An Adaptive Compression Algorithm for Energy-Efficient Wireless Sensor Networks

Beihua Ying*

* *School of Information Science and Engineering, Ningbo Institute of Technology, Zhejiang University, Ningbo, Zhejiang, 315100, China*

yingbh@nit.zju.edu.cn

***Abstract*—Energy efficiency is one of the most important design metrics for wireless sensor networks. As sensor data always have redundancies, compression is introduces for energy savings. However, different emphases on algorithm design influence the operation effect of compression under various applications and network environments. In order to improve the energy utilization efficiency for the whole network, an adaptive data compression is proposed in this paper, which realizes a real-time adjustment of compression strategy. By prediction and feature extraction of several relevant parameters, the algorithm provides optimal execution strategies for each sensor node in the network. The simulation results show that, the proposed compression scheme enables all nodes to complete data communication with near optimal energy consumptions, and the maximum deviation against the ideal condition is no more than 5%. Moreover, the algorithm can effectively act on different data precision, transmit power and retransmission rate to meet the dynamic requirements of the network with only a few costs introduced.**

***Keyword*—wireless sensor networks, data compression, energy efficiency, adaptive mechanism**

I. INTRODUCTION

WIRELESS sensor network (WSN) is an emerging and promising networking technique that has attracted more and more attention in recent years. It facilitates humans to sense and monitor the region of interest, and is widely used in many application fields such as agricultural planting, medical care, smart homes, ecological monitoring and so on [1]–[3].

Since the power of sensor nodes supplied by batteries is high-limited and not easy to complement commonly, the most important issue in WSNs is prolonging network lifetime by energy-efficient strategy. Data compression is introduced into WSNs due to its ability to reduce the data amount by exploiting the redundancy resided in sensing data [4]. Meeting the application requirement as a prerequisite condition, such kind of in-network information processing is strongly recommended to decrease energy consumptions in data communication and prolong the lifetime of WSNs.

However, from the implementation perspective and reevaluation, data compression may not achieve total energy savings in any case [5]. On one hand, sensor nodes are densely deployed which permits a low transmit power during data collection. On the other hand, if high-resolution data are required by applications, it is hard to get a satisfied compression ratio. Thus, in-network data compression may increase rather than decrease the total energy consumptions when the savings in communication cannot compensate the additional costs in data processing. Thus, a compression arbitration system has been proposed in [6] by which compression algorithm in time domain is examined carefully to assess its energy efficiency before compression. The case in which compression is unnecessary will be avoided and sensor node will transmit raw data directly instead of the compressed ones.

Based on our previous works, it is reasonable to believe that data compression in WSNs should be carefully carried out. The variety of application scenarios will affect its efficiency profoundly. In order to obtain more energy savings for whole networks, more researches need to be done on data compression. Among them, the adaptability of algorithm is one of the most important design considerations, because it is an effective way to deal with the variability of different situations. In this paper, we pay greater attention to this adaptability and propose an adaptive algorithm that enables a real-time adjustment of compression strategy to increase the energy efficiency of the whole network.

The remainder of this paper is structured as follows: in Section 2, we discuss the related work on the adaptability of compression algorithms and the motivation for our adaptive data compression. The proposed system and its mathematical analysis are presented in Section 3. The process of building prediction models is detailed described in Section 4, and subsequently, Section 5 presents the results of algorithm simulation and implementation using an environmental application. Finally, Section 6 concludes the paper.

II. RELATED WORK AND MOTIVATION

Most existing works enhance the adaptability of compression algorithm in WSNs by using tunable data processing methods. In these researches, data precision is

Manuscript received December 31, 2015. This work was sponsored by the Nature Science Foundation of Zhejiang Province (Project No. LQ13F010005) and Ningbo Natural Science Foundation (Project No. 2011A610185). The research was supported by Ningbo Sc. & Tech. plan project (2014B82015). The author would like to appreciate the valuable datasets from the TAO Project Office of NOAA/PMEL, the ShakeMap Working Group, and the NWISWeb Support Team.

Beihua Ying is with the School of Information Science and Engineering, Ningbo Institute of Technology, Zhejiang University, Ningbo, Zhejiang, 315100, China (corresponding author to provide phone: 86-574-88130020; fax: 86-574-88229505; e-mail: yingbh@ nit.zju.edu.cn).

restricted as an error tolerance, which is specified by each application. The compression can be lossless or lossy for different needs, such as wavelet transformation [7], predictive compression [8], data fitting [9], discrete cosine transform (DCT) [10], compressive sensing [11]–[12], fuzzy transform [13], and so on. Moreover, some lossless compression methods are improved to adapt to WSN applications. For example, an adaptive Huffman code is proposed in [14] that can achieve tunable compression with required accuracy.

Another meaningful work is about the energy consumption in compression that has received more and more attentions instead of compression ratio. Different from other applications, energy saving is the ultimate design purpose of WSNs in most cases. As a result, compression cannot merely pursue high compression ratio, but take energy costs into full consideration [15]–[16]. It also reflects the adapt degree to WSN applications. Several studies have begun to focus on this. In order to reduce the total energy consumptions, a trade-off between computation during data compression and communication energy is made carefully. [15] constructs several energy models of computation and communication for mathematical analysis, but gzip is adopted which cannot be implemented in the resource constrained sensor nodes. In [17], error radius of prediction algorithm are tuned for optimizing the desired tradeoffs between data quality and energy saved, and a similar work is proposed in [18] based on the discrete cosine transform.

