An Optimal Distribution of Data Reduction in Sensor Networks with Hierarchical Caching

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Abstract. Reducing data transmission to conserve energy and provide cost-efficient query answers in sensor networks is the topic of this paper. We consider a sensor network logically organized into a tree structure. The sensors at the lowest level cache raw data, and data is stored with greater degree of compression as we move up the tree. Thus a query answered using data at a lower level has less error but requires more energy. We have proposed a model for accounting the cost of resources consumed and the error in the result obtained. We have formulated an optimization problem for the trade-off between the error cost and the resource cost of answering queries. Its solution enables us to determine the optimal distribution of data reduction at each level. We have presented numerical solutions for some sample data, illustrating the practicality of the scheme.

Keywords: wireless sensor networks, energy-efficient, optimization.

1 Introduction

Conserving energy in sensor nodes is one of the crucial problems in wireless sensor networks. This is specially true for a large sensor network deployed in inaccessible fields. Data transmission is the major energy consumer in wireless sensor networks [1]. To reduce the amount of data transmitted, we investigate a data reduction scheme for efficiently answering queries in a hierarchical data caching structure of large sensor networks while meeting user accuracy requirements. In the caching structure, data at different levels is with a corresponding degree of compression [2]. Sensors at the leaf level cache raw data, compress the data and transmit the compressed data to the intermediate upper level. As we move up the levels, data is compressed to greater extents, but is cached for longer duration. The root node receives user queries, routes the query to an appropriate level and returns the result obtained from lower levels. Caching of the compressed data enables to answer greater historical queries efficiently as some queries can be answered at higher levels instead of being sent to the lower levels. This caching also reduce data transmission in the network since not all the raw

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data is sent to upper levels. These gains are at the cost of query result accuracy. Queries answered at higher levels will get larger error in the results.

The rest of the paper is organized as follows. The cost model is proposed to describe the cost of query answering in Section 2. Section 3 presents an optimal distribution scheme for data reduction by optimizing the trade-off between energy consumption and user error tolerance. Section 4 reports the experimental results which indicate that our scheme can be adapted depending on the user requests and some network parameters. We present related work in Section 5 and conclude our work in Section 6.

2 Cost Model

Caching data hierarchically with different compression degrees can reduce data transmission. While queries answered with data at higher level get larger error in results. To quantitatively analyze the trade-off between energy consumption and result accuracy, we define two costs, *transmission cost* and *error cost*, to represent the cost for query answering. As energy consumption on computing in a sensor node is orders of magnitude lower than the consumption on transmission, we ignore computation cost in this paper [1].

We define the energy consumption for data transmission as *transmission cost*, denoted by C_T. Let c_t denote the unit cost for data transmission, which can be quantified as cents per bit in practice. Let B_t denote the total amount of data transmitted. Thus, C_T is given by $c_t B_t$. As the transmission for queries and query results is much less than the one for sensor data, and data compression techniques will not be applied on query results, we ignore it in this paper. Besides the transmission cost, we define *error cost* to represent cost generated by errors, which is denoted by C_E. When queries are answered at upper levels where compressed data are cached, the errors are generated in the results. We use relative error as a measure of this error, which is defined as:

$$\frac{|result\ obtained - exact\ result|}{exact\ result}$$

Let c_e denote the unit error cost, which can be quantified as cents per relative error in practice. Let E denote the average relative error on all query answers. Thus C_E is given by $c_e E$. When queries are answered in the caching structure, the transmission cost and error cost will change with varying compression degree of data. We use *cumulative reduction ratio* to represent compression degree on the raw data, denoted by R, which is defined as the ratio between the compressed data size and raw data size. *Reduction ratio* is used to represent the data compression degree between two adjacent levels in the hierarchical structure and the definition is given in Section 3. When the cumulative reduction ratio increases, more data are transmitted to upper levels, the transmission cost increases. On the other hand, the increase in cumulative reduction ratio leads to less errors in query results, thus the error cost decreases. The relationship between the the costs and cumulative reduction ratios are illustrated in Fig. 1. In this paper, we aim to find a data reduction scheme with minimum total cost for query

