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I. Introduction

Wireless sensor networks (WSNs), consisting of a larger number of low cost and low power sensor nodes which are usually supplied by battery power, have been applied to more and more applications such as environment monitoring, machine condition control, remote health care, logistic, etc. In many applications it is hard to recharge or replace the dying nodes due to the harsh physical environment, which would lead to fragmentations of the whole network and loss of potentially critical information. Thus, how to achieve the energy efficiency and to extend the lifetime of WSNs have received a lot of attention from the research community.

Because of the inherent existence of temporal and spatial correlations in the physical phenomena, many researches focus on the study of temporal and spatial compression approaches to achieve energy efficiency in the past decades. For instance, several techniques reduce the energy consumption of each node by predicting the information based on its own historical data [1]- [3]. In [4] and [5], sensor nodes are scheduled to compress their readings based on the correlated data from other nodes to decrease the communication cost. Other proposals like [6], [7] and [8] save the energy cost of communication by forwarding an approximation of aggregates based on the temporal or spatial correlations. These approaches mainly reduce the energy cost at node-level. They still need network level strategies to balance the cost of each node and hence prolong the network lifetime.

In [9], a framework, achieving the trade-off between communication and computation power consumption, is proposed to maximize the network lifetime. It decides when should the sensor nodes transmit data with temporal compression. An enabling/disabling prediction scheme is presented in [10]. The cluster head estimates whether it is worthy for the sensor nodes to further predict future data based on their historical measurements, and adaptively switches their prediction states. A number of other researches study the spatial correlations to extend the network lifetime. The approaches in [12] and [13] conserve energy by periodically selecting only a subset of sensors to send data while others can be switched off. An approach called ASAP [11] increases the network lifetime by predicting the information through the use of probabilistic models based on temporal and spatial correlations. Another collaborative broadcasting and compression (CBC) approach is proposed in [14] to improve the network lifetime by controlling the nodes to cooperate in transmitting, receiving and compressing data.

These works mainly focus on specific applications. Although CBC [14] is able to generally schedule spatial compression techniques, it only provides suboptimal solutions and the models assumed in the work are too simple to reflect the realistic scenarios. In this paper, we propose an altruistic compression-scheduling (ACS) scheme using more realistic models. It is a general and optimal scheduling scheme, which works on the top of temporal and spatial compression techniques to schedule when and how to execute them, and can easily cooperate with other energy efficient protocols. Additionally, in order to address the problem that the spatial compression approaches cannot work in the networks with isolated nodes, we propose a transmission power increment (TPI) method to increase the spatial compression possibility. Combining with ACS, the network lifetime can be further extended.

The remainder of this paper is organized as follows. In Section II, the energy models for compression and communication are analyzed. In the following section, the ACS scheme and the corresponding grouping and filtering (GF) algorithm are presented. The TPI method is proposed in the next section.

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We demonstrate the efficiency of ACS and TPI by extensive simulation results in Section V and summarize our work and present the future research direction in the final section.

II. Energy Cost Model

In a cluster-based WSN, we consider the data gathering period is constant and the cluster head is less energy constrained. The network lifetime is dominated by the sensor node who firstly runs out of energy [23]. Since one of the most energy intensive processes is data communication [3], we restrict ourselves to modeling the energy cost of communication related activities. The actual reduction in communication energy achieved by a given compression technique depends on the compression ratio. In order to provide a solid mathematical foundation, this section we use entropy coding to model the temporal and spatial compression ratios. Then we formulate the energy cost of sensor nodes including compression and communication.

A. Modeling Temporal and Spatial Compression Ratios

Entropy coding plays an important role in data compression algorithms and has been applied in WSNs recently [15] [16] [17]. It consists of two phases: modeling and coding. During the modeling phase, a statistical model is established to assign probabilities to the symbols, and in the coding phase a bit sequence from these probabilities is produced with shorter coding being given to the symbol with higher probability. By using temporal and spatial correlations, the coding length can be further reduced, which is proportional to the temporal and spatial compression ratios, r_t and r_s.

For the sake of simplicity, we assume the Gaussian random fields for the modeling phase, which are simple and reasonable models for many natural phenomena [19]. Let $\boldsymbol{X_t} = (x_{t_1}, \cdots, x_{t_m})$ be the vector formed by the random variables collected at m time steps of an individual node and $\boldsymbol{X_s} = (x_{s_1}, \cdots, x_{s_m})$ be the vector of random variables measured at m different nodes at the same time. The random variables are assumed to be continuous and uniformly quantized with the same quantization step. Both $\boldsymbol{X_t}$ and $\boldsymbol{X_s}$ are Gaussian processes and satisfy $m-$dimensional multivariate Gaussian distribution. For conciseness, we let $\boldsymbol{X} = (x_1, \cdots, x_m)$ represent either X_t or X_s, and it has density

$$f_{\boldsymbol{X}}(x_1, \cdots, x_m) = \frac{\exp\Big(-\frac{1}{2}(\boldsymbol{X}-\boldsymbol{\mu})^T\boldsymbol{\Sigma}^{-1}(\boldsymbol{X}-\boldsymbol{\mu})\Big)}{\sqrt{(2\pi)^m|\boldsymbol{\Sigma}|}}$$

where $\boldsymbol{\mu}$ is a m-dimensional mean vector and $\boldsymbol{\Sigma}$ is a $m \times m$ covariance matrix. The elements in the covariance matrix hold $\boldsymbol{\Sigma}_{i,i} = \sigma^2$ and $\boldsymbol{\Sigma}_{i,j} = \sigma^2\rho_{ij}$, where $\rho_{ij} = corr(x_i, x_j)$ is the correlation function between x_i and x_j. In the time domain, ρ_{ij} is a function of the sampling distance, $\tau_{ij} = |\tau_i - \tau_j|$, of the measurements collected at two different time points, i.e, $\rho_{ij} = \rho_t(\tau_{ij})$. Whereas, in the space domain, it is a function of the distance d_{ij} of the observations collected at two different space points, namely $\rho_{ij} = \rho_s(d_{ij})$. There are several available spatial correlation models as summarized in [18]. The common observation is that as the distance increases, the correlation decreases.

