Synthetically Active Radiation from many positions under the large redwood canopies. These data are never before available to the plant biology community. Figure 1 shows a typical example of a WSN, which consists of a base station and a number of sensor nodes. The base station collects the information from the sensor nodes and transform the collected information into the requested form to cater for different applications. The sensor nodes, on the other hand, sense the environmental information and finally send some sensed information to the base station based on some data precision [1] requirement. We call the process of this transformation as *data aggregation* in this paper.

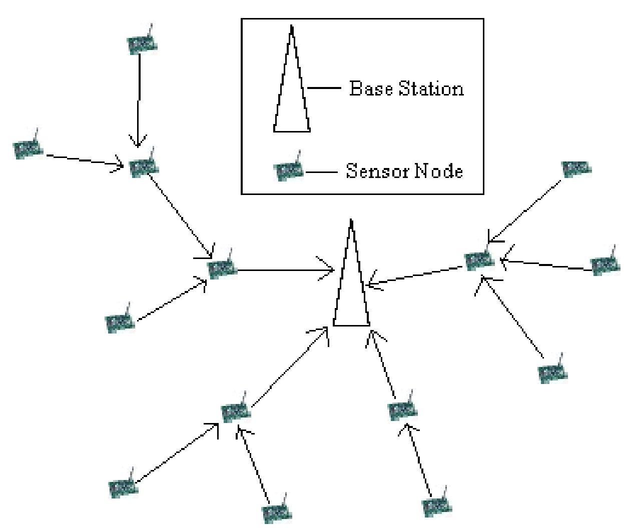

Fig. 1. Architecture for Wireless Sensor Networks

In a WSN, the base station normally has enough power supply to fulfil a given task, while the sensor nodes are power-constrained and are located in the areas that are difficult to

[1]In this paper, data precision is specified in the form of quantitative error bounds.

reach. When a sensor node is out of power, it cannot continue its mission. Once too many such cases happen, the coverage loss will be remarkable, making the WSN fail to accomplish its mission. In this paper we define the time duration that the WSN fails to accomplish its mission as *network lifetime* [1]. In WSNs, data precision and network lifetime are two tradeoff factors that affect the performance of WSNs. For each application, the higher the data precision requires, the shorter the network lifetime is; versus is the same. From the view of data precision, data aggregation can be classified as *exact data aggregation (EDA)* and *approximate data aggregation (ADA)*. In EDA, each sensor node has to report every information update to the base station, which requires substantial energy consumption. While in ADA, each sensor node sends part of its information updates to the base station given that the data precision arrives at the desired level. Obviously, it is desirable to apply EDA for achieving the best data precision. However, this is generally impractical due to the network lifetime requirement for the whole network and the energy limitation for each sensor node. For most of the research on ADA, the objective is focused on extending the network lifetime. Though the network lifetime is of great importance for WSNs, data precision is also very significant for many applications. In many ecosystem experiments, only the data in a designated duration are necessary. For example, the biologists in the Sonoma Redwoods project [22] would like to receive as much detailed data from the sensor networks as possible, so that they can try various physical models and test various hypothesis over the data. In this case, data precision is the dominant factor given that the network lifetime arrives the required duration.

The above analysis shows that it is of theoretical and practical significance to exploit the tradeoff between data precision and network lifetime for approximate data aggregation in WSNs to cater for different applications. In this paper we address the problem of minimizing the total error bound under the constraint that the predefined network lifetime is achieved. To the best of our knowledge, this problem has not yet been studied. The main contributions of this paper are summarized as follows:

- We address the problem of improving data precision by minimizing the total error bound under the constraint that the predefined network lifetime is achieved for approximate data aggregation in both single-hop and multi-hop WSNs.
- We formulate this problem as an optimization problem by combining the changing pattern of sensor readings, the residual energy of sensor nodes, and the communication cost from the senor node to the base station.
- We present an optimal solution for the problem, which is evaluated by extensive simulation experiments. To the best of our knowledge, this is the first study on studying data precision optimization while achieving the desirable network lifetime.