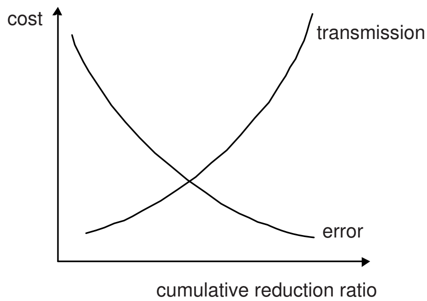


Fig. 1. Relationship between Transmission Cost and Error Cost

answering. Let C denote the total cost, i.e. the sum of transmission cost and error cost, which is given by:

$$C = C_T + C_E = c_t B_t + c_e E.$$

3 Optimal Distribution of Data Reduction

Given a group of queries to be answered in the hierarchical caching structure, we concern the optimal compression degree for data at each level to keep the overall cost minimum. For instance, there is a three-level caching structure. The lowest level is level 0, and the root node is at level 2. The number of queries to be answered at level 0, 1, 2 are 500, 300, 100 respectively. Thus the total cost of answering this group of queries is $C = c_t(B_1+B_2)+c_e(500e_0+300e_1+100e_2)/900$, where B_1 and B_2 are the amount of data transmitted from level 0 to 1 and from level 1 to 2 respectively, e_0, e_1, e_2 are the average relative error in query results at level 0 to 2 respectively. If the number of queries to be answered at level 0, 1, 2 changes to be 100, 400, 400 respectively, in order to obtain minimum overall cost, it is expected that e_1 and e_2 decrease to make the error cost low. The decrease in e_1 and e_2 need the increase in B_1 and B_2, thus the transmission cost increases. Hence, we want to find the best average relative error and the amount of data to be transmitted at each level to get minimum overall cost of query answering. This is essentially the problem of finding the data compression degree at each level. To solve this problem we formulate an optimization problem in this section to give a general statement.

We first consider the data transmission cost. Suppose there are l levels in the hierarchical structure, numbered as 0 to $l-1$ from bottom to upper levels. At level 0, each sensor node produces raw data at the rate of b_0. At a certain upper level i, a sensor receives compressed data from its children at the rate of b_i. Each sensor at level i has n_{i-1} children. We then define *reduction ratio* at level i as the ratio between the data received in a node at level i and the one received in all its children at level $i-1$. Let r_i denoted the reduction ratio, which is given by:

$$r_i = \frac{b_i}{n_{i-1}b_{i-1}}.$$

Defining *reduction ratio* enables us to determine the compression degrees among the levels. In fact, the cumulative reduction ratio R can be calculated by the reduction ratios. Let R_i denote the compression ratio of the data at level i, there is $R_i = \prod_{j=1}^{i} r_j$. Let N_0 be the total number of sensors at level 0. Then the amount of data received at level i, denoted by B_i, is given by:

$B_i = N_0 b_0 R_i = N_0 b_0 \prod_{j=1}^{i} r_j \quad i \in [1, l-1]$

Thus the total amount of data transmitted is:

$B_t = \sum_{i=1}^{l-1} B_i = N_0 b_0 \sum_{i=1}^{l-1} \prod_{j=1}^{i} r_j \quad i \in [1, l-1]$

The total transmission cost is:

$$C_T = c_t B_t = c_t N_0 b_0 \sum_{i=1}^{l-1} \prod_{j=1}^{i} r_j \tag{1}$$

We next consider the error cost of query answering. Let e_i denote the average relative error of a query result when the query is answered at level i. Let q_i denote the number of queries answered at level i. Given a group of queries, the average relative error E of all the queries is:

$E = \frac{e_0 q_0 + e_1 q_1 + \ldots + e_{l-1} q_{l-1}}{q_0 + q_1 + \ldots + q_{l-1}} = \frac{\sum_{i=0}^{l-1} e_i q_i}{\sum_{i=0}^{l-1} q_i}$

In this equation, $\sum_{i=0}^{l-1} q_i$ is the total number of queries posed at the hierarchical caching structure. For simplicity, let q denote the total number of queries, i.e. $q = \sum_{i=0}^{l-1} q_i$. e_0 is 0 as the raw data is cached at level 0. The error e_i is due to the compressed data and is a function of cumulative reduction ratio. In general, e_i can be represented as:

$$e_i = g(R_i) \tag{2}$$

With different compression techniques applied on the sensor data, this function will be different. Further description on this function is given later in this section. Hence, the total error cost is given by:

$$C_E = c_e \frac{\sum_{i=1}^{l-1} e_i q_i}{\sum_{i=0}^{l-1} q_i} = c_e \frac{\sum_{i=1}^{l-1} q_i g(\prod_{j=1}^{i} r_j)}{\sum_{i=0}^{l-1} q_i} \tag{3}$$