The distribution of x_m conditional on the previous $(m-1)$ variables, denoted as $\boldsymbol{X_{m-1}} = (x_{m-1}, \cdots, x_1)$, is a normal distribution, $(x_m|\boldsymbol{X_{m-1}} = \boldsymbol{a}) \sim N(\bar{\mu}, \bar{\sigma}^2)$, where $\bar{\mu} = \mu_m + \boldsymbol{\Sigma_{12}}\boldsymbol{\Sigma_{22}^{-1}}(\mathbf{a} - \boldsymbol{\mu_{m-1}})$ and $\bar{\sigma}^2 = \sigma^2 - \boldsymbol{\Sigma_{12}}\boldsymbol{\Sigma_{22}^{-1}}\boldsymbol{\Sigma_{21}}$ by partitioning $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ as follows

$$\boldsymbol{\mu} = \begin{bmatrix} \mu_m \\ \boldsymbol{\mu_{m-1}} \end{bmatrix} \text{ with sizes } \begin{bmatrix} 1 \times 1 \\ (m-1) \times 1 \end{bmatrix}$$

$$\boldsymbol{\Sigma} = \begin{bmatrix} \sigma^2 & \boldsymbol{\Sigma_{12}} \\ \boldsymbol{\Sigma_{21}} & \boldsymbol{\Sigma_{22}} \end{bmatrix}$$

with sizes

$$\begin{bmatrix} 1 \times 1 & 1 \times (m-1) \\ (m-1) \times 1 & (m-1) \times (m-1) \end{bmatrix}.$$

Then the entropy rates[1], $R_m = H(x_m|\boldsymbol{X_{m-1}})$, as m increases are:

$$\begin{aligned} R_1 = H(x_1) &= \frac{1}{2}\ln\left(2\pi e\sigma^2\right) \\ R_2 = H(x_2|x_1) &= \frac{1}{2}\ln\left(2\pi e\sigma^2\alpha 1\right) \\ R_3 = H(x_3|x_2, x_1) &= \frac{1}{2}\ln\left(2\pi e\sigma^2\Big(1 - \frac{\alpha 2}{\alpha 1}\Big)\right) \\ R_4 = H(x_4|x_3, x_2, x_1) &= \frac{1}{2}\ln\left(2\pi e\sigma^2\Big(1 - \frac{\alpha 3}{\alpha 1 - \alpha 2}\Big)\right) \\ &\vdots \end{aligned}$$

where

$$\begin{aligned} \alpha 1 =& 1 - \rho_{12}^2 \\ \alpha 2 =& \rho_{13}^2 + \rho_{23}^2 - 2\rho_{12}\rho_{13}\rho_{23} \\ \alpha 3 =& \rho_{14}^2 + \rho_{24}^2 + \rho_{34}^2 - \rho_{12}^2\rho_{34}^2 - \rho_{13}^2\rho_{24}^2 - \rho_{14}^2\rho_{23}^2 \\ & - 2\rho_{12}\rho_{14}\rho_{24} - 2\rho_{13}\rho_{14}\rho_{34} - 2\rho_{23}\rho_{24}\rho_{34} \\ & + 2\rho_{12}\rho_{13}\rho_{24}\rho_{34} + 2\rho_{12}\rho_{14}\rho_{23}\rho_{34} + 2\rho_{13}\rho_{14}\rho_{23}\rho_{24} \end{aligned}$$

Assuming that the initial transmission data size is $R = R_1$ bits, the corresponding compression ratio $r(x_m|\boldsymbol{X_{m-1}})$ is a functions of ρ_{ij}:

$$\begin{aligned} r(x_1) &= \frac{R_1}{R} = 1 \\ r(x_2|x_1) &= \frac{R_2}{R} = 1 + \frac{\ln(\alpha 1)}{R} \\ r(x_3|x_2, x_1) &= \frac{R_3}{R} = 1 + \frac{\ln\Big(1 - \frac{\alpha 2}{\alpha 1}\Big)}{R} \\ r(x_4|x_3, x_2, x_1) &= \frac{R_4}{R} = 1 + \frac{\ln\Big(1 - \frac{\alpha 3}{\alpha 1 - \alpha 2}\Big)}{R} \\ &\vdots \end{aligned}$$

[1] We use differential entropy instead of entropy here, since for an uniformly quantized continuous random variable, they only differ by a constant [19].

Then the temporal compression ratio, denoted as r_t, is a function of $\rho_t(\tau_{ij})$, namely

$$r_t = r(x_m|\boldsymbol{X_{m-1}}) \tag{1}$$

Whereas the spatial compression ratio $r_s = r(x_m|\boldsymbol{X_{m-1}})$ is a function of $\rho_{ij} = \rho_s(d_{ij})$. It becomes more complicated as the number of the node's neighbors increases, since the distribution of the nodes are typically asymmetrical.