Once the energy consumption of compression is considered, the practicality of several algorithms will be greatly reduced, especially for the one with high computational complexity. What is more, compression itself cannot get energy saving in some situations. According to this point, we introduce a novel pre-judgment mechanism to data compression. Once system estimates that compression cannot save energy, sensor node will send raw data directly. A similar work is presented in [19], which decides whether compressing or not based on time delay.

As shown in our previous works, using “compression pre-judgment” can remarkably make sensor nodes more energy efficiency in most cases. It also makes our compression system more suitable for WSN applications [20]. Nevertheless, this system is still insufficient in two aspects. Firstly, the compression arbitration in [20] focuses on a single node, but not a whole network. Decisions about whether or not to compress data are made at the node-level, which are not involved in the ubiquitous multi-hop communication mode. As a result, data receiving is neglected when the total energy costs are calculated and subsequently compared. Since data reduction not only affects the energy dissipation in sending, but also in receiving, it is not comprehensive to estimate the energy-saving benefits of compression algorithms without data reception at the network-level.

More importantly, the compression arbitration is proposed under the assumption that only one compression algorithm is adopted in the whole network, which would be unable to make the best use of data compression. According to the evaluation results of compression algorithms presented in [5], different algorithms show different properties though they are all aimed to be used in WSNs. Take the existing algorithms for example: LAA [21] and predictive coding [22] represent one kind of algorithms that have low complexity, whereas their compression effects are not prominent. Conversely, PMC-MR [23] and LTC [9] tend to achieve better compression ratio at the costs of more energy losses in calculation. It is clear that, in those algorithms, compression effect and algorithm complexity are two major considerations, but have different emphasis during the design. This is probably the main reason causing the differences between compression algorithms. As a result, when various settings of applications are selected such as data type, precision requirement, communication quality, node location, and so on, energy-saving benefits obtained by compression algorithms are distinct.

In summary, from the point of view of the entire network, it is reasonable to believe that single compression algorithm cannot achieve better energy efficiency. An adaptive data compression with tunable precision is urgently needed which is able to determine the optimal execution strategy according to different application requirements and network settings. Benefit from the adaptability, compression algorithms with distinct characteristics will be adopted to maximize energy savings at the network-level.

III. Adaptive Compression System

A. System Description

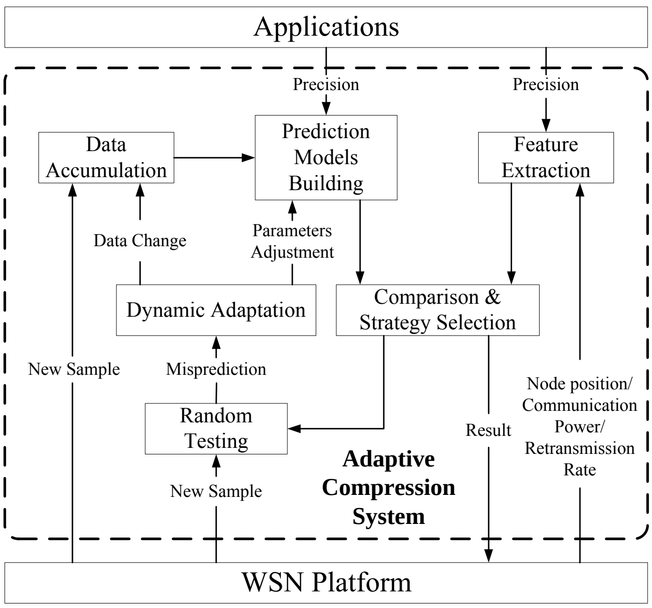


Fig. 1. Framework of the adaptive compression system

In order to make the best use of different compression algorithms for the total energy savings, a lightweight strategy selection mechanism is proposed in this paper. Before compressing, an optimal executive strategy for each sensor node is derived by predicting and feature extracting of all related parameters, which makes the whole network achieve energy efficiency to the greatest degree. The adaptive compression system framework is shown in Fig. 1. According to the function of each module, the whole procedure can be divided into four steps:

1. Prediction modeling

Before deciding on the optimal strategy, two models are established to predict the compression ratio and compression time on-line. Data compression under various algorithms is performed during this initial stage. Compression ratio and execution time for each algorithm based on different datasets and application requirements are recorded. These data are the basis for the prediction model building. Since this is done on-line, only a few samples are used to save energy.

2. Feature extraction

When starting the decision-making process, three types of feature need to be extracted, including raw data, algorithm and network. Among them, data type, error tolerance and algorithm type, which represent the features of raw data and algorithm respectively, are used to calculate the compression ratio and the required time. Moreover, the useful information extracted from the network include node position, communication power and retransmission rate.