Given the costs of transmission and error above, we want to find the optimal reduction ratio at each level to keep the overall cost minimum. Thus, this problem is formulated as an optimization problem:

Minimize

$$C = c_t N_0 b_0 \sum_{i=1}^{l-1} \prod_{j=1}^{i} r_j + c_e \frac{\sum_{i=1}^{l-1} (q_i g(\prod_{j=1}^{i} r_j))}{\sum_{i=0}^{l-1} q_i} \quad 1 \le i \le l-1 \tag{4a}$$

This problem is under following constraints:

– The errors in query results meet user specified accuracy requirement, i.e.

$$0 < g(\prod_{j=1}^{i} r_j) < T_{ei} \tag{4b}$$

where T_{ei} is the threshold of error tolerance at level i, which is decided by the user accuracy requirement. The discussion on user accuracy requirement and T_{ei} is given later in this section.

- reduction ratio at each level is between 0 and 1.

$$0 < r_i < 1 \tag{4c}$$

- As one of the characters of the hierarchical caching structure, older historical data is cached at higher levels than the data at lower levels. Let t_i be the time span for data cached at level i, there is:

$$0 < t_{i-1} < t_i \tag{4d}$$

Let M_i be the memory space for caching in a sensor node at level i, the time span for data cached at this node is given by:

$t_i = \frac{M_i}{b_i} = \frac{M_i}{b_0 \prod_{k=0}^{i-1} n_k \prod_{j=1}^{i} r_j}$.

Description of e_i and T_{ei}

As mentioned in Equation(2), the average error in query results at level i is the function of ratio R_i. This function is determined by the compression technique used. In our previous work, we proposed data approximation algorithms for sensor data [3]. Using some real life data sets, we also analyzed the relationship between the data cumulative reduction ratio and the error generated from the approximated data. Based on our experiment results, we set the error function as following to further illustrate the optimization problem in the next section.

$$e_i = g(R_i) = \frac{k(1 - R_i)}{R_i} \quad (k > 0) \tag{5}$$

where k is the coefficient of the function. With different compression algorithms or on different data sets, the value of k will be different. We set k as 2 in this paper. In this function, if R_i is 0, then $e = \infty$. This means that when data is totally compressed to size 0, the queries are not able to be answered. If $R_i = 1$, $e = 0$. This indicates that when the raw data is sent to the upper levels, there will be no error for query answering. If $R_i > 1$, the value of e is less than zero which is meaningless. Thus, it complies with our requirement that the value of R_i should be between 0 and 1. The graph of this function is illustrated in Fig. 2.

We use the idea presented by Ganesan *et al* to define the relationship between user accuracy requirement and the error with the compressed data [4]. Users generally expect less errors for queries referring to recent data. If queries refer to the older data, larger error is tolerable. With data cached at the hierarchical caching structure, the errors are represented by a step function. Fig. 3 illustrates the relationship between the user requirements and the errors, where $z(t)$ represents user requirements, $f(t)$ represents the errors obtained. The values of $f(t)$ should be less than $z(t)$ to meet user requirements. For instance, within $(t_1, t_2]$, $f(t_1)$ should be less than $z(t_1)$ to keep $f(t)$ over $(t_1, t_2]$ satisfy the user requirements. Thus $z(t_1)$ is threshold of error tolerance for level 2, which is defined as T_{e2}. To

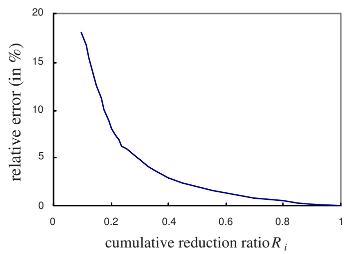


Fig. 2. Error Function $g(R_i)$

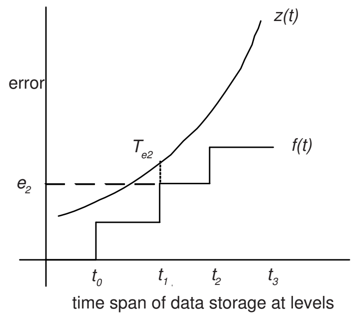


Fig. 3. User Error Requirement $z(t)$ and Result Error $f(t)$

answer queries with data at level 2, there is $e_2 < T_{e2} = z(t_1)$. In general, the error threshold is given by:

$T_{ei} = z(t_{i-1})$.