For simplicity, when we calculate the spatial compression ratio for a node with multi-neighbors, we approximate it by assuming that the data of its neighbors are uncorrelated[2]. For example, in the formula of $r(x_3|x_2, x_1)$, the correlation between x_1 and x_2 is assumed to be 0, i.e, $\rho_{12} = 0$. Then the compression ratio that node x_3 compresses based on both of them is:

$$r(x_3|x_1, x_2) = 1 + \frac{\ln(1 - \rho_{13}^2 - \rho_{23}^2)}{R} \approx 1 - \frac{\rho_{13}^2 + \rho_{23}^2}{R}$$

It can be approximated by the product of $r(x_3|x_1)$ and $r(x_3|x_2)$, since

$$\begin{aligned}\prod_{j=1}^{2} r(x_3|x_j) &= \left(1 + \frac{\ln\left(1 - \rho_{13}^2\right)}{R}\right) \cdot \left(1 + \frac{\ln\left(1 - \rho_{23}^2\right)}{R}\right) \\ &\approx \left(1 - \frac{\rho_{13}^2}{R}\right) \cdot \left(1 - \frac{\rho_{23}^2}{R}\right) \\ &\approx 1 - \frac{\rho_{13}^2 + \rho_{23}^2}{R} + \frac{\rho_{13}^2 \cdot \rho_{23}^2}{R^2} \\ &\approx r(x_3|x1, x2)\end{aligned}$$

In this case, the spatial compression ratio that a node compresses based on $(m-1)$ neighbors can be approximated as the product of the ratio that the node compresses based on each neighbor, namely,

$$r_s = \prod_{j=1}^{m-1} r(x_m|x_j) \tag{2}$$

This expression is consistent with the one in [14]. It is used only for the sake of conciseness but not a limitation of our scheduling scheme.

As we mentioned before, there are several available spatial correlation models. We select one of them in [16], which is verified using real phenomena datasets, to obtain the compression ratio based on one neighbor as given by:

$$r(x_m|x_j) = 1 - \frac{c}{d_{mj} + c} \tag{3}$$

where c is a constant that characterizes the extent of spatial correlation in data and d_{mj} is the distance between node m and node j.

[2] This assumption for the approximated spatial compression ratio is only for the sake of conciseness. It does not affect the process of the proposed scheduling algorithm, since it is only one of the required input parameters.

B. Energy Cost Models

The individual communication and compression energy cost models for a node are presented firstly. Combining them with the temporal and spatial compression ratios, the total energy cost of the node during one data gathering period is formulated.

In [20], a detailed communication cost model is proposed. Besides the energy consumption of the data packets transmission, the energy consumed by overhead activities are also considered, such as radio startup, channel accessing, control packets, turnaround, idle listening, overhearing, collision and retransmission. The simplified model is given by:

$$E_{cmn} = E_o + E_{rx/tx(d_i)} \cdot R$$

where E_o is the energy spent on the overhead activities; E_{rx} is the receiving energy cost for receiving 1 bit data; $E_{tx(d_i)}$ is the transmission energy cost by transmitting a single bit. It is a function of the transmission distance, d_i. R is the size of the transmission data.

According to [21], the unit energy consumption for receiving and transmitting are

$$\begin{aligned}E_{rx} &= E_{elc} \\ E_{tx(d_i)} &= (E_{elc} + E_{apl} \cdot d_i^{\alpha})\end{aligned} \tag{4}$$

where E_{elc} is the energy dissipated by the electronic circuits of the transceiver to transmit or receive 1 bit data; E_{apl} is the energy cost of the transmit amplifier for transmitting 1 bit data at 1 m distance; and α is the path loss exponent which is 2 in typical applications [22].

The computation cost for data compression is proportional to the data size. We define the energy cost for processing 1 single bit of data is E_p.

Without using any compression, the energy of a node is spent in transmitting R bits data to the cluster head with overhead E_o, i.e,

$$E_{no} = E_o + E_{tx(d_i)} \cdot R \tag{5}$$

When the node uses its history data (previous n_t time steps) to execute temporal compression, the total energy cost of it consists of processing $(n_t + 1) \cdot R$ bits data and transmitting $R \cdot r_t$ bits of compressed data to the cluster head with overhead E_o as given by:

$$E_t = E_p \cdot (n_t + 1) \cdot R + E_o + E_{tx} \cdot R \cdot r_t \tag{6}$$

Similarly, the total energy cost of the node employing spatial correlation with the data of n_s neighbors includes receiving $n_s \cdot R$ bits data, processing these data and its own data, then transmitting $R \cdot r_s$ bits of compressed data to the cluster head with the incorporated overhead in receiving and transmitting processes:

$$E_s = E_o + E_{rx} \cdot n_s \cdot R + E_p \cdot (n_s + 1) \cdot R + E_{tx} \cdot R \cdot r_s \tag{7}$$

When the node simultaneously compresses based on temporal and spatial compressions, it is obviously that each node executes temporal compression firstly can reduce more communication cost in receiving. The total energy cost consists of three parts: a) the temporal compression cost when the node compresses its current data based on the data of previous n_t time steps; b) the spatial compression cost when it receives information from its n_s neighbors and executes spatial compression; c) transmission energy cost when it transmits the compressed data to the cluster head. It is formulated as follows by incorporating the overhead during receiving and transmission processes into E_o.

$$\begin{aligned} E_{ts} =& E_p \cdot (n_t+1) \cdot R \\ &+ E_{rx} \cdot n_s \cdot R \cdot r_t + E_p \cdot (n_s+1) \cdot R \cdot r_t \\ &+ E_o + E_{tx} \cdot R \cdot r_t \cdot r_s \end{aligned} \quad (8)$$

III. Altruistic Compression-Scheduling Scheme

In this section, we first present our altruistic compression-scheduling (ACS) scheme and formulate the maximization of the network lifetime as a linear program (LP). In order to reduce the complexity of LP and obtain the optimum solution, a grouping and filtering (GF) method is proposed.

A. ACS Scheme and LP Problem

Before communicating with the cluster head, each node has different options to deal with the data packet: without any compression, compressing it using its historical data, selecting the possible number of its neighbors to execute spatial compression, or compressing it with both temporal and spatial correlations. Each option corresponds to a state with different energy consumption. The states of node i are denoted by the vector $\boldsymbol{E(i)}$.

The optimal n_t used for temporal compression can be calculated off-line. There is only one state for a node executing temporal compression. Whereas, the number of states using spatial compression depends on the number of its neighbors. When the distance between node i and its neighbor node j, d_{ij}, is not larger than the transmission distance of node j, d_j, i.e, $d_{ij} \le d_j$, node i is able to compress based on node j.

