Energy-efficient Data Aggregation Scheme for Underwater Acoustic Sensor Networks

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ABSTRACT
Energy-efficient data aggregation becomes important for underwater acoustic sensor networks due to its energy constrained character. In this paper, we propose a new energy-efficient data aggregation scheme derived from distributed compressed sensing (DCS) theory to reduce communication cost and prolong network lifetime. First, we introduce a distributed compressed sensing model for cluster-based UASNs. Second, we propose a kind of measurement matrix with strictly restricted isometry property (RIP), namely block upper triangular matrix, which takes multi-hop communication cost into account. Finally, a distributed compressed sensing reconstruction algorithm called DCS-SOMP is adopted to recover sensor readings at the sink. We carry out simulations on real sensor readings. The results demonstrate that the new data aggregation scheme can preserve sensor readings fidelity at a reduced communication cost.

Categories and Subject Descriptors
I.5.4 [**Applications: Signal processing**]

General Terms
Algorithms, Design

Keywords
underwater acoustic sensor networks, distributed compressed sensing, measurement matrix

1. INTRODUCTION
Underwater acoustic sensor networks (UASNs) are considered to consist of a number of static sensor nodes or vehicles that are deployed over a region of interest to monitor a physical phenomenon. The applications of such networks include oceanographic data collection (e.g., temperature, salinity, and zonal), field monitoring and disaster prevention [1, 2]. Compared to the terrestrial sensor network, more transmission power for sensor node is required while battery power is severely limited in UASNs. As data aggregation is one of the major research topics for wireless sensor networks due to its promising effect in reducing data traffic. It is particular important for UASNs because of its energy constrained character.

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The paper presents a kind of energy-efficient aggregation scheme based on DCS for cluster-based UASNs. To prolong UASNs lifetime without information loss of observed field, we address the following problems. One is how to gather and transmit less measured data. The other is how to reconstruct the sensor readings from a small number of measured data.

2. SYSTEM MODEL
A grid network is deployed to monitor a physical phenomenon over a long period of time. The network consists of $N = I \cdot J$ sensor nodes uniformly distributed on a two-dimensional plane, with I and J sensor nodes in x and y directions respectively. These sensor nodes are denoted as sn_{ij} $(1 \le i \le I, 1 \le j \le J)$. Several senor nodes adjacent in space are organized as a cluster and one sensor node of the cluster is selected as the cluster-head (CH). The sensor readings are transmitted to their corresponding CHs, and then the CHs send their collected data to the sink through multi-hop. At last, the physical phenomenon of destination monitor area will be denoted at the sink when all data in the monitoring area are collected.

Let $S_i = \begin{bmatrix} s_{i1} & s_{i2} & \cdots & s_{iN} \end{bmatrix}^T$ be the vector composed of sensor readings collected by N sensor nodes at i^th time instance. For convenience, only two adjacent time instances are considered in the paper. In [3], three joint sparsity models are defined in the context of wireless sensor networks that are applied in different situations. We use JSM-2 as our distributed compressing model. In this model, all signals are constructed from the same sparse set of basis vectors, but with different coefficient values, given as

$$S_i = \Psi \theta_i, \quad i = 1,2 \qquad (1)$$

where each θ_i is different but has the same support of size K in Ψ domain. We choose a measurement matrix Φ_i that satisfies RIP. Using this measurement matrix, the source vector S_i is reduced to vector Y_i of size M, denoted as:

$$Y_i = \Phi_i S_i, \quad i = 1,2 \qquad (2)$$

Where Φ_i is a $M \times N$ measurement matrix subjected to $M << N$.

3. DATA AGGREGATION SCHEME
Supposing the N sensor nodes are divided into k clusters in UASNs. Thus, there are n (n=N/k) sensor nodes in each cluster. Each CH collects sensor readings within its own cluster. Let $X_i = [x_{i1} \quad x_{i2} \quad \cdots \quad x_{in}]^T$ be these sensor readings in the i^th cluster whose corresponding CH is CH_i. In traditional cluster-based data aggregation scheme, to transmit X_i to the sink, CH_1 sends X_1 to CH_2.Then CH_2 not only sends X_2 but also X_1 to CH_3. Similarly, CH_i contributes to relay sensor readings for all its previous CHs

besides transmitting its own sensor readings. The scheme is depicted in Fig.1.