4 Solution of the Optimization Problem

It appears that the optimization problem in Equation(4) is too difficult to solve in general. However, we can solve it numerically for a given set of parameters. In the following, we use two sets of parameters to illustrate the capability and usefulness of the proposed optimization technique.

4.1 Sample Problem with Two Levels

We consider a sensor network with two-level caching. At level 0, there are N_0 sensors and each sensor produces data at the rate of b_0. The raw data is compressed and sent to level 1 at reduction ratio r_1. For this case, the problem described by Equation(4) can be simplified as following:

Minimize

$$C = c_t b_0 N_0 r_1 + k c_e \frac{q_1}{q_0+q_1} \frac{1-r_1}{r_1} \tag{6a}$$

Subject to:

$$0 < k\frac{1-r_1}{r_1} < z(t_0); \tag{6b}$$
$$0 < r_1 < 1; \tag{6c}$$
$$0 < t_0 < t_1. \tag{6d}$$

For simplicity, we assume the user specified accuracy requirement is a linear function, i.e. $z(t) = t$. The time span for data at level 0 is t_0, which equals M_0/b_0. Thus, the constraint(6b) can be rewritten as:

$0 < k\frac{1-r_1}{r_1} < \frac{M_0}{b_0}$

To obtain the minimum value of C, let $C^{'} = 0$. Then we can get:

$r_1 = \sqrt{kc_e \frac{q_1}{q_0+q_1}(c_t b_0 N_0)^{-1}}$

To illustrate the nature of the solution, we use sample values in the equations above. Some of them are based on the typical values presented in the literature [5,6].

$c_t = 10^{-6}¢/b$ $c_e = 1¢/\%$ $b_0 = 10Kb/s$
$N_0 = 500$ $M_0 = 512KB$ $q_0 = 10,\ q_1 = 20,\ q = 30$

The optimal reduction ratio for this case is $r_1^* = 0.516$.

Fig. 4 indicates the effect of ratio r_1 on the transmission and error cost. We observe that, in accordance with Equation(1) and (3) respectively, the transmission cost increases linearly and the error cost reduces dramatically with r_1. Furthermore, the optimal reduction ratio will be different with varying network parameters, such as c_t and c_e. In Fig. 4(a), the transmission cost changes slower than the error cost over the reduction ratio 0.1 to 0.9. Increased the unit transmission cost c_t to $3 \times 10^{-6}¢/b$, we get another curve of transmission cost illustrated in Fig. 4(b), where the transmission cost increases rapidly. The optimal reduction ratio then decreases, which indicates that the data is sent to level 1 at higher compression degree when the unit transmission cost increases.

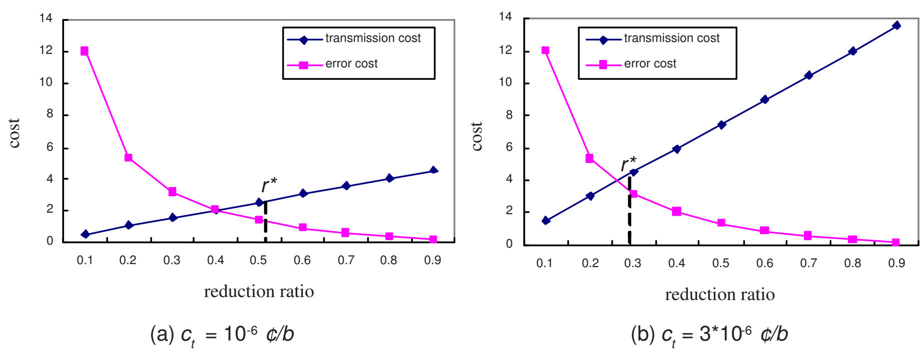


Fig. 4. Cost Trade-off for the 2-level Caching Structure ($b_0 = 10Kb/s, c_e = 1¢/\%, N_0 = 500, k = 2, q_0 = 10, q_1 = 20$)

Except the network parameters, the time span of data requested by queries also affects the optimal reduction ratio r_1^*. This is illustrated in Fig. 5. Given a group of queries, when there are more queries referring historical data at level 1, i.e. q_1/q increases, the optimal reduction ratio increases. This enables more data send to level 1, so that those queries get less errors in results. We also plot another curve by changing the value of the error function coefficient k. Since the increase in k causes the rapid increase in errors, r_1^* will increase to allow more data send to level 1. This is verified by the experiment results reported in Fig. 5, where r_1^* increases rapidly with $k = 3$ comparing the one with $k = 2$.