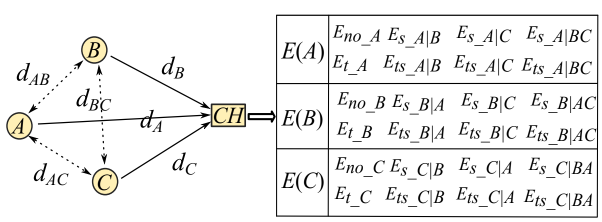

Fig. 1. The states of each node in a cluster-based WSN

For illustration, let us consider a network with three nodes, node A, B and C, and a cluster head CH, as depicted in Fig. 1. The three nodes can hear each other. Each node can choose either or both of its neighbors to execute spatial compression. There are $\sum_{k=1}^{2}\binom{2}{k}$ kinds of possibilities. Combining them with the states related with temporal and no compression, the total number of states of each node is $2 \cdot \sum_{k=1}^{2}\binom{2}{k} + 2 = 8$ as shown in Fig. 1: without compression E_{no_i}, with temporal compression E_{t_i}, with spatial compression based on either or both of its neighbors (e.g., $E_{s\_A|B}$, $E_{s\_A|C}$, $E_{s\_A|BC}$ for node A), and with both temporal and spatial compression (e.g, $E_{ts\_A|B}$, $E_{ts\_A|C}$ and $E_{ts\_A|BC}$ for node A).

In a general cluster, if node i can hear n_s nodes, there are total $2 \cdot \sum_{k=1}^{n_s}\binom{n_s}{k} + 2$ of states in $\boldsymbol{E(i)}$. Since decompression is typically very energy intensive, we require that the node is able to execute spatial compression only using uncompressed data, i.e, its neighbor is not using spatial compression. For the network in our example, at least one of the nodes is required to transmit without spatial compression during several data gathering periods. If only node B transmits without spatial compression, node A has to reduce its states to $\boldsymbol{E(A)} = (E_{no\_A}, E_{t\_A}, E_{s\_A|B}, E_{ts\_A|B})$ and select a state with the minimum energy cost, $min\{\boldsymbol{E(A)}\}$ as its current state and so does node C. The current states of A, B and C combining the periods in these states constitute a ACS strategy. In the next several periods, node A and/or node C will be selected as the one without doing spatial compression. Since all the nodes cannot do spatial compression at the same time, there are total $2^3 - 1 = 7$ possible strategies for this specific network under our condition. Each of them works for several periods. The sequence of these strategies combining with the number of their effective periods constitute an ACS scheme.

More formally, for a cluster with n sensor nodes, the total possible number of strategies, K, equals $2^n - 1$. Assuming the number of the execution periods of each strategy is t_k, the corresponding ACS scheme can be represented by:

$$\boldsymbol{S} = \Big\{(s_1, t_1), \cdots, (s_k, t_k), \cdots, (s_K, t_K)\Big\},$$

where (s_k, t_k), $1 \le k \le K$, indicates that strategy s_k controls the states of all sensor nodes for t_k (t_k is a non-negative integer, $t_k \in Z^*$) data gathering periods.

Assuming the initial energy of each node is $E_{int}(i)$ and the energy consumption of each node under each strategy in one data gathering period is $E_k(i)$, the total energy cost of each node using ACS scheme has to be less than or equal to its initial energy, i.e., $\sum_{k=1}^{K} t_k \cdot E_k(i) \le E_{int}(i)$. When the first node exhausts its energy, it runs totally $\sum_{k=1}^{K} t_k$ periods, which is the network lifetime as defined in Section II. Thus, maximizing the whole network lifetime is equal to maximize $\sum_{k=1}^{K} t_k$ under a bounded amount of initial energy. This problem can be expressed in LP canonical form:

$$\begin{aligned} &\arg\max_{t_k} && \sum_{k=1}^{K} t_k \\ &subject\ to: && t_k \ge 0 \\ &and && \sum_{k=1}^{K} t_k \cdot E_k(i) \le E_{int}(i) \qquad (i = 1, \cdots, n) \end{aligned}$$

This LP problem can be solved with a LP-solver (e.g., Matlab) and we can obtain the optimum running periods of each strategy, $(t_1, \cdots, t_K)$, which corresponds to the optimal ACS scheme. However, as the number of sensor nodes raises, the number of possible strategies increases exponentially. It becomes increasingly expensive to find the optimal solution for LP. In the following section, we reduce the complexity of the above LP problem.

B. GF Method for Complexity Reduction

There are redundancies among the strategies in an ACS scheme. Not every node is able to benefit from data compression. Moreover, the states of a certain number of nodes have no impact on the network lifetime. Besides, some of the strategies may produce less profits than others.

Our GF method firstly finds the nodes for whom data compression is unworthy. From (5) and (6), it is worthy to do temporal compression only when

$$r_t < 1 - \frac{E_p \cdot (n_t + 1)}{E_{tx(d_i)}}. \quad (9)$$

Since the transmission cost is usually much lager than the computation cost, assuming n_t is small, this condition can be easily satisfied.

From (5)-(8), a node profits from doing spatial compression only when $E_s < E_{no}$ and/or $E_{st} < E_t$, namely,

$$r_s < 1 - \frac{E_{rx} \cdot n_s}{E_{tx(d_i)}} - \frac{E_p \cdot (n_s + 1)}{E_{tx(d_i)}}. \quad (10)$$

In the following we aim to find which nodes have the opportunity to satisfy this condition. The minimum energy cost of node i compressing based on n_s neighbors happens when the compressed data is sufficiently small (r_s is too small) and the transmission energy cost can be neglected in (7) and (8). If the minimum energy cost is larger than or equal to without spatial compression, i.e. (8) $\geq$ (6) and/or (7) $\geq$ (5), we obtain that:

$$E_{rx} \cdot n_s + E_p \cdot (n_s + 1) \geq E_{tx(d_i)} \quad (11)$$

Node i can definitely not benefit from the compression. Since the transmission energy cost is a function of the distance d_i, there exists a maximum transmission distance $d_{max|n_s}$. If $d_i \leq d_{max|n_s}$, compressing based on n_s or more nodes can definitely not save energy.