3. Compression evaluation & strategy selection

Once the required parameters are ready, system can evaluate all kinds of alternative strategies by calculating the total energy consumptions including data compression and data transmission from each source node to sink. The optimal executive strategy can be obtained based on the comparison results. The selected strategy leading to the lowest energy loss may be an alternative compression algorithm, or may not perform any compression.

4. Model modification

Since compression ratio and execution time will greatly influence the energy consumptions in communication and calculation respectively, ensuring the predict precision can effectively improve the accuracy of the strategy selection. In view of this, model modification is used to guarantee the accuracy of the two predictions. Raw datasets are randomly selected to verify the predicted results. The model parameters will be modified if the prediction accuracy is not satisfied.

B. Mathematical Analysis

In our system, the optimal strategy choosing is based on the total energy costs of each sensor node in data communication. Correct energy calculation is very important, because it will directly affect the judgment of the strategy. Thus, the energy losses in both communication and calculation are considered here.

$$E_{comp} = P_{MCU} * L * T_{MCU}(e) + P_{TX}(d) * L * CR(e) * T_{tran} * (1+\gamma),\ h = 1 \quad (1)$$

$$\begin{aligned} E_{comp} = {} & P_{MCU} * L * T_{MCU}(e) + \sum_{i=1}^{h} P_{TX}(d_i) * L * CR(e) * T_{tran} * (1+\gamma_i) \\ & + \sum_{i=1}^{h-1} P_{RX} * L * CR(e) * T_{tran} * (1+\gamma_i),\ h > 1 \end{aligned} \quad (2)$$

$$E_{uncomp} = P_{TX}(d) * L * T_{tran} * (1+\gamma),\ h = 1 \quad (3)$$

$$\begin{aligned} E_{uncomp} = {} & \sum_{i=1}^{h} P_{TX}(d_i) * L * T_{tran} * (1+\gamma_i) \\ & + \sum_{i=1}^{h-1} P_{RX} * L * T_{tran} * (1+\gamma_i),\ h > 1 \end{aligned} \quad (4)$$

The proposed system is analyzed where E_{uncomp} denotes the energy consumption for transmitting the raw data directly and E_{comp} denotes the total energy costs for compressing the same data and then transmitting the compressed one. It is clear that E_{uncomp} only involve the communication costs, whereas E_{comp} is related to the compression costs in MCU and the communication costs in RF module. Considering that the cost in RF wake-up is the same, regardless of whether compression is executed, it will not affect the final decision results. On the other hand, since the length of the frame head is much smaller than the data part, it also can be ignored. As a result, E_{comp} and E_{uncomp} can be simplified as (1) to (4).

L denotes the original data size and CR describes the compression ratio which is a function of the error bound e. T_{tran} is the time cost for transmitting one byte of data and T_{MCU} is the time overhead for compressing one byte, which is strongly dependent on e. The transmit power P_{TX} is closely related to the communication distance d, while the MCU power P_{MCU} and the received power P_{RX} are approximately constant when the related modules work in the active mode. It is clear that CR (e) and T_{MCU} (e) are obtained by the two prediction models. As the sink is a super node with unlimited energy, there is no need to consider receiving energy consumption for its neighbors whose hop count h is equal to 1. The data retransmission rate γ_i reflects the quality of communication channel in the multi-hop routing. The worse the communication channel becomes, the higher the data retransmission rate is.

(2) shows that for different compression methods, the characteristics of each algorithm determine the energy saving benefits of sensor nodes. For the compression with low complexity, T_{MCU} will be very small, which leads to a lower computational energy costs. If sensor nodes are close to the sink (h is small), computational costs will account for a large proportion, especially when P_{TX} is turned down for the short-range communication. In this regard, algorithm with low complexity will bring a huge advantage. With the increase of h, the proportion of computational costs will be decreased, while the corresponding communication costs is obviously increased. At this point, the influence of compression ratio on communication energy consumptions will directly act on the total energy costs. Therefore, compression algorithm, which focuses on the compression effect gradually, shows its energy saving advantages with the increase of node hops.

IV. Adaptive Mechanism in Prediction Modeling

Accurate prediction of compression ratio and execution time is an important part of ensuring the correct selection of strategy. Thus, an adaptive mechanism is introduced into our proposed system. This mechanism requires fewer samples to build the prediction models, which makes on-line modeling possible. Even if the initial models are somewhat inaccurate, they will be adjusted adaptively to the best results. The adaptive mechanism is illustrated in Table I.

The beginning of the adaptive mechanism uses an initial sample step with a given range. Once a new sample is ready for verification, the compression ratio and execution time are both measured. The comparison then determines whether the difference between the predicted value and the real one exceeds a preset error bound. If the prediction error is large, the information including the compression ratio and time overhead are recorded for the new model. Two prediction models are rebuilt when the sample step (*step*) reaches the minimum value or the sample step is reduced continuously. Alternatively, the sample step is increased until the maximum value.