2-level case is a special example as it only has one reduction ratio parameter r_1. As it can clearly show the effect on costs from the change of reduction ratio,

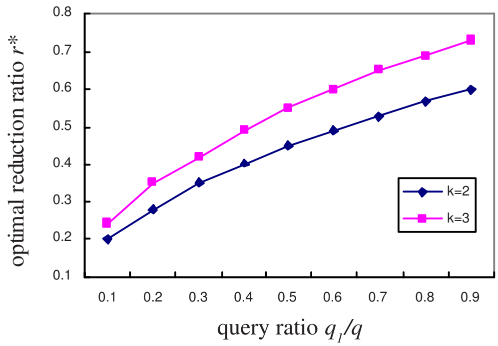


Fig. 5. Reduction Ratios as A Function of q_1/q ($c_t = 3 \times 10^{-6}$¢$/b, b_0 = 10Kb/s, c_e =$ 1¢/%$, N_0 = 500$)

we discuss it in a separate section. In the following, an example of multi-level is used to analyze the effect on reduction ratios from the change of data requests and network parameters.

4.2 Sample Problem with Four Levels

We use 4-level caching structure in a sensor network as an example to illustrate the multi-level problem. The transmission cost in Equation(1) can be simplified as:

$$C_T = c_t b_0 N_0 \sum_{i=1}^{4-1} \prod_{j=1}^{i} r_j = c_t b_0 N_0 (r_1 + r_1 r_2 + r_1 r_2 r_3)$$

Same error function e_i and user requirement function $z(t)$ as the ones in the 2-level case are used here. Then the error cost is:

$$C_E = c_e \sum_{i=1}^{4-1} (q_i g(\prod_{j=1}^{i} r_j)) / \sum_{i=0}^{4-1} q_i = \frac{kc_e}{q}(q_1 \frac{1-r_1}{r_1} + q_2 \frac{1-r_1 r_2}{r_1 r_2} + q_3 \frac{1-r_3}{r_3})$$

The threshold of error tolerances on level 1 to level 3 is $T_{ei} = z(t_{i-1}) = t_{i-1}, i \in [1, 3]$. Suppose all the nodes have same number of children n. Then Equation(4) is simplified as:

Minimize:

$$C = c_t b_0 N_0 (r_1 + r_1 r_2 + r_1 r_2 r_3) + \frac{kc_e}{q}(q_1 \frac{1-r_1}{r_1} + q_2 \frac{1-r_1 r_2}{r_1 r_2} + q_3 \frac{1-r_1 r_2 r_3}{r_1 r_2 r_3})$$

Subject to:

$0 < k\frac{1-r_1}{r_1} < \frac{M_0}{b_0}$	$0 < k\frac{1-r_1 r_2}{r_2} < \frac{M_1}{n b_0}$	$0 < k\frac{1-r_1 r_2 r_3}{r_3} < \frac{M_2}{n^2 b_0}$
$0 < r_1 < 1$	$0 < r_2 < 1$	$0 < r_3 < 1$
$0 < t_0 < t_1 < t_2 < t_3$		

Suppose the relevant parameters are set as:

$c_t = 1 \times 10^{-6}$¢$/b$	$c_e =$ 1¢/1%	$b_0 = 10Kb/s$
$n = 8$	$N_0 = 512$	$k = 2$
$M_0 = M_1 = M_2 = 512KB$		$q_0 = 10,\ q_1 = 500,\ q_2 = 100, q_3 = 80$

This nonlinear constraint problem can be solved using Matlab tool and the solution is:

$r_1^* = 0.50, r_2^* = 0.58, r_3^* = 0.89$

Next, we consider the effect of the user queries and network parameters on the reduction ratios. The results are reported in Fig. 6. Fig. 6(a) illustrates the effect on the reduction ratios when the percentage of q_1 increases. r_1^* increases along with the increase in q_1/q. This enables more data sent to level 1 so that less error generated in answering queries at this level. r_2^* and r_3^* decrease because of the decrease in the percentage of q_2 and q_3. Fig. 6(b) reports the effect of the increase in percentage of q_2 on reduction ratios. r_2^* increases along with the increase in q_2/q. This enables more data sent to level 2 so that less error generated at this level. When q_2/q is less than 50%, its rise leads to the slight decrease in r_1^* because of the decrease in $q1/q$. When q_2/q is over 50%, its effect on r_1^* turns to be determinant, thus r_1^* starts to rise. Because of the decrease in $q3/q$ and the increase in r_2^*, r_3^* rapidly drops. Fig. 6(c) shows the effect of the increase in $q3/q$. The effect on r_1^* is similar with the one in Fig. 6(b). When q_3/q is less than 50%, r_2^* shows a gradual increase as the consequence of the interaction between the slight decrease in r_1^* and rapid increase in r_3^*. When q_3/q is over 50%, its effect turns to be determinant. Thus r_2^* approximately reaches 1 to allow more data to be received at level 2 and to be sent to level 3. In a summary, Fig. 6 indicates that the change in the percentage of queries at certain level has direct effect on the reduction ratio at the corresponding level and also strong effect on the immediate upper level. Furthermore, the results show that more queries are answered at a certain level, more data is sent and less errors will be generated at this level.

Unit transmission cost c_t and unit error cost c_e also have effect on the reduction ratios. Fig. 7(a) illustrates the effect of c_t on r_i^*, where $log(c_t)$ is used as x-axis value for better display. When c_t increases from 10^{-6}¢$/b$, r_1^* firstly decreases while r_2^* and r_3^* keep constant. When c_t increases up to $3.16 * 10^{-5}$¢$/b$ (i.e. $log(c_t) = -4.5$), r_1^* stops decreasing and r_2^* starts to decrease. The similar process is taken place on r_2^* and r_3^*. When c_t reaches $3.16 * 10^{-3}$¢$/b$ (i.e. $log(c_t) = -2.5$), r_2^* stops decreasing and r_3^* starts to rapid decrease. The decrease process among r_i^* indicates that the increase in c_t gradually affects the reduction ratios from lower level. This is due to the total amount of data transmitted at lower levels is larger than the one at higher levels. Fig. 7(b) illustrates the effect of c_e on r_i^*. The reduction ratios in the hierarchical structure shows the same change order as the ones in Fig. 7(a), but with different change direction. The increase process among r_i^* indicates that the c_e also gradually affects the reduction ratios from lower levels. The first increase of r_1^* enables more data to be sent from lower level, and alleviates total error cost.

In summary, these results show the effect of reduction ratio on the cost of query answering, and the effect of user requests and network parameters on the distribution of data reduction. We observe that the scheme is adaptive to keep the overall cost minimum. Further, in this scheme, the increase in the percentage