For a WSN cluster, there may be M possible $d_{max|n_s}$, $1 \leq n_s \leq M$, where M is determined by the node with the farthest distance to the cluster head. According to their positions, the sensor nodes can be divided into M groups, $G_0, \cdots, G_{n_s}, \cdots, G_{M-1}$, as illustrated in Fig. 2. If $d_i \in \left(0,\ d_{max|1}\right]$, node i is assigned to the group G_0, which is unworthy to execute spatial compression; If $d_i \in \left(d_{max|n_s},\ d_{max|n_s+1}\right]$, node i is assigned to the group G_{n_s}. It can not save energy by spatial compression based on $(n_s + 1)$ or more nodes.

Given a node $i \in G_{n_s}$ who can hear N neighbors, it is worthy to compress based on at most $min\{n_s, N\}$ nodes. The states using more than this number to do spatial compression can be removed and there remains $\sum_{k=0}^{min\{n_s,N\}} \binom{N}{k}$ kinds of states for the node.

Next, we focus on acquiring the nodes whose states are irrelevant to the network lifetime. We can assign them to G_0 as well. Let $\boldsymbol{E_{max}} = \{E_{max}(1), \cdots, E_{max}(i), \cdots, E_{max}(n)\}$ and $\boldsymbol{E_{min}} = \{E_{min}(1), \cdots, E_{min}(i), \cdots, E_{min}(n)\}$ denote

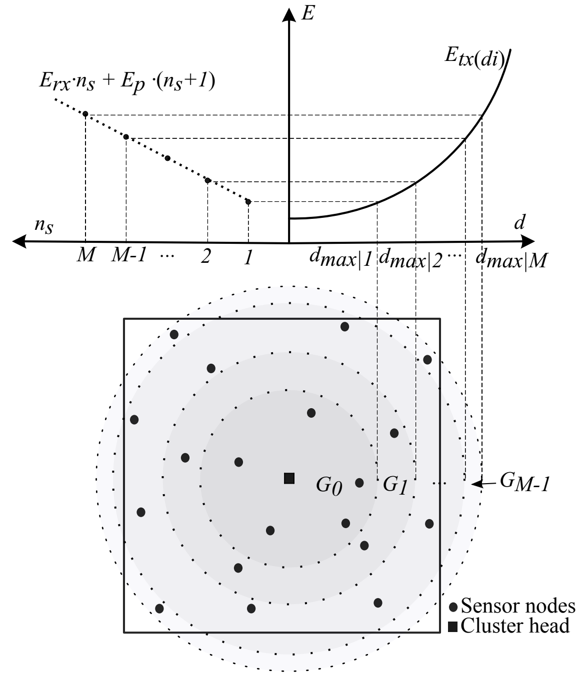

Fig. 2. Dividing the sensor nodes into M groups

the vectors of the maximum and minimum energy cost states of each node respectively. If $E_{max}(i) < max\{\boldsymbol{E_{min}}\}$, node i is an irrelevant node, since it can stay in its worst state without affecting the network lifetime. It is assigned to the group G_0 (no spatial compression) to benefit other nodes.

Let us denote by n_0 the number of nodes that are assigned to group G_0. There are $K' = 2^{(n-n_0)}$ possible strategies remaining.

We further reduce the complexity by filtering the suboptimal ACS strategies. Let $\boldsymbol{E_i} = \{E_i(1), E_i(2), \cdots, E_i(n)\}$ and $\boldsymbol{E_j} = \{E_j(1), E_j(2), \cdots, E_j(n)\}$ denote the vectors of the energy cost of each node using strategy s_i and s_j respectively, where $i, j \in K'$ and $i \neq j$. The difference between these two vectors is denoted as $\boldsymbol{\varepsilon_{ij}} = \boldsymbol{E_i} - \boldsymbol{E_j}$. If all components of $\boldsymbol{\varepsilon_{ij}}$ are nonnegative, the strategy s_i is suboptimal. It can be eliminated without degrading the network lifetime.

After finding the optimal strategies by grouping and filtering, the complexity is reduced and the optimal ACS scheme can be obtained by solving the aforementioned LP problem. The pseudo-code of the algorithm is given in Algorithm 1.

IV. Transmission Power Increment Method

In a WSN, there may exist isolated nodes who cannot hear any other node. If one of them is the farthest from the cluster head in the network, this node dominates the whole network lifetime. The spatial compression techniques that aim to improve the lifetime can no longer make contributions. In this situation, an additional method which can increase the spatial compression possibility is urgent.

We propose a transmission power increment (TPI) method to address the above problem. Once TPI enables the spatial

Algorithm 1 ACS scheme

Input: A cluster-based WSN with the specific temporal and spatial compression ratios
Output: ACS scheduling scheme $\{(s_1, t_1), \cdots, (s_K, t_K)\}$
Calculate $d_{max|n_s}$, $n_s \in [1, M]$
for $i = 1 : n$ **do**
  if $d_i \in (d_{max|n_s}, d_{max|n_s+1}]$ **then**
    $G_{n_s} \leftarrow$ node i
  end if
  find neighbors
  Calculate $\boldsymbol{E(i)}$ using (5)-(8).
end for
Calculate $\boldsymbol{E_{max}}$ and $\boldsymbol{E_{min}}$
for $i = 1 : n$ **do**
  if $E_{max}(i) < max\{\boldsymbol{E_{min}}\}$ **then**
    $G_0 \leftarrow i$
  end if
end for
for each $i, j \in K'$, $i \neq j$ **do**
  Calculate $\boldsymbol{E_i}$ and $\boldsymbol{E_j}$ when using s_i and s_j
  Let $\boldsymbol{\varepsilon_{ij}} = \boldsymbol{E_i} - \boldsymbol{E_j}$
  if $all(\boldsymbol{\varepsilon_{ij}}) >= 0$ **then**
    Filter out strategy s_i
  end if
end for
Solve the LP problem

compression techniques, ACS can further prolong the network lifetime. It is based on the observation that wireless sensor node can prolong its communication distance by enhancing its transmission power [20] [21]. We give this isolated node an opportunity to execute spatial compression by increasing the transmission power of its neighbors. This operation extends the network lifetime when it satisfies the conditions: a) the isolated node can conserve energy from spatial compression and b) after enhancing the transmission power, the neighbors do not degrade the network lifetime.