TABLE I
PROCESS OF THE ADAPTIVE MECHANISM

Algorithm Adaptive mechanism for prediction modeling

```
set an initial sample step (step)
set an allowable step range [step_min, step_max]
if (sample is awaiting verification) then
  measure CR and T_MCU
  if ((|prediction error of CR|>=error bound)
        or (|prediction error of T_MCU |>=error bound)) then
    record compression ratio and time overhead for the sample
    if (step == step_min) then
      rebuild the models with the recorded samples
      reset step
    else
      decrease step
    end if
  else
    increase step until step_max
  end if
end if
```

V. PERFORMANCE EVALUATION

A. Experimental setting

In order to verify the energy saving effect of the proposed system, the experimental settings are confirmed, such as original datasets, network topology, alternative strategies and experimental platform.

1. Original datasets

Datasets from the Tropical Atmosphere Ocean Project (TAO) [24], which collects real-time oceanographic and meteorological data in the Pacific Ocean, are selected for the experiments. Among the various types of datasets, air temperature, sea level pressure and relative humidity are chosen because of their very different data characteristics.

2. Network topology

Grid-based network topology is adopted with nodes even distribution, as show in Fig. 2.

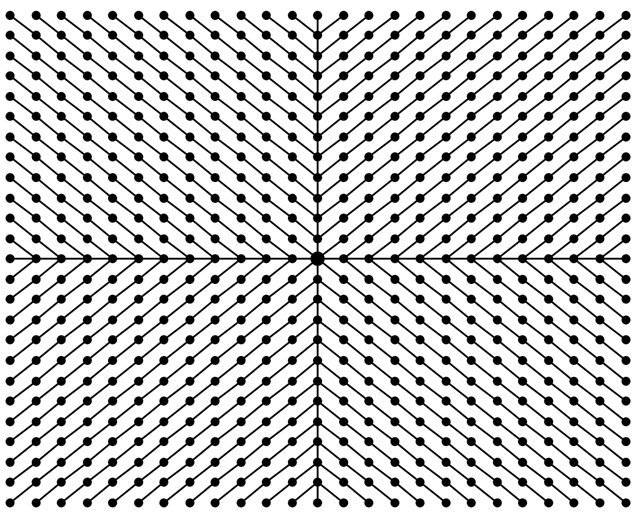


Fig. 2. Network topology in the test

The network size is 25*25, and the total number of sensor nodes is 625. In these nodes, sink node is located in the center of the whole network, which is denoted by a large solid circle. The rest of the nodes are homogeneous. Each source node is routed to the sink using SPT (Shortest Path Tree) [25]. Because of the even distribution, sensor nodes are assumed to transmit data with a uniform RF power level and retransmission rate.

3. Alternative strategies

Based on the evaluation results of data compression in [5], the tests select four different algorithms with better performances, as shown in Table II. Combined with the implementation of not compressed, sensor nodes can choose the best on from these five alternative strategies.

TABLE II
COMPRESSION ALGORITHM IN THE TEST

Algorithm	Type	Remark
Single Moving Average	Predictive compression	N=3
LAA	Linear regression	——
PMC-MR	Linear regression	——
LTC	Linear regression	——

4. Experimental platform

We choose MicaZ nodes as the test platform for our experiments. They are commonly used in WSNs. The processor is an 8-bit Atmel ATmega128L microcontroller, and the processor speed is fixed at 8MHz. As the results shown in [26], supply current of processor is nearly constant in active mode. Therefore, we consider P_{MCU} as a fixed value in the test. T_{MCU} is obtained by ATMEL AVR Studio [27]. In MicaZ node, a CC2420 unit is responsible for communicating with other nodes. It is a single-chip RF transceiver that operates at 2.4 GHz. According to [28], the data transmission rate of a MicaZ node is up to 250 kbps. Besides, transmit power is configurable; in that case, CC2420 can be powered down by setting control register when communication distance is short. In the test, we assume that source nodes send information up to 100 m when the transmit power level is set to 31. Experimental parameters mentioned above are listed in Table III.

TABLE III
VALUES OF THE EXPERIMENTAL PARAMETERS

Symbol	Value	Unit	Remark
d	5-100	m	Outdoor monitoring
P_{MCU}	26.4	mW	8mA current draw
P_{TX}	57.42	mW	PA_Level=31
P_{RX}	62.04	mW	18.8mA current draw
T_{tran}	32	μs	250kbps data rate

5. Relevant assumption

Several reasonable hypotheses are given in our experiments. First, when source nodes, which are homogeneous, establish a communication route with the sink using SPT, they are able to get the communication hops h and the transmit power P_{TX}. Second, accuracy requirement of the data is given by WSN applications, and this information is sent to the whole network by the sink. Third, the test network is uniform distribution, so the node density determines the RF transmit power required by the single hop communication. With the failure of the nodes, the density will be reduced, and the RF power and data retransmission rate will be increased accordingly.

B. *Impact of the characteristics in data and network*

In order to explore the impact of the characteristics in original data and network on energy saving strategy selection, we choose data accuracy, transmit power level and data retransmission rate as test variables for the deeply analysis.