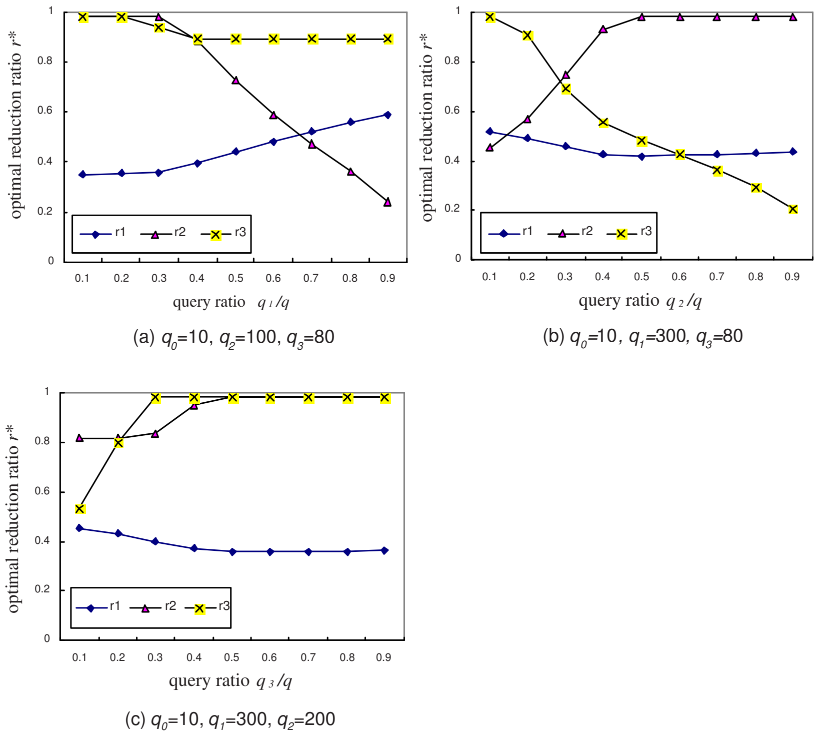
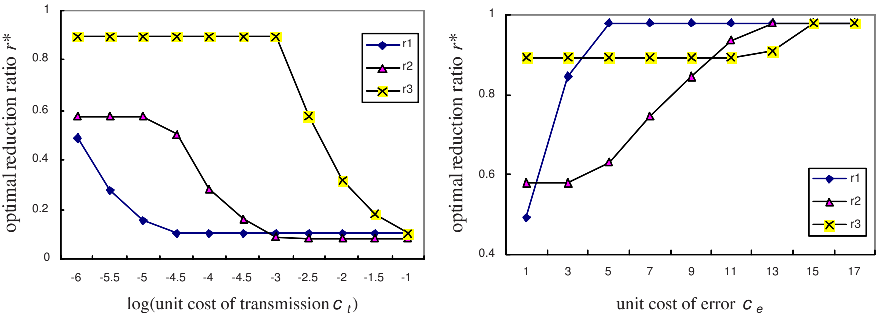


Fig. 6. Reduction Ratios as A Function of $q_1/q, q_2/q, q_3/q$ ($c_t = 10^{-6}¢/b, b_0 = 10Kb/s, c_e = 1¢/1\%, n = 8, N_0 = 512, k = 2, M_0 = M_1 = M_2 = 512KB$)

of queries posed at a certain level leads to the increase in the reduction ratio at this level, i.e., less compression is applied on the data sent to this level.

5 Related Work

A wide range of methods have been proposed to reduce data transmission to conserve energy in wireless sensor networks. These can be roughly divided into three categories: data routing, data compression, data prediction. Some researchers investigate to route the sensor data efficiently. Meliou *et al* present an algorithm to compute the optimal communication path for data transmission [7]. An analytical model and a heuristic algorithm are proposed in [8] to construct an energy efficient routing for real time data aggregation gathering. Exploiting the correlation character in sensor data, some researchers have devoted to sensor data compression or approximation to reduce data transmission. Exploiting spatial correlation in sensor data, a distributed wavelet compression algorithm is proposed in [9]. Lazaridis *et al* represent sensor data in an approximate format by dividing the time series into segments [10]. Some researchers investigate to reduce data transmission by predicting data in sink node. For example, an ARIMA



(a) c_e= 1 ¢/%   (b) c_t= 1*10^{-6} ¢/b

Fig. 7. Effect of Unit Cost on Reduction Ratio ($b_0 = 10Kb/s, N_0 = 512, k = 2, M_0 = M_1 = M_2 = 512KB, q_0 = 10, q_1 = 300, q_2 = 100, q_3 = 80$)

model is used to predict data in sink node in [11]. Although these work consider the trade-off between energy consumption and data quality, they neither pay attention on the cost of query answering nor put the error cost in overall cost for optimizing their solutions.

Our work is similar to that of Ganesan *et al*, where the compressed data is stored in a hierarchical structure [4]. Their work focuses on optimizing the memory usage, i.e. how long the data can be cached at each level, to satisfy user accuracy requirements given the limited total memory capacity. Our work focuses on optimizing the data reduction ratios while keep the overall cost to a minimum.

6 Conclusion

Given a group of queries to be answered with hierarchically cached sensor data, different data reduction schemes lead to different costs of data transmission and error. In this paper, we provided a technique for determining the optimal strategy for data compression to minimize the energy consumed while meeting the user requirement. We used example data drawn from the literature to illustrate the practicality of the technique presented. The results show that the optimal data reduction scheme can adaptively change according to network parameters and user requirements.

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