

A practical information coverage approach in wireless sensor network



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ABSTRACT

In order to improve energy-effectiveness in wireless sensor network, in practice some sensors in observation points are selected not to gather data. In this case, the insufficient data gathered by the rest of sensors have to cover the total network so that the complete information of the whole environment could be estimated rationally, which is similar to compressive sensing. However, the process of estimation has to cost a lot of energy, which is a crucial problem. This paper proposes a practical and effective information coverage approach in which an actual constrained condition is considered for consensus estimation to reduce unnecessary energy cost reasonably. In our experiments, the method has been proved valuable and feasible.

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1. Introduction

In wireless sensor network, it is vital to guarantee energy-effectiveness for prolonging the lifetime of the network. In this case, some sensors are considered not to gather data to reduce energy cost, by e.g. a sleep schedule [1]. This approach is effective and practical for power-saving. However, environment information of the areas where sleep sensors are deployed cannot be sensed directly, therefore information coverage has been a potential challenge. It means that the rest of sensors (unsleeping or wake) have to estimate these un-sensed areas to perceive the global situation of the network. Consensus estimation [2,3] had been proposed to apply to the values of part of sensors to estimate one of their neighbors. That is, information coverage could be achieved by this scheme rationally. Nevertheless, there is a challenge for current consensus estimation methods in actual applications, which is in that it is unnecessary for all wake sensors to undergo con-

sensus estimation, since some of them have no real effect on estimation. In other words, these approaches have unnecessary information exchange in the procedure of consensus which is bound to waste energy. Hence, an effective information coverage approach should be designed for consensus estimation.

This Letter focuses on the actual constraint in the process of consensus estimation. The previous work of Q. Ling et al. [4] is related to ours. However, our design is more practical for information coverage by distinguishing different wake nodes, and energy cost of computation and communication in the network could be further reduced reasonably. Meanwhile, two influence parameters are adopted to embody the relationship between the number of wake sensors and accuracy of estimation separately to generate the formulation. In our work, we firstly optimize the consensus estimation formulation in practice. In detail, wake sensors are divided into two kinds, one being crucial sensors in whose neighbors there is at least one sleep sensor, and the other is common sensors in whose neighbors there is not any sleep sensors. In addition, wake sensors are considered to be capable of finding a neighboring node waking

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at the same time. Obviously, the environment information of the area where sleep sensors are deployed is relevant to the data closely sensed by crucial sensors and hardly by common sensors. Therefore, in our formulation crucial sensors are considered instead of all wclosewake sensors in general consensus estimation (GCE). In this case, the practical scheme reduces the computation and communication costs. In order to generate our formulation, the relationship between the number of wake sensors and accuracy of estimation is embodied with two influence parameters. In the process of consensus estimation, each crucial sensor preserves its estimates itself and sleep sensors of its neighbors. Consequently, crucial sensors of their neighboring also reach consensus for sleep sensors of their neighbors. As a result, crucial sensors conserve their values and numerical estimates of its neighbors. Through values of wake sensors themselves and estimates of crucial sensors, information coverage could be reached. In this method, the number of crucial sensors is similar to the selection of measurement in compressive sensing technique [5] for accurate estimation. Experiments show that our algorithm outperforms general consensus estimation method.

Our contributions in the Letter are summarized as follows:

- a) Crucial wake sensors are picked out from all the wake ones for more effective energy saving.
- b) The relationship between the number of wake sensors and accuracy of estimation is reflected by two influence parameters for universal formulation.

The rest of this paper is organized as follows. Section 2 introduces briefly related background. Section 3 proposes our optimized algorithm. Experiments in actual environments and simulations are given in Section 4. Finally, conclusions are drawn in Section 5.

2. Background

Consensus estimation, as a decentralized estimation method, is employed to local estimates in wireless sensor network [6,7]. In general, estimators in this scheme are always formulated as a solution of convex minimization problem via iteration. In current methods, every iteration comprises of two steps, one step is communication for interchanging information between sensors and their neighbors and the other step is update for renewing their local estimation via interchanged information. For instance, the sample average estimator was applied to analyze consensus parameters in ensemble learning [8] as an optimization problem. Kar et al. [9] and Thanou et al. [10] discussed respectively two kinds of distributed consensus based on deterministic and random signals.

In the process of estimation, sensors need to dynamically exchange their estimates to neighbor sensors and update their local estimates until the global network converges. By updating local estimations iteratively, the whole network could achieve consensus which minimizes the estimation error. In this case, information will reach global coverage even if not all sensors are available. Therefore, it is suitable to utilize consensus estimation to obtain infor-

mation of the whole network based on the part of sensors. However, it is crucial to propose an objective optimization function and corresponding constraint condition for better estimation, which is the essential mission of our work.