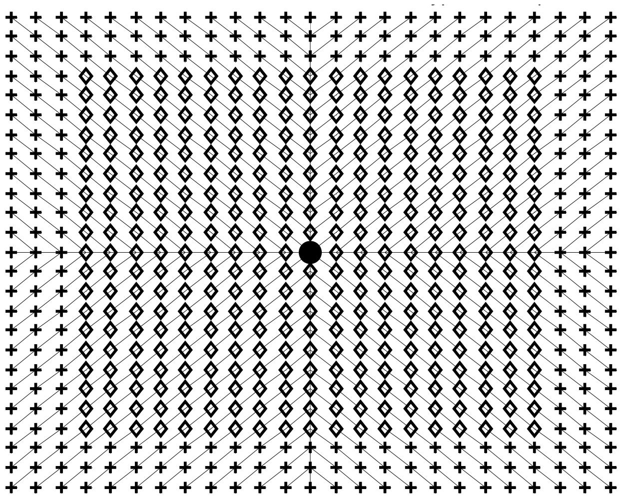
Taking air temperature as an example, Fig. 3 shows the results of selecting the best compression implementation strategy by our adaptive compression method, which are set by the different data accuracy requirements, the transmit power level and the data retransmission rate. Among them, taking into account the actual situations of WSN applications, the variation grades of data accuracy, transmission power and retransmission rate are set to 1-12, 3-31, 10%-150%, respectively.

Comparing Fig. 3(a) and Fig. 3(b) reflects the impact of the data accuracy on strategy selection. It can be seen that there are three alternative strategies in the results: PMC-MR, LTC and no compression. When the accuracy level is set higher (the numerical value is small), source nodes near the sink are more inclined to choose no compression, which is in good agreement with the conclusion that compression may not achieve total energy savings in any case. At that time, due to the compression algorithms cannot achieve satisfactory compression effect, the energy savings in communication may not compensate for costs in calculation. Therefore, from the point of view of total energy costs in nodes, transmitting raw data without compression will obtain lower energy losses. With the increase of the distance between source nodes and the sink, the benefit of compression is also increasing. As a result, the nodes tend to select the algorithm (LTC in Fig. 3) which has a better compression effect.

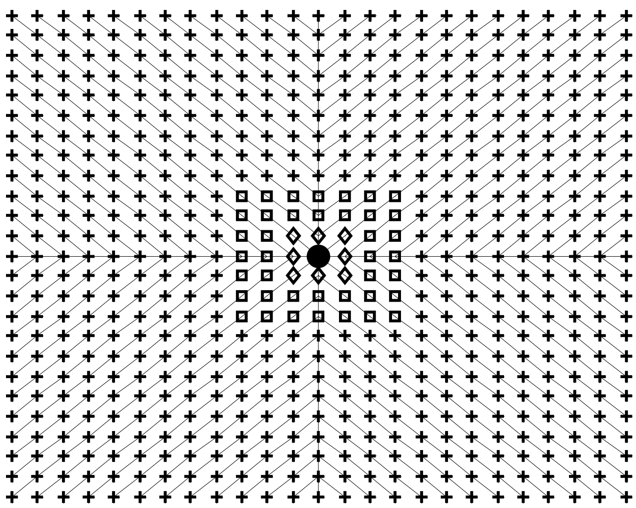
Reducing data accuracy requirements, the effect obtained by data compression is gradually clear. Sensor nodes mostly choose to compress at first, and send the compressed data instead of the original ones. Furthermore, during the selection of different algorithms, nodes near the sink will make a trade-off between computational complexity and compression effect, whereas nodes away from the sink will still consider the compression effect as a primary goal. Therefore, from the results of Fig. 3(b), although LTC can achieve the minimum compression ratio among the four compression algorithms, source nodes near the sink still select PMC-MR as the best energy saving strategy in virtue of its high computational costs.

Comparing Fig. 3(a) and Fig. 3(c) reflects the impact of the transmission power level on strategy selection. The lower the transmission power level is, the higher the probability that compression wastes the total energy costs. As a result, there are over 50% of the nodes do not compress the raw data in Fig. 3(a). With the increase of the transmission power, the advantage of compression in energy savings becomes more obvious. Thus, more nodes choose to perform the compression operation, as shown in Fig. 3(c).

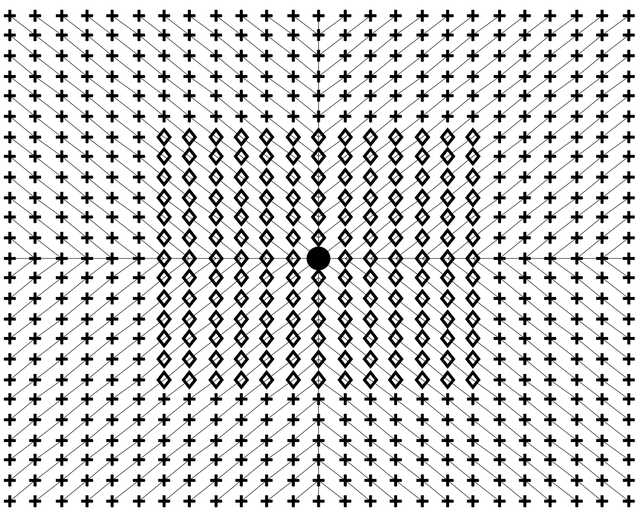
The impact of the retransmission rate on strategy selection can be seen in Fig. 3(b) and Fig. 3(d). The lower the data retransmission rate, the more likely that node that is close to the sink selects no compression. With the deterioration of channel quality, retransmission rate and communication energy costs increase correspondingly, and nodes will gradually tend to select the algorithm which has good compression effect.