The rest of the paper is organized as follows. In Section II, we describe models for data aggregation and energy consumption. We propose and analyze solutions for improving data precision for approximate data aggregation in single-hop and multi-hop WSNs in sections III and IV, respectively. In Section V, we describe simulation model and discuss performance evaluation. Section VI presents related work. Finally, we summarize our work and conclude this paper in Section VII.

II. Models for Data Aggregation and Energy Consumption

In this paper, we model the process of data aggregation in WSNs as described in Figure 2 as a spanning tree [11], [12], in which the information update from a node will be first transferred to its parent until it arrives at the base station, i.e., the root of the tree. The set of sensor nodes is denoted by $\{s_1, s_2, \cdots, s_n\}$ and the base station is denoted by b. The height of the tree, denoted by h, is defined as the maximal hops that an information update from a leaf can be transferred to the base station. In this paper, we study both single-hop WSNs (i.e., $h = 1$) and multi-hop WSNs (i.e., $h > 1$).

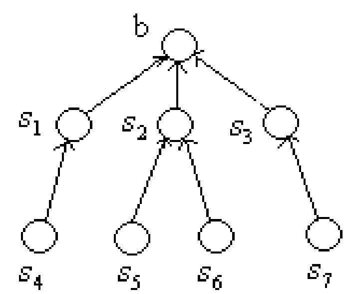

Fig. 2. Data Aggregation Model

In this paper, we assume that there is no energy constraint at the base station. The energy-constrained sensor nodes are inconvenient to replace; thus, communication is the dominant way for consuming energy. We denote the energy consumed by s_i to transmit and receive an information update by t_i and r_i, respectively. The network lifetime, denoted by P, is defined as the time duration before the first sensor node runs out of energy. Our analysis can be easily extended to the case in which the network lifetime is defined as the time duration before a given number of sensor nodes run out of energy.

We consider approximate data aggregation in this paper. If the energy of each sensor node is infinite, then the sensor node can send every information update to the base station to collect all the information updates. However, the sensor nodes are energy-constrained, it is impossible, actually not necessary, for the sensor nodes to send all its information updates to the base station. Therefore, we set each sensor node s_i an error bound, denoted by e_i, for deciding whether an information update from s_i should be transferred to the base station or

TABLE I
NOTATION SUMMARY

Notation	Description
$(s_1, s_2, \cdots, s_n)$	Set of sensor nodes in the network
P	Predefined network lifetime
S	Sensing rate
v_i	Value sensed at s_i
e_i	Error bound designed to s_i
$u_i(\cdot)$	Precision driven update rate of s_i
U_i	Information update rate sent by s_i
t_i	Energy Cost for s_i to transmit an information update
r_i	Energy Cost for s_i to receive an information update
l_i	Left energy at s_i

not. Let v_i denote the value sensed by s_i. Whenever the sensed value v_i changes to $v_i^{'}$, s_i checks whether $v_i^{'} \in [v_i - e_i, v_i + e_i]$ or not. If $v_i^{'} \notin [v_i - e_i, v_i + e_i]$, then a new approximation of v_i, i.e., $v_i^{'}$, is sent to the base station. Otherwise, there is no need to transmit the update to the base station. Therefore, both communication cost and energy consumption are reduced. This paper considers five aggregation functions, i.e., SUM, AVG, COUNT, MIN and MAX. As discussed in [16], these functions can be treated as a collection of SUM or AVG function, which apply in our case as well. Therefore, we focus our discussion on the SUM aggregation function in this paper.

The notations used in this paper are described in Table I.

III. Precision Decision in Single-Hop WSNs

In this section, We investigate the problem of precision decision in single-hop WSNs, where each sensor sends its local information directly to the base station. Single-hop WSNs have a number of advantages [18]. First of all, the analytical results for single-hop WSNs provide insights on the analysis for multi-hop WSNs. Second, it is not beneficial for energy saving to transmit the information sensed at each sensor to the base station through some intermediate nodes. Finally, the limitation of sensor designs (e.g., simplex MAC with limited buffer) may make relaying practically infeasible. The problem of precision decision in single-hop WSNs is to determine the minimal error bound for each sensor node such that the total error bound is minimized given that the network lifetime is no less than the predefined network lifetime and the error bound for each sensor node is greater than the predefined error bound.