3. The proposed information coverage algorithm

To estimate precisely and save energy, we adopt valid (or crucial) wake sensors and exclude invalidated wave sensors for information coverage. In this Letter, an optimized formulation for consensus estimation is proposed and then information converge algorithm is presented.

3.1. Optimized formulation

Consider a network with N sensors comprised of wake sensors W and sleep sensors S and $N = |W| + |S|$, where $|\bullet|$ denotes cardinality. Sensors i are deployed at the position p_i , $i \in N$. The set of wake sensors W consists of the subset of crucial sensors C_r and the subset of common sensors C_o . The former is defined as a sensor which has at least one sleep neighbor, and the latter is defined as a sensor which has zero sleep neighbors. Both sets satisfy $W = C_r \cup C_o$ and $|W| = |C_r| \cup |C_o|$. Suppose sensors are just single-hop communications, so that the i -th sensor can only communicate with sensor j in its neighborhood $j \in N_i$, $N_i \subseteq [1, N]$. The connectivity of network is symmetric and the topology of the network is an undirected graph whose vertices are sensors and its edges represent available communication links. Environment information is sensed by wake sensors and these local sensed data can provide a well approximated estimate about the global area. Let $e = [e_1, e_2, \dots, e_N]^T$ denote the environment information vector, where s_i corresponds to be value at p_i . Similarly, $d = [d_1, d_2, \dots, d_N]^T$ denotes the sensed data by all sensors. Here, d_i is null if the i -th sensor is a sleep sensor. In practice, information occurring at the position p_i may influence its neighborhood A_i . We formulate the influence function $f_i(p)$ which is non-zero only for positions $p \in A_i$ and normalized to obey $f_i(p_i) = 1$. The sensed data d_i can be regarded as the superposition of the influence in the neighborhood of the point p_i .

To achieve consensus estimation, two premises should be satisfied:

Premise 1 (Connectivity). The network should be connected based on all sensors or all wake sensors.

Premise 2 (Influence range). If the distance of any two sensors is larger than their communication range, their influence function is equal to 0.

For Premise 1, it is easy to employ route algorithms to judge the connectivity of the network. For Premise 2, it is a reasonable assumption since information hardly influences the sensed data in a faraway location. Hence, the function of the communication range of sensors is discussed in Section 4.

Based on two premises, sensed data d_j of sensor j can be represented as $d_j = \sum_i f_i(p_j)e_i + n_j$, where $e_i \geq 0$ and

n_j denotes a noise or interference. Intuitively, the minimal value of $\sum_W |d_j - \sum_i^N f_i(p_j)e_i|$ could be solved for consensus estimation. In the Letter, we will employ crucial sensors to estimate information instead of all wake sensors to reduce the redundancy energy cost. More importantly, the relationship between the accuracy of estimation and the number of crucial sensors is also considered. Accordingly, our optimized formulation for consensus estimation is given:

$$\min_s \sum_{c \in C_r} \alpha \left(d_c - e_c - \sum_{i \in N_c} f_i(p_c)e_i \right)^2 + \beta \sum_{i \in C_r \cup S} e_i \quad (1)$$

s.t. $|C_r| \geq 0, \alpha > \beta > 0$

The above objective function contains a least-squares ℓ_2 norm term, an ℓ_1 norm term and two positive weighting coefficients α and β which reflect the tradeoff between these two terms, which is more universal than those in the previous works. According to this formulation, only crucial sensors are needed to estimate sleep neighbors. Hence, it could reduce efficiently the energy cost and accelerates convergence during iterations. The corresponding distributed algorithm is presented in the next subsection.

3.2. Information coverage algorithm

In our algorithm, each crucial sensor conserves local copies of its decisions. The decisions on every sleep sensor are enforced to reach consensus among the entire crucial sensors of their neighborings. Accordingly, the network will consent on the global optimal estimations. In this case, we introduce a set of slack variables to indicate the measurement errors. Similar with [4], crucial sensors minimize a Lagrangian function [11], and the detailed algorithm is as follows:

Algorithm: Information coverage based on consensus estimation optimization.