In the following we aim to find an optimal candidate who can maximize the gain among its neighbors. The analysis commences by considering all nodes using temporal compressions. It is easy to obtain the same results when considering all nodes without it.

For illustration purpose, let us consider a simple scenario (see Fig. 3): a WSN consists of 2 sensors and 1 head. Node B is an isolated node and it cannot hear node A. The initial transmission data of them are R bits.

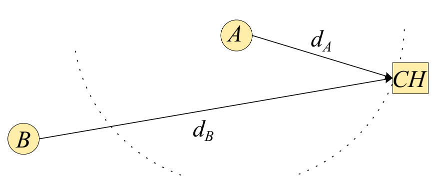

Fig. 3. A simple WSN with isolated node

By increasing the transmission power of node A, the transmission distance of it is increased from d_A to d_{AB}. Node B is able to execute spatial compression. By using (6) and (8), it is easy to obtain E_{t_B} and $E_{ts\_B|A}$. To satisfy condition a), it requires $E_{ts\_B|A} < E_{t\_B}$. According to (3) and (4), the distance between them should satisfy

$$d_{AB} < \frac{(E_{apl} \cdot d_B^{\alpha} - 2 \cdot E_p) \cdot c}{E_{elc} + 2 \cdot E_p}$$

After node A enhancing its transmission power, the energy cost of it with the temporal compression becomes

$$E_{t\_ehc\_A} = E_p \cdot (n_t + 1) \cdot R + E_o + E_{tx(d_{AB})} \cdot R \cdot r_t.$$

Under the condition $E_{t\_ehc\_A} < E_{t\_B}$, it requires $d_{AB} < d_B$.

Thus, the network lifetime can be prolonged only when

$$d_{AB} < min\left\{\frac{(E_{apl} \cdot d_B^{\alpha} - 2 \cdot E_p) \cdot c}{E_{elc} + 2 \cdot E_p}, d_B\right\} \quad (12)$$

For a general WSN, let I be the dominated isolated node and $\boldsymbol{N_i^*}$ be the set of its neighbors. Each of them meets (12). If there are more than one node in $\boldsymbol{N_i^*}$, the node j^* who can maximize the gain will be chosen to enhance the transmission power. It satisfies:

$$j^* = \arg\min_{j \in N_i^*} \Big\{max\big(E_{ts\_I|j}, E_{t\_ehc\_j}\big)\Big\} \quad (13)$$

where $E_{ts\_I|j}$ is the energy cost of I when it compresses based on node j and $E_{t\_ehc\_j}$ is the energy cost of node j with temporal compression when it enhances the transmission power.

After using our TPI method, the network lifetime can be increased by spatial compression techniques. With the parameters returned by these techniques, ACS can further increase the gain.

V. Simulation Results

In this section, we estimate the efficiency of ACS scheme in extending the network lifetime. The profits by using ASC scheme are presented with respect to the initial network lifetime. The superiority of ACS is demonstrated by comparing it with another general scheduling scheme, CBC [14]. To illustrate the performance of our TPI method, we further present the increase of network lifetime by using the combination of TPI and ACS.

In the experiments, we randomly generate the WSNs in the area of 100 m $\times$ 100 m with a cluster head in the center. The typical energy related parameters are taken from [14]: $E_{elc} = 50$ nJ/bit, $E_{apl} = 100$ pJ/bit/m^2, $E_p = 5$ nJ/bit, the path loss $\alpha = 2$. Each node has 5 J initial energy and sends $R = 400$ bits of data to the cluster head during each data gathering round. According to the real measurements in [16], $c = 25$ m. The overhead energy cost, E_o, is assigned to 5% of the transmission energy cost. The impact of E_o on the increase of the lifetime is analyzed in more detail in the later simulation. Each simulation is repeated 100 times with

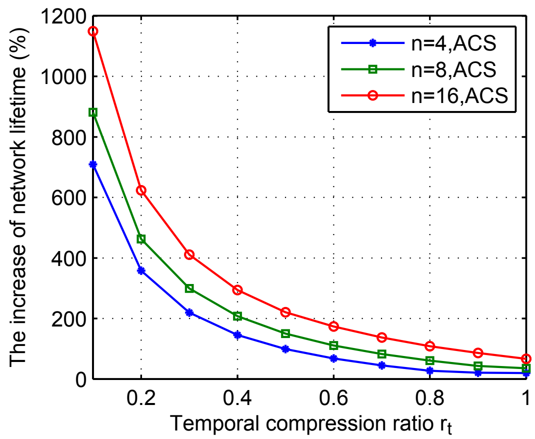

Fig. 4. The increase of network lifetime by exploiting the ACS scheme with respect to the initial lifetime

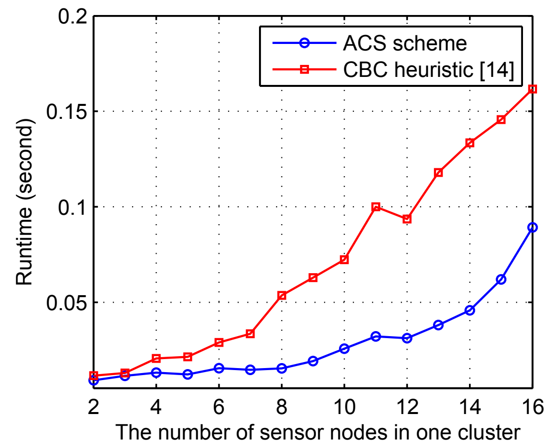

Fig. 5. The comparison of runtime between ACS scheme and CBC heuristic method [14]

random networks and the results corresponds to the average values.