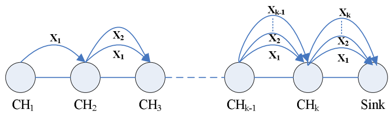

Fig.1 Traditional cluster-based data aggregation

The traditional cluster-based data aggregation scheme collects all original data sensed by all sensor nodes regardless of their characteristics of sparseness in a certain domain. Actually, the signals in UASNs are natural signals, which have strong correlation in time and space. This correlation makes it possible to get a sufficiently accurate approximation of the data with a reduced number of gathering, resulting in energy saving.

Different from traditional cluster-based data aggregation scheme, CH_i delivers measurements of sensor readings, instead of individual readings, to the sink. CH_1 multiplies its collected sensor readings X_1 with a random coefficient Φ_{11} and sends the products to CH_2. We call the values multiplied by the random coefficient as measurements. Then CH_2 multiplies its collected sensor readings X_2 with a random coefficient Φ_{22} to the sink. Simultaneously, CH_2 multiplies its collected sensor readings X_2 with a random coefficient Φ_{12} and sends the sum $\Phi_{11}X_1 + \Phi_{12}X_2$ to the sink. Similarly, CH_i contributes to relay measurements for all its previous CHs by adding its own products step by step besides transmitting its own measurements. Finally, the sink receives k weighted sums of all the sensor readings. It looks like the sensor readings are measured by a block upper triangular matrix Φ, given as

$$\Phi = \begin{bmatrix} \Phi_{11} & \Phi_{12} & \cdots & \Phi_{1k} \\ & \Phi_{22} & \cdots & \Phi_{2k} \\ & & \ddots & \vdots \\ & 0 & & \Phi_{kk} \end{bmatrix} \qquad (3)$$

Where Φ is a $M \times N$ measurement matrix subjected to $M << N$. The scheme is depicted in Fig.2.

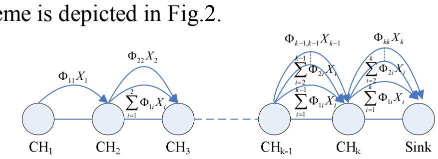

Fig.2. Data aggregation through block upper triangular measurement matrix

If we ignore the transmission consumption within the cluster, the total number of transmitted data in our prosed scheme could be calculated as (1+k)•M/2, while the total number in traditional scheme is (1+k) • N/2. Obviously, communication cost is significantly reduced for M is much less than N.

4. SIMULATION RESULTS

The real oceanographic data are provided by the Ocean Monitoring System — regional ocean modes (ROMS), NASA, and can be downloaded from website: http://ourocean.jpl.nasa.gov. One thousand and two hundred sensor nodes (N=1200) are distributed in the South Pacific at latitude [32.5,32.58], longitude [238.8,243]. In our scheme, these nodes are divided into 10 clusters (k=10) and there are 120 nodes in each cluster (n=120). The sensor readings were collected at 3 o'clock (GMT) and 15 o'clock (GMT) on Feb. 11th, 2012, denoted by “s1” and “s2”, respectively. These sensor readings are sparse in frequency domain. SOMP and DCS-SOMP are used to recover original data based on without and with JSM-2 signal ensemble model respectively. The reconstruction error is defined as $\|\hat{s}_i - s_i\|_{l_2} / \|\hat{s}_i\|_{l_2}$, where s_i is the original sensor readings and $\hat{s}_i$ is the recovered data.

Fig.3 shows the reconstruction error. The joint and independent reconstructions are denoted by “Joint” and “Sepa” respectively. The x-axis denoted by M is the measurement number existed at the sink.

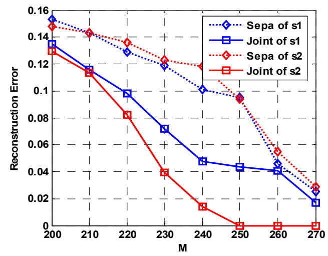

Fig.3. Performance with different measurement number

We can find the reconstruction error decreases as the increasing of measurement number. The reconstruction error of s2 has dropped to zero when M is 250 if applying joint reconstruction.

5. CONCLUSION

In this paper, we propose an energy-efficient data aggregation scheme for cluster-based UASNs derived from DCS. The key issue is to generate RIP preserving measurement matrix. Block upper triangular matrix proposed in this paper are good matches for cluster-based UASNs. Simulations results demonstrate that the new data aggregation scheme can preserve sensor readings fidelity while reducing communication cost.

6. ACKNOWLEDGMENTS

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