Input: Each crucial sensor sets the decision variable, slack variable, and multiplier factors as 0

Output: The rate of crucial node in the network

- 1 Judge the connectivity of the network via all wake nodes. (Avoiding invalid estimation)
- 2 **If** the network is connected, **then**
- 3 Each crucial sensor c transmits its decision variables to its neighbors
- 4 **Repeat**
- 5 c updates its slack variable g_c via multiplying parameters (2)–(4) respectively. Then it transmits its current slack variable and corresponding Lagrange multiplier factors to its crucial neighbors. Then, it updates decision variables of itself e_c and its sleep neighbors $e_{S \cap N_i}^c$ by (5), (6)
- 6 **Until** convergence
- 7 All crucial sensors transmit their estimators of itself and its sleep neighbors to the sink
- 8 **End If**

$$g_c(n+1) = \frac{\mu}{2\alpha m_i^2 + \beta\mu} \left(\sum_{i \in (N_c \cap C_r) \cup c} f_{ic}e_i(n) + \sum_{i \in N_c \cap S} f_{ic}e_i^c(n) \right)$$

$$+ \sum_{i \in C \cup N_c} \left(\frac{m_{ic}(n)}{\beta} - \ell_{ic}(n) \right) \quad (2)$$

$$\ell_{ic}(n+1) = \begin{cases} f_{ic}e_i(n) + \frac{d_i - \sum_{i \in (N_c \cap C_r) \cup c} f_{ic}e_i^c(n) - \sum_{i \in N_c \cap S} f_{ic}e_i^c(n)}{h_c} + \frac{m_{ic}}{\mu} + \frac{\sum_{i \in C \cup N_c} m_{ic}(n)}{\mu h_c}, & i \in (N_c \cap C_r) \cup c \\ f_{ic}e_i^c(n) + \frac{d_i - \sum_{i \in (N_c \cap C_r) \cup c} f_{ic}e_i^c(n) - \sum_{i \in N_c \cap S} f_{ic}e_i^c(n)}{h_c} + \frac{m_{ic}}{\mu} + \frac{\sum_{i \in C \cup N_c} m_{ic}(n)}{\mu h_c}, & i \in N_c \cap S \end{cases} \quad (3)$$

$$m_{ic}(n+1) = \begin{cases} m_{ic}(n) + \mu(f_{ic}e_i(n) - \frac{g_c(n+1)}{h_c} - \ell_{ic}(n+1)), & i \in (N_c \cap C_r) \cup c \\ m_{ic}(n) + \mu(f_{ic}e_i^c(n) - \frac{g_c(n+1)}{h_c} - \ell_{ic}(n+1)), & i \in N_c \cap S \end{cases} \quad (4)$$

$$\phi_{cij}(n+1) = \phi_{cij}(n) + \mu(e_i^c(n) - e_j^i(n)), \quad i \in S \cap N_c \cap N_j, j \in C_r \cap N_c \quad (5)$$

$$e_c(n+1) = \max \left\{ \frac{h_c(n+1)}{r_c(n+1)}, 0 \right\} \quad (6)$$

where

$$r_c(n+1) = \begin{cases} \mu \sum_{i \in (N_c \cap C_r) \cup c} f_{ci}^2, & c \in C_r \\ \mu(f_{ic}^2 + 2|N_c + N_i + C_r|) \end{cases}$$

$$e_i^c(n+1) = \max \left\{ \frac{h_i^c(n+1)}{r_i^c(n+1)}, 0 \right\}, \quad i \in S \cap N_c$$

$$h_c(n+1) = \begin{cases} \sum_{i \in (N_c \cap C_r) \cup c} \mu f_{ci} \times \left(\frac{g_i(n+1)}{h_i} + \ell_{ci}(n+1) - \frac{m_{ci}(n+1)}{\mu} \right) - 1, & c \in C_r \\ \sum_{j \in N_c \cap N_i \cap C_r} (2\mu e_i^c(n) - \phi_{ijc}(n+1) + \phi_{jik}(n+1)) + \mu f_{ci} \left(\mu f_{ci} \times \left(\frac{g_c(n+1)}{h_c} + \ell_{ic}(n+1) - \frac{m_{ic}(n+1)}{\mu} \right) \right) - C_r^c, & c \in S \cap N_c \end{cases} \quad (7)$$

According to this algorithm, crucial sensors are able to estimate information of the rest un-sensed areas when convergence achieves, and it is suitable for distributed sensor networks, since information is exchanged based on distributed environment. In the practical applications, it is noticed that the topology of the network needs to be reconfigured when sensors alter their sleeping status via a random or synchronized mechanism and our algorithm also should be operated again based on the altered new arrangement of the network. Furthermore, the crucial sensors shall contain adequate information for information coverage in order to estimate successfully. That is, the density of wake sensors in the network could not be too small. Otherwise, the process of optimization may result in incorrect results. This scene is similar to the selection of measurement in compressive sensing technique for precise recovery.