In Fig. 4, we report the increase of network lifetime when the temporal compression ratio r_t varies from 0.1 to 1.0 and the number of sensor nodes, n, equals 4, 8 and 16. Obviously, ACS dramatically extends the network lifetime. As r_t approaches 0, the gain increases. For example, when n equals 16, ACS increases the network lifetime by a factor of 1.67 to 12.49 (from 67 % to 1149 %) depending on different temporal correlations. Even when r_t is 1.0, which means sensor nodes do not employ the temporal compression, the network lifetime can still be extended by the spatial compression. Specifically, the percentage increase of network lifetime is 20%, 35% and 67% for n equals 4, 8 and 16, respectively. Note that the gain of the increase becomes larger when the number of sensor nodes raises. Since the density of the network increases, the spatial correlation gets higher. Besides, each node has opportunities to hear more neighbors and compress based on them.

In order to evaluate the feasibility of ACS, we measure its runtime and compare it with the CBC heuristic approach. Note that in CBC, nodes do not execute temporal compression. At the same time CBC only allows each node to compress based on at most one neighbor and does not consider all of possible strategies. The runtime of them are shown in Fig. 5. Both of them slightly grows as the number of nodes increases. In any case ACS consumes less than 0.2 s. Although our ACS scheme considers the temporal compression and produces the optimal scheduling solution, it is even more time efficient. This is due to the reduction of the computational complexity by our GF algorithm. Taking one experiment for instance, when the number of sensor nodes is 15, there are $2^{15}-1$ initial ACS strategies; after grouping nodes and finding the irrelevant nodes, 7 nodes are assigned to group G_0 and the number of ACS strategies decreases to 2^8; by further filtering the suboptimal strategies, only 16 strategies remains.

Next, we demonstrate the superiority of our ACS scheme versus CBC heuristic approach and validate the accuracy of our more realistic models. We first compare their increase of network lifetime using CBC simple models. In the models, the overhead energy cost is not considered. Additionally, they neglect the impact of distance on the spatial correlation. In order to provide a fair comparison, we disable the temporal compression in our ACS scheme to be consistent with CBC. The gain of ACS would be larger if the temporal compression is used.

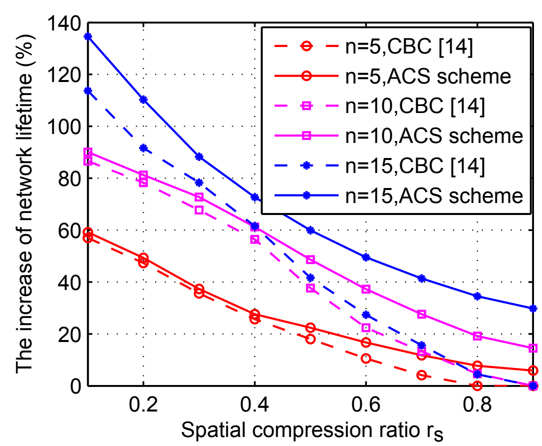

Fig. 6. The comparison of network lifetime increase between ACS scheme and CBC heuristic method with the simple communication and spatial models used in [14]

As depicted in Fig. 6, ACS is always more efficient than CBC heuristic method, since it provides the optimal scheduling scheme. As the number of the sensor nodes increases, this superiority becomes more significant. Besides, the advantage of ACS increases when the spatial compression ratio, r_s, is lager. It is relevant to the proportion of the transmission energy cost. When r_s is small, the transmitting energy cost is only a small proportion of the total energy. Its variation by using the scheduling scheme is unable to significantly alert the network lifetime. Whereas, this variation becomes more obvious when r_s is higher. As a result, the difference of the gains using ACS and CBC gets larger.

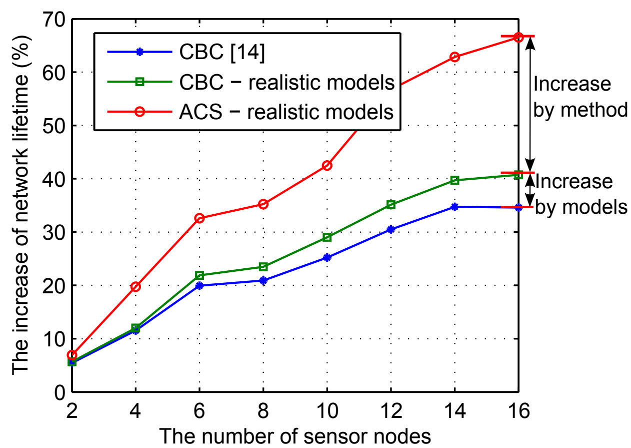

Fig. 7. The comparison of the impact of different models on the increase of network lifetime and the superiority of ACS scheme

As the models used in [14] are too simple to reflect the realistic scenario, we analyze the impact of more realistic models on the increase of network lifetime and the superiority of ACS. We first obtain the scheduling solution of CBC using its simple models. By plugging this solution to the real scenario, with more realistic communication and compression models proposed in Section II, the actual increase of lifetime is obtained. We then compare the increase in network lifetime of CBC and ACS using our realistic models. The results are illustrated in Fig.7. The trend of the gain of both ACS and CBC methods are consistent with the aforementioned analyses. Using the same realistic models, ACS is still more efficient than CBC, especially when the number of nodes is larger. In addition, the gains of CBC using two models are different. With our more realistic models, the network lifetime can be extended more.