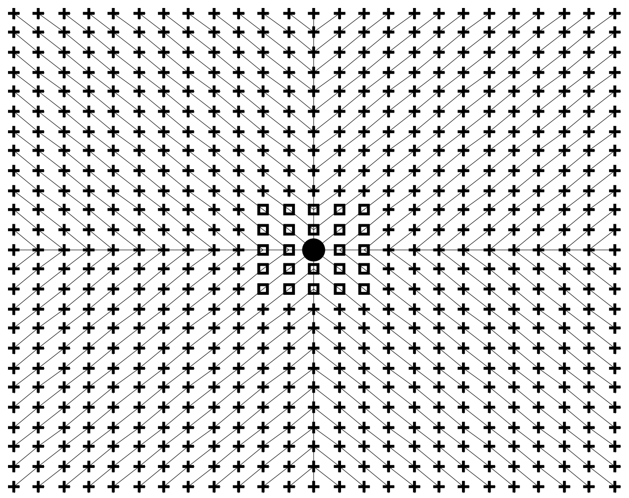
(a)



(b)



(c)



(d)

□: PMC-MR +: LTC ◊: No compression

Fig. 3. Best compression strategy in different situations: (a) data accuracy: level 1; transmission power: level 3; retransmission rate: 10%; (b) data accuracy: level 12; transmission power: level 3; retransmission rate: 10%; (c) data accuracy: level 1; transmission power: level 23; retransmission rate: 10%; (d) data accuracy: level 1; transmission power: level 3; retransmission rate: 100%.

C. *Energy-saving effect of the adaptive compression*

In order to evaluate the energy-saving effect of the proposed compression algorithm quantitatively, the total energy consumptions of the sensor nodes are measured in the following two cases. One is that all nodes use a single data compression algorithm or do not perform any compression, and the other is that each node adopts the adaptive compression to choose the best one from the five alternative strategies.

In fact, if the nodes use the optimal strategy in each data transfer, it can be considered as the best situation of energy costs. Taking this ideal case as a reference, the statistical results of the total energy costs in different cases are compared in the form of maximum deviation (expressed as a percentage), as shown in Table IV. In this table, E, RF and γ represent the level of data accuracy, transmission power and retransmission rate, respectively. That is to say, E2_RF7_γ0.1 denotes that the data accuracy and the transmission power are in level 2 and level 7, and the retransmission rate is 10%.

From the results of Table IV, it is clear that the proposed compression method can make the whole sensor nodes complete data transfer tasks with nearly optimal energy consumptions, no matter how the precision requirement, transmit power and retransmission rate change. It should mainly owe to the adaptive mechanism introduced into the data compression that uses strategy selection for energy efficiency. When the accuracy requirement is high, like E2, data compression cannot obtain a satisfied compression ratio. Instead of saving energy costs, compression increases the additional computational losses. Thus, the total energy consumption has a greater deviation from the optimal once complex compression is executed. At that time, no compression or compression algorithm with lower complexity will make the energy consumption approximate to the optimal. With the decrease of the accuracy requirement, the compression method gradually reveals the advantages of energy savings. More and more sensor nodes adopt compression methods, especially the one with good compression effect and low implementation complexity, and no compression gradually increases the degree of deviation from the ideal situation.

Due to the limitation of prediction accuracy in compression ratio and execution time, erroneous judgment will inevitably occur during the process of compression evaluation and the following strategy selection. It also probably leads to that a single compression algorithm is more close to the optimal energy consumption than the proposed one in some cases, for example E10_RF7_γ0.1. But in general, the adaptive compression method can provide a relatively accurate energy efficient strategy, so that sensor nodes can complete data transmission under an approximate optimal energy costs, and the highest degree of deviation is no more than 5%.

Certainly, the introduction of adaptive mechanism will also bring two aspects of the costs, namely the overhead of computation and storage. By simulation, the time cost of executing the proposed method once is about 0.4ms (about 3000 clock cycles), which is approximately equal to the time overhead of using the LAA algorithm to compress 50 bytes