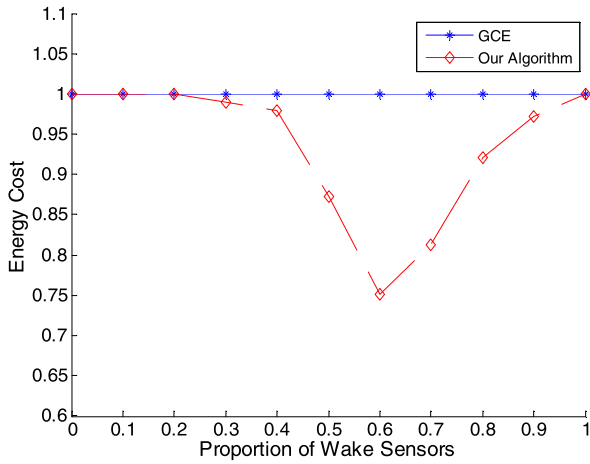


Fig. 1. The relation between wake sensors and energy cost.

4. Experiments

In our experiments, both the proposed approach and the general consensus estimation GCE scheme are compared. Sensors are placed outdoors to gather the temperature of environment. Crucial sensors estimate information of its sleep neighbors and simultaneously the network constructs corresponding routing along all wake sensors. Experiments show that our method outperforms GCE. To further test the performance of the algorithm, simulations are shown in cases of different influence parameters.

4.1. Actual environment

Sensors are used to gather data of environment and the size of network is 60. After information coverage, data sensed by wake sensors and estimates of crucial sensors are transmitted to the sink node. The protocol system of wireless network in our experiments includes physical layer, data link layer and net layer. To guarantee the accuracy of the results, we experiment 100 times and calculate the average value.

To represent the validity of our algorithm intuitively, the simple metric parameter of the efficiency is adopted, which is the relative energy cost between two schemes. Suppose E_c denotes energy cost for our algorithm and E'_c for GCE, then the relative energy cost is equal to E_c/E'_c . Fig. 1 illustrates that our scheme outperforms GCE as a whole. In the figure, we set E_c to 1. When the proportion of wake sensors is lower than 40%, all of them are probably regarded as crucial sensors and therefore their energy costs are the same as GCE's. That is, the gathered data should contain adequate information to estimate successfully. As the proportion of wake sensors increases, the energy cost of our algorithm reduces and reaches nearly 75% when there are 60% wake sensors in the network. Afterwards, the cost increases as the proportion of sleep sensors decreases. Therefore, the density of wake sensors in the network should be selected suitably, which means not too small to avoid incorrect results or not too large to avoid unnecessary wastes.

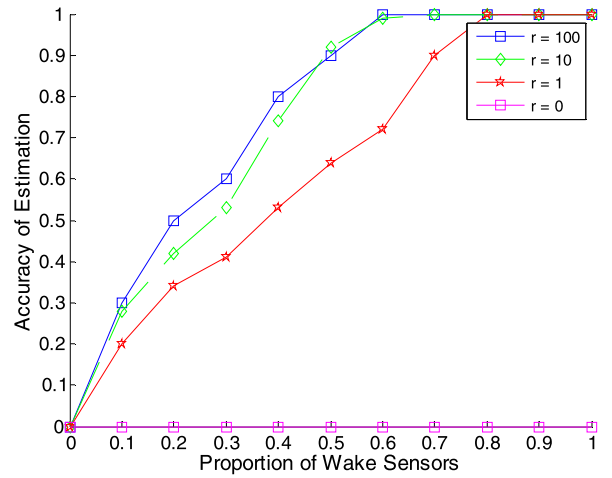


Fig. 2. The relation between wake sensors and accuracy of estimation.

4.2. Simulations

Our simulations focus on the influence of tradeoff parameters of the proposed formulation based on NS-2. We verify the influence of two parameters α , β in (1). Fig. 2 shows the situations when the ratio $r = \alpha/\beta = 0, 1, 10, 100$. When the ratio is equal to 0, it means that our algorithm could not estimate any information; when the ratio is equal to 100, it means that the algorithm may approximately degenerate into general consensus estimation. According to the results, the ratio should be selected larger as long as the consumption of energy is still within a permitted range, which effectively directs us to choose the suitable tradeoff parameters for balancing the accuracy and energy cost.

5. Conclusion

In this paper, a practical information converge is presented based on consensus estimation in wireless sensor network. In the process of convergence, crucial sensors are considered for further reduction of energy cost, and the relationship between the number of wake sensors and accuracy of estimation is revealed with two influence parameters for universal formulation. Experiments have shown that our algorithm outperforms general consensus estimation method.

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