We further estimate the impact of overhead energy consumption, E_o, on the gain of network lifetime. Fig. 8 shows , in the realistic scenarios there exists a threshold of E_o. Before the threshold, the gain decreases when E_o accounts for larger proportion in the transmission energy. However, our ACS scheme outperforms CBC significantly. After the threshold, due to the fact that E_o cannot be reduced by neither temporal nor spatial compression, both ACS and CBC with the realistic models realize that it is no longer worthy to do any compression. The network lifetime cannot be extended any more. Whereas CBC heuristic method using the simple models does not consider this impact of E_o. It produces a scheduling scheme which actually degrades the performance when the proportion exceeds 35%.

In order to evaluate the performance of TPI, we randomly generate WSNs with one cluster head and 10 sensor nodes for 100 times. There are 19 networks have isolated nodes

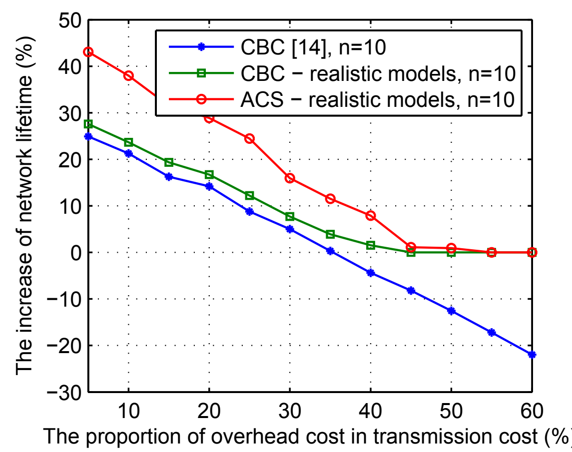

Fig. 8. The impact of overhead energy cost on the increase of network lifetime

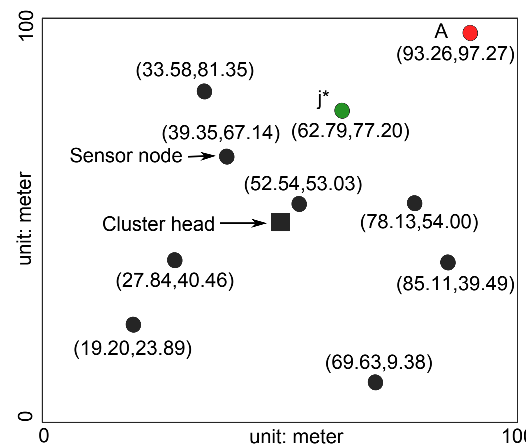

Fig. 9. A typical WSN with isolated nodes in the area of 100 m×100 m

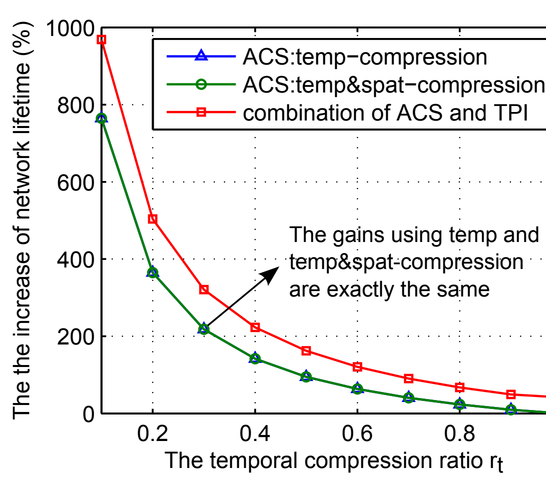

Fig. 10. The increase in lifetime of networks with isolated nodes when applying the combination of TPI and ACS

and cannot benefit from spatial compression. One of them is shown in Fig. 9. Node A is the farthest and isolated node, it is unable to compress based on others. Without TPI, the network lifetime cannot be increased by using spatial compression. As depicted in Fig. 10, the gains of ACS using both temporal and spatial compressions are the same as only using temporal compression. This is consistent with the analyses in Section IV. Whereas, with the TPI method, node j^* which satisfies (13) is chosen to enhance the transmission power and node A can benefit from compressing based on node j^*. Combining with ACS, the network lifetime is further extended by more than 200% when $r_t = 0.1$.

VI. Conclusion and Future Work

In order to maximize the network lifetime, we propose an altruistic compression-scheduling (ACS) scheme for the data compression techniques using temporal and/or spatial correlations. Given the related parameters of the network and the compression techniques including compression ratios, computation and communication energy cost, ACS can produce an optimum scheduling scheme off-line. The scheme specifies when and how each node executes compression techniques, i.e, without compression, with either of temporal and spatial compression or with both of them. The maximization of the network lifetime is modeled as a linear programming (LP) problem. When the number of sensor nodes increases, it is infeasible to solve this problem, since its complexity exponentially increases. To address this, we provide a grouping and filtering (GF) method. Besides, for the spatial compression techniques that cannot work in the networks with isolated nodes, we propose a transmission power increment (TPI) method to increase the spatial compression possibility. It can be combined with ACS to further extend the lifetime of such networks.

The GF method makes ACS feasible for typical WSNs applications. It consumes less than 0.2 s execution time. Extensive simulation results demonstrate the efficiency of our ACS scheme in extending the network lifetime. For instance, it prolongs the lifetime of typical WSNs by a factor of 1.67 to 12.49 as the compression ratio varies, when there are 16 sensor nodes in the cluster. Compared with previous approaches, it extends more network lifetime with even less runtime. Additionally, TPI successfully improves the spatial compression possibility. The combination of TPI and ACS further prolongs the network by more than 200% in a typical scenario.

In the future, we plan to study concrete temporal and spatial compression models using real measured datasets, and to develop an on-line altruistic approach to make it more flexible for dynamic WSNs.

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