Now we begin to formulate the problem. First, we look at the objective. Obviously, the objective is to minimize the total error bound, i.e., $\min \sum_{i=1}^{n} e_i$. Then we look through the constraints. The first constraint is that the network lifetime should be no less than the predefined lifetime. Since the left energy at s_i is l_i and the energy consumption rate of s_i is $u_i(e_i) \cdot t_i$, the expected lifetime of s_i is given by $\frac{l_i}{u_i(e_i) \cdot t_i}$. Therefore, the network lifetime is given by $\min_{1 \le i \le n} \{\frac{l_i}{u_i(e_i) \cdot s_i}\}$. So the first constraint can be expressed as $\min_{1 \le i \le n} \{\frac{l_i}{u_i(e_i) \cdot s_i}\} \ge P$. The second constrain is that the error bound at each sensor node should be no more than the predefined error bound, i.e., $e_i \le e$ for $i = 1, 2, \cdots, n$. Here, we assign each sensor node the same error bound. Our analysis can be easily extended to the case in which the error bounds assigned to each sensor node are different. Based on the above analysis, we can formulate the problem as follows:

$$\begin{cases} \min \sum_{i=1}^{n} e_i \\ s.t. \ \min_{1 \le 1 \le n} \{\dfrac{l_i}{u_i(e_i) \cdot t_i}\} \ge P \\ \qquad e_i \le e \ \ (i = 1, 2, \cdots, n) \end{cases} \tag{1}$$

Now we begin to present an optimal solution for (1). For simplicity, we assume that $u_i(\cdot)$ (for $i = 1, 2, \cdots, n$) is a continuous function with its inverse function denoted by $u_i^{-1}(\cdot)$. The following theorem gives an optimal solution for (1).

Theorem 1: An optimal solution for (1) is $e_i^* = \min\{e, u_i^{-1}(\frac{l_i}{P \cdot t_i})\}$ for $i = 1, 2, \cdots, n$.

Proof: Obviously, $\min_{1 \le 1 \le n} \{\frac{l_i}{u_i(e_i) \cdot t_i}\} \ge P$ is equivalent to $\frac{l_i}{u_i(e_i) \cdot t_i} \ge P$ (for $i = 1, 2, \cdots, n$). Since u_i^{-1} is continuous and non-increasing, we have $e_i \le u_i^{-1}(\frac{l_i}{P \cdot t_i})$ $(i = 1, 2, \cdots, n)$. With the constraint $e_i \le e$ $(i = 1, 2, \cdots, n)$, it is easy to see that $\sum_{i=1}^{n} e_i^* = \min \sum_{i=1}^{n} e_i$, where $e_i^* = \min\{e, u_i^{-1}(\frac{l_i}{P \cdot t_i})\}$. Hence, the theorem is proven. ■

In practice, it is difficult to have the exact form of $u_i(\cdot)$ due to the dynamic patterns of sensor readings. Thus, we apply the adaptive precision location method proposed in [21] to solve this problem. The key idea is to decide the normalized energy consumption rate of each sensor node according to historical sensor readings.

IV. Precision Decision in Multi-Hop WSNs

In this section, we investigate the problem of precision decision in multi-hop WSNs, where each sensor sends its local information directly to its parent node, i.e., the base station cannot cover the radio of all the sensor nodes. It has been shown that in-network aggregation is an important technique to reduce the network traffic of data collection in multi-hop networks [8], [19], [20]. In-network aggregation has the following benefits. First, it yields more manageable data streams avoiding overwhelming sources with massive amounts of information. Second, it performs some filtering and preprocessing on the data, making the task of further processing the data less time and resource consuming. Specially, the sensor nodes are organized as a tree structure with its root at the base station. On receiving information updates from its children, each intermediate sensor node aggregates the information updates before sending them upstream; thus, the amount of information updates is cut down over the upper-stream links in the networks. In a spanning tree, t_i refers to the energy cost for s_i to send an information update to its parent, and r_i refers to the energy cost for s_i to receive an information update from one of its child.