TABLE IV
MAXIMUM DEVIATION OF THE TOTAL ENERGY COSTS IN DIFFERENT SITUATIONS

Parameters	**Forecast**	**LAA**	**PMC-MR**	**LTC**	**No comp.**	**Adaptive comp.**
E2_RF7_γ0.1	59.84%	31.99%	36.17%	43.17%	12.99%	4.77%
E2_RF7_γ1.0	32.07%	17.66%	15.69%	19.32%	13.89%	3.07%
E2_RF15_γ0.1	46.78%	25.17%	26.51%	31.94%	13.17%	4.00%
E2_RF15_γ1.0	25.69%	14.64%	11.08%	13.86%	13.99%	3.08%
E2_RF23_γ0.1	38.07%	20.66%	20.07%	24.45%	13.32%	3.54%
E2_RF23_γ1.0	21.57%	13.68%	8.15%	10.36%	14.07%	3.08%
E5_RF7_γ0.1	52.98%	40.97%	15.70%	32.13%	48.00%	4.96%
E5_RF7_γ1.0	34.34%	41.80%	5.89%	12.47%	49.56%	3.83%
E5_RF15_γ0.1	43.44%	41.13%	9.29%	22.33%	48.30%	3.87%
E5_RF15_γ1.0	32.76%	41.89%	5.86%	9.84%	49.73%	3.76%
E5_RF23_γ0.1	37.61%	41.27%	5.69%	16.16%	48.56%	3.64%
E5_RF23_γ1.0	32.77%	41.97%	5.88%	8.41%	49.88%	3.78%
E10_RF7_γ0.1	64.93%	97.17%	3.37%	40.58%	133.31%	3.55%
E10_RF7_γ1.0	65.65%	99.70%	3.79%	24.36%	137.68%	3.79%
E10_RF15_γ0.1	65.04%	97.57%	3.43%	36.29%	134.01%	3.43%
E10_RF15_γ1.0	65.59%	99.50%	3.75%	26.82%	137.34%	3.75%
E10_RF23_γ0.1	65.14%	97.93%	3.49%	32.92%	134.62%	3.49%
E10_RF23_γ1.0	65.78%	99.85%	3.81%	24.44%	137.77%	3.81%

of raw data. Since the execution frequency of the method depends on the change frequency of error tolerance, transmit power and retransmit rate, it can be considered that the computational energy consumptions of the adaptive mechanism is acceptable.

On the other hand, the implementation of the adaptive mechanism is based on a set of alternative strategies. Therefore, it needs to embed all kinds of alternative strategies into sensor nodes. Through the realization of each compression algorithm, the storage overhead is obtained, as shown in Table V. Compared to the overhead of data acquisition and communication (about 12540 bytes), the storage cost of the adaptive mechanism is also acceptable.

TABLE V
STORAGE OVERHEAD OF COMPRESSION ALGORITHMS

Algorithm	Storage cost	Unit
Single Moving Average	902	byte
LAA	356	byte
PMC-MR	690	byte
LTC	2490	byte

VI. CONCLUSION

Different emphases on algorithm design will influence the energy efficiency of data compression under various applications and network environments. In order to raise the energy efficiency of data compression for the whole network, this paper presents an adaptive data compression with tunable precision, which enables a real-time adjustment of compression strategy.

By the prediction and feature extraction of the relevant parameters, the method can provide the optimal energy saving strategy for different sensor nodes. Experimental results show that, by means of the network level energy-saving improvement, all nodes can complete the data transfer task with near optimal energy consumptions, and the deviation degree is no more than 5%. Furthermore, the method only introduces low costs in computation and storage, and can effectively act on different error tolerance, transmit power and retransmission rate to meet the dynamic requirements of the network.

ACKNOWLEDGMENT

In this paper, the research is sponsored by the Nature Science Foundation of Zhejiang Province (Project No. LQ13F010005) and Ningbo Natural Science Foundation (Project No. 2011A610185). The work is supported by Ningbo Sc. & Tech. plan project (2014B82015). The author would like to appreciate the valuable datasets from the TAO Project Office of NOAA/PMEL, the ShakeMap Working Group, and the NWISWeb Support Team.

REFERENCES

[1] I. F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "Wireless sensor networks: a survey," *Computer Networks*, vol.38, pp.393–422, 2002.

[2] K. Romer, F. Mattern, "The design space of wireless sensor networks," *IEEE Wireless Communications*, vol. 11, no. 6, pp.54 – 61, 2004.

[3] J. Yick, B. Mukherjee, and D. Ghosal, "Wireless sensor network survey," *Computer Networks the International Journal of Computer & Telecommunications Networking,* vol. 52, no. 12, pp. 2292-2330, 2008.

[4] A. Mainwaring, D.Culler, J. Polastre, R. Szewczyk, and J. Anderson, "Wireless sensor networks for habitat monitoring," in *Proceedings of the First Acm International Workshop on Wireless Sensor Networks & Applications*, Atlanta, Georgia, USA, 2002, pp. 88-97.

[5] B. Ying, Y. Liu, H. Yang, and H. Wang, "Evaluation of tunable data compression in energy-aware wireless sensor networks," *Sensors,* vol. 10, no. 4, pp. 3195-217, 2010.

[6] B. Ying, W. Liu, Y. Liu, H. Yang, and H. Wang, "Energy-efficient node-level compression arbitration for wireless sensor networks," in *Proceedings of the 11th International Conference on Advanced Communication Technology*, Phoenix Park, Korea, 2009, pp. 564-568.

[7] Z. J. Ming, L. Y. Ping, Z. S. Wang, "Haar wavelet data compression algorithm with error bound for wireless sensor networks," *Journal of Software,* vol. 21, no. 6, pp. 1364-1377.

[8] Y. Liang, "Efficient temporal compression in wireless sensor networks," in *IEEE the 36th Conference on Local Computer Networks (LCN*), Bonn, Germany, 2011, pp.466-474.