Let U_i be the information update rate sent by s_i to its parent. Obviously, the information updates sent by s_i consist of two parts. One part includes the information updates from s_i itself, i.e., $u_i(e_i)$ and the other part includes the information updates from the children of s_i, i.e., $\sum_{c \in C(s_i)} U_c$. Since the left energy at s_i is l_i, the expected lifetime of s_i is given by $\frac{l_i}{U_i \cdot t_i + \sum_{c \in C(s_i)} U_c \cdot r_i}$. Therefore, the network lifetime is given by $\min\{\frac{l_i}{U_i \cdot t_i + \sum_{c \in C(s_i)} U_c \cdot r_i}\}$. Therefore, we can formulate the problem as follows:

$$\begin{cases} \min \sum_{i=1}^{n} e_i \\ s.t. \ \ \min\{\frac{l_i}{U_i \cdot t_i + \sum_{c \in C(s_i)} U_c \cdot r_i}\} \geq P \\ \qquad e_i \leq e \ \ (i = 1, 2, \cdots, n) \end{cases} \tag{2}$$

where $U_i = 1 - \frac{(1-u_i(e_i))}{S} \cdot \prod_{c \in C(s_i)} (1 - \frac{U_c}{S})$ and $C(s_i)$is the set of nodes that are children node of s_i.

From $\frac{l_i}{U_i \cdot t_i + \sum_{c \in C(s_i)} U_c \cdot r_i} \geq P$, we can calculate e_i as follows:

$$e_i \geq u_i^{-1} \left(S - \frac{S \cdot t_i - P \cdot l_i + \sum_{c \in C(s_i)} U_c \cdot r_i}{t_i \cdot \prod_{c \in C(s_i)} (1 - \frac{U_c}{S})} \right) \tag{3}$$

Corollary 1: An optimal solution for (2) is calculated as follows:

$$e_i^* = \min \left\{ e, u_i^{-1} \left(S - \frac{S \cdot t_i - P \cdot l_i + \sum_{c \in C(s_i)} U_c \cdot r_i}{t_i \cdot \prod_{c \in C(s_i)} (1 - \frac{U_c}{S})} \right) \right\} \tag{4}$$

The proof of Corollary 1 can be easily obtained based that of Theorem 1. Based on Corollary 1 and (3), we can obtain an optimal solution for (2) by the following algorithm.

Algorithm 1**:** Precision Decision for Multi-Hop WSNs

for $i = 1$ to n do

if $C(s_i) = \phi$ then

$e_i^* = \min\{e, \frac{l_i}{u_i(e_i) \cdot t_i}\}$

else

$$e_i^* = \min \left\{ e, u_i^{-1} \left(S - \frac{S \cdot t_i - P \cdot l_i + \sum_{c \in C(s_i)} U_c \cdot r_i}{t_i \cdot \prod_{c \in C(s_i)} (1 - \frac{U_c}{S})} \right) \right\}$$

From Algorithm 1, we can see it works as follows: If s_i is an intermediate sensor node, it collects the lists of error bounds, data update rates and energy consumption rates from all of its children and computes its optimal error bound. If s_i is a leaf sensor node, it computes its optimal error bound directly. Regarding to the time complexity of Algorithm 1, it can be easily verified that its time complexity is $O(n)$, where n is the total number of sensor nodes in the network.

V. Simulation Model and Performance Evaluation

A. Simulation Model

The simulation is conducted based on ns-2 (version 2.27) [26] and NRLs sensor network extension [25]. The sensor nodes send and receive message. For simplicity, we assume in the simulation that there is no energy consumption when the sensor is in the sleeping mode. The energy consumption for sending a message is determined by a cost function: $s \cdot (\alpha + \beta \cdot dq)$, where s is the message size, α is a distance-independent term, β is the coefficient for a distance-dependent term, q is the component for the distance-dependent term, and d is the distance of message transmission. In the simulation, we set $\alpha = 40nJ/b$, $\beta = 100pJ/b/m^2$, and $q = 2$. The energy consumption for receiving a message is given by $s \cdot \gamma$, where γ is set at $30nJ/b$. We set the size of a data update message at 8 bytes, and the size of a refresh message at 4 bytes. The initial energy budget at each sensor node was set at 0.1 Joule. We conduct the simulation on a multi-hop network of 100 sensor nodes. The sensor readings are Poisson distribution with mean inter-reading time of 1 second. The main metric used in the performance evaluation is the average error bound, which is defined as the summation of the error bound set (i.e., the total error bound) to each sensor node divided by the number of sensor nodes. The error bound can be specified in a form of quantity (temperature and humidity for instance).

We include the following schemes in the simulation for the purpose of performance comparison.

- Uniform Precision Decision (UPD): This scheme allocates each sensor node the same error bound. Obviously, this scheme does not consider the effect caused by the changing pattern of sensor readings, the residual energy of sensor nodes, and the communication cost from the senor node to the base station.

- Burden-based Precision Decision (BPD) [16]: This scheme decides the error bound for each sensor node according to the objective of minimizing the total communication cost between data sources and the data sink.
- Adaptive Precision Decision (APD) [21]: This scheme decides the error bound for each sensor node with the objective of maximizing the network lifetime.
- Optimal Precision Decision (OPD): This scheme is proposed in this paper, which decides the error bound for each sensor node with the objective of minimizing the total error bound while achieving the predefined network lifetime.

B. Performance Evaluation

The first experiment explores the relationship between the average error bound and network lifetime. As we know, the frequencies of data updates should be lowered to maintain a longer network lifetime since data updates consume the limited power of each senor node. Therefore, the longer the network lifetime, the larger the average error bound. From Figure 3, we can see that the average error bound increases for each scheme as the network lifetime becomes longer. We can also see that the average error bound decided by our proposed scheme is lower than the other three schemes for each specific network lifetime. This can be validated from the optimality of our scheme, while the other schemes consider this problem from other points of view. Specifically, the mean improvements of OPD over UPD, BPD, and APD are 21.3% , 15.3%, and 14.9%, respectively.

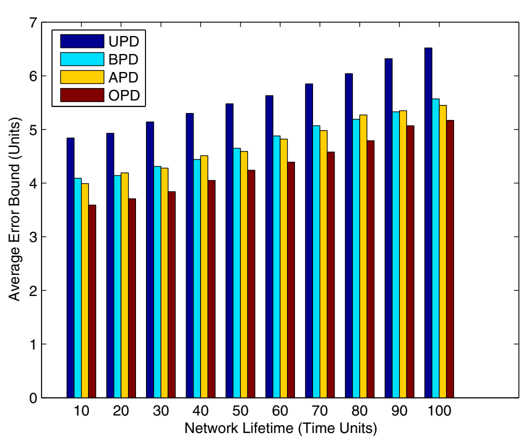

Fig. 3. Average Error Bound vs. Network Lifetime

This second experiment explores the relationship between the average error bound and energy consumption speed (the average amount of power consumed per unit time, second for instance). Figure 4 shows that all schemes tend to have a larger error bound when energy consumption speed becomes larger (i.e., ,more data updates are sent to the base station). From the figure, we can also see that our scheme allocate each sensor node a lower error bound than other schemes. Specifically, the average improvements of OPD over UPD, BPD, and APD are 18.7% , 13.2% , and 11.8% , respectively.