[9] T. Schoellhammer, E. Osterweil, B. Greenstein, M. Wimbrow, D. Estrin, "Lightweight Temporal Compression of Microclimate Datasets," in *Proceedings of the 29th Annual IEEE International Conference on Local Computer Networks,* Tampa, Florida, USA, 2004, pp.516-524.

[10] Y. I. Kefu, J. Wan, T. Bao, L. Yao, "A DCT regularized matrix completion algorithm for energy efficient data gathering in wireless sensor networks," *IEEE Communications Letter*, vol. 19, pp. 54-57, 2015.

[11] R. Hussein, A. Mohamed, M. Alghoniemy, "Adaptive compression and optimization for real-time energy-efficient wireless EEG monitoring systems," in *The 2013 Biomedical Engineering International Conference (BMEiCON-2013),* Krabi, Thailand, 2013, pp.1-5.

[12] X. Xing, D. Xie, G. Wang, "Data Gathering and Processing for Large-Scale Wireless Sensor Networks," in *IEEE 9th International Conference on Mobile Ad-hoc and Sensor Networks,* Dalian, China, 2013, pp.354-358.

[13] M. Abdelaal, O. Theel, "An Efficient and Adaptive Data Compression Technique for Energy Conservation in Wireless Sensor Networks," in *IEEE Conference on Wireless Sensor (ICWISE),* Kuching, Sarawak, Malaysia, 2013, pp.124-129.

[14] Y. Mo, Y. Qiu, J. Liu, Y. Ling, "A Data Compression Algorithm Based on Adaptive Huffman Code for Wireless Sensor Networks," in *The 4th International Conference on Intelligent Computation Technology and Automation,* Shenzhen, China, 2011, pp.3-6.

[15] N. Arastouie, M. Sabaei, H. S. Shahreza, "Adaptive Approach for Reducing Energy Consumption, Considering Nodes' Mission in Wireless Sensor Networks," in *The 2nd International Conference on Communication Software and Networks,* Singapore, 2010, pp.152 - 156.

[16] S. Eswaran, J. Edwards, A. Misra, T. Porta, "Adaptive In-Network Processing for Bandwidth and Energy Constrained Mission-Oriented Multihop Wireless Networks," *IEEE Transaction on Mobile Computing*, vol. 11, no. 9, pp. 1484-1498, 2012.

[17] M. I. Mohamed, W. Y. Wu, M. Moniri, "Adaptive data compression for energy harvesting wireless sensor nodes," in *The 10th IEEE International Conference on Networking, Sensing and Control (ICNSC),* Evry, France, 2013, pp.633-638.

[18] K. Hua, H. Wang, W. Wang, S. Wu, "Adaptive Data Compression in Wireless Body Sensor Networks," in *IEEE the 13th International Conference on Computational Science and Engineering,* Hong Kong, China, 2010, pp.1-5.

[19] X. Deng, Y. Yang, "Online adaptive compression in delay sensitive wireless sensor networks," *IEEE Transactions on Computer,* vol. 61, no. 10, pp.1429-1442, 2012.

[20] B. Ying, Y. Liu, H. Wang, "Improved adaptive compression arbitration system for wireless sensor networks," *Tsinghua Science and Technology,* vol. 15, no. 2, pp. 202-208, 2010.

[21] L. Ying, S.W. Loke, M.V. Ramakrishna, "Energy-saving data approximation for data and queries in sensor networks," in *The 6th International Conference on ITS Telecommunications,* Chengdu, China, 2006, pp. 782-785.

[22] C. Hui, L. Cui, "Forecast-based temporal data aggregation in wireless sensor networks," *Computer Engineering and Applications*, vol. 43, no. 21, pp. 121-125, 2007.

[23] I. Lazaridis, S. Mehrotra, "Capturing sensor-generated time series with quality guarantees," in *IEEE International Conference on Data Engineering*, Bangalore, India, 2003, pp. 429-440.

[24] Tropical Atmosphere Ocean Project [Online]. Available: http://www.pmel.noaa.gov/tao/index/shtml
[25] T. S. Moh, M. Dumont, T. S. Moh, “Evaluation of dynamic tree-based data gathering algorithms for wireless sensor networks,” in *IEEE International Symposium on Signal Processing and Information Technology,* Athens, Greece, 2005, pp.170-175.
[26] M. Kramer, A. Geraldy, “Energy Measurements for Micaz Node,” *Technical Report*, Technical University Kaisers Lautem, GI/ITG KuVS, 2006, pp. 1-7.
[27] ATMEL AVR Studio [Online]. Available: http://www.atmel.com/dyn/Products/tools_card.asp?tool_id=2725
[28] CC2420 Data Sheet [Online]. Available: http://inst.eecs.berkeley.edu/~cs150/Documents/CC2420.pdf

Beihua Ying received her Ph.D. degree from Tsinghua University, Beijing, China, in 2010 and the BS degree from Xidian University, Xi’an, China, in 2004, both in Electronic Engineering. She is currently a lecturer with the school of Information Science and Engineering, Ningbo Institute of Technology, Zhejiang University. Her research interests include design and analysis of energy-efficient data process for wireless sensor networks, data gathering and routing protocol in wireless ad hoc and sensor networks, and optimization problems.