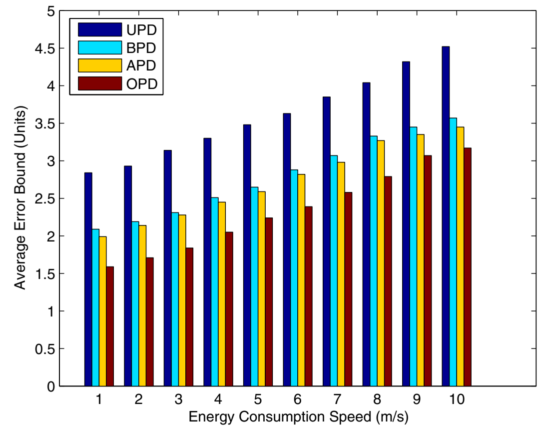

Fig. 4. Average Error Bound vs. Energy Consumption Speed

This last experiment explores the relationship between the average error bound and sensing range (the diameter that each sensor can sense data) for a given network lifetime. In the simulation, we assume that the sensing ranges for each sensor node are the same. Figure 5 shows that all schemes have a larger error bound when the sensing range becomes larger. Specifically, the average improvements of OPD over UPD, BPD, and APD are 13.2% , 9.5% , and 8.6% , respectively.

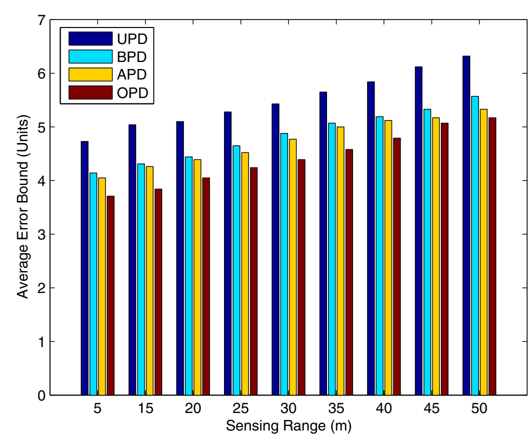

Fig. 5. Average Error Bound vs. Sensing Range

Comparing the performance of different precision decision schemes, we can see our proposed scheme significantly outperforms the other schemes. In general, data precision measured by the average error bound decreases with increasing network lifetime. This is because a higher data precision requires more data updates, which consumes more energy and leads to shorter network lifetime. This is also true for the relationship between the average error bound and the energy consumption speed, and the average error bound and the sensing range.

VI. Related Work

As we mentioned previously, data aggregation can be classified into two categories, i.e., exact data aggregation (EDA) and approximate data aggregation (ADA). For EDA, each sensor will send every information update to the base station, while for ADA, only the information updates that violated the allocated error bound will be transferred to the base station. Although EDA can guarantee a very higher data precision [7], [14], [15], it is not applicable for most of the applications to transfer all information updates to the base station due to the energy limitation for each sensor node. Therefore, ADA has been widely deployed in WSNs [2], [3], [6], [24].

In this paper, we concentrate on ADA. In [5], the authors presented a precision allocation scheme for data aggregation based on online estimation of potential gains to reduce the number of messages in the network. In [9], the authors developed quality-aware data collection protocols that enable quality requirements of the queries to be satisfied while minimizing the energy consumption. In [16], the authors proposed decides a scheme for determining the error bound for each sensor node according to the objective of minimizing the total communication cost between data sources and the data sink. In [21], the authors proposed optimal solutions for extending network lifetime for precision-constrained data aggregation in WSNs. In [23], the authors modeled the problem of maximizing network lifetime for data aggregation in WSNs as a multicommodity flow problem and proposed a fast approximate algorithm. In this paper, we address the problem of minimizing the total error summation under the constraint that the predefined network lifetime, which is complementary to the current research on maximizing network lifetime in WSNs.

Other inspiring work includes querying approximate data over distributed caches and streams in database literature. Olston et al [17] presented a query-driven replica maintenance scheme for approximate data replication. Similarly, in [10], Kalman Filters were used to reduce the amount of data communicated in distributed data streams. In [13] the authors employed piecewise constant approximation schemes for data compression and prediction. The authors in [4] applied predictive models to solve the problem of maintaining accurate quantile summaries over distributed data sources.

VII. Conclusions

In this paper, we explored the relationship between data quality and network lifetime by minimizing the total error bound while achieving desirable network lifetime in both single-hop and multi-hop WSNs. We proposed optimal solutions for precision decision in terms of network lifetime. We also conducted simulation experiments to evaluate our proposed scheme by comparing with existing schemes. The simulation results show that our scheme significantly outperforms other schemes in terms of all the performance metrics.

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