Efficient Data Gathering with Compressed Sensing Multiuser Detection in Underwater Wireless Sensor Networks

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Abstract. Bandwidth and energy constraints of underwater wireless sensors networks necessitate an intelligent data transmission between sensor nodes and the fusion center. This paper considers a data gathering underwater networks for monitoring oceanic environmental elements (e.g. temperature, salinity) and only a portion of measurements from sensors allows for oceanic information map reconstruction under compressed sensing (CS) theory. By utilizing the spatial sparsity of active sensors' data, we introduce an activity and data detection based on CS at the receiver side, which results in an efficient data communication by avoiding the necessity of conveying identity information. For an interleave division multiple access (IDMA) sporadic transmission, CS-CBC detection that combines the benefits from chip-by-chip (CBC) multi-user detection and CS detection is proposed. Further, by successively exploring the sparsity of sensor data in spatial and frequency domain, we propose a novel efficient data gathering scheme named Dual-domain compressed sensing (DCS). Simulation results validate the effectiveness of the proposed scheme and an optimal sensing probability problem related to minimum reconstruction error is explored.

Keywords: Compressed sensing · Data gathering · Multiuser detection
Underwater wireless sensor networks

1 Introduction

Underwater wireless sensor networks (UWSN) [1] are widely applied in various advanced applications including environmental monitoring, marine fuel exploration, basic marine sciences and so on. Two main constraints of UWSN enabled by acoustic communications are the limited available bandwidth and the difficulty of frequently recharging the batteries of sensors with regard to economic efficiency and technical consumption. UWSN is believed to be a typical energy-limited and bandwidth-limited system, and hence a robust and efficient network data aggregation scheme is an essential foundation for reliable high-performance in large-scale ocean environmental monitoring networks.

Due to the observation that sensory data are mainly oceanic nature signal which are sparse or compressible in an appropriate basis, compressive sensing (CS) [2, 3] can be

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applied to provide an efficient data gathering scheme, which allows the aggregation node reconstruct the information map with relatively small amount of measurements rather than the raw data from the whole wireless networks [4]. To the best of our knowledge, authors in [5] are the first attempt to introduce the application of compressed sensing in network data processing. The appealing reduction in signal processing and resource requirement has spawned a range of advanced data gathering schemes in wireless sensor networks. For example, Fazel et al. have develop a networking scheme, namely Random Access Compressing Sensing (RACS), that combines compressed sensing and the concepts of random channel access aiming at achieving energy and bandwidth efficiency by only randomly activating a small part of sensor nodes [6]; Xue et al. propose a CS-based medium access control scheme for efficient data transmission in data gathering networks and in-depth analyze the effect of SNR on the accuracy of transmission symbol recovery [7]. Such been investigated data gathering networks either require complicated control overhead including identity information of active sensor nodes or no in-depth eliminate the effect of multiple access interference on data transmission, and hence there are still imperfections to be improved on.

Recently, a novel PHY layer approach for multi-user detection has been investigated, namely multi-user detection based on compressed sensing [8], that allows for jointly reliable user activity and data detection for direct random access in a sporadic communication scenario, where only a small portion of transmitters are active at a given time instant. For such sporadic transmission, the coordination of node access enabled by access reservation protocol would consume a significant amount of additional control overhead. From the view of whole networks' physical topology, the location distribution of active sensors can be viewed as one kind of sparse in spatial domain, and hence compressed sensing can be applied to jointly detect the activity and data information of active sensors, while at the same time a highly resource-efficient transmission can be expected. These advantages greatly innovates the development of multi-user detection based on compressed sensing. In [9], in order to perform a reliable MUD in the case of different sparsity, the author adopted a switching MUD schemes from linear minimum mean square error (LMMSE) to Orthogonal matching pursuit (OMP), which is the most famous of CS reconstruction algorithms. Bringing CS to MUD attracts many researchers to develop MUD schemes based on CS. So far, the multi-user detection based on CS has been applied to many wireless systems, see [10, 11] and references therein.

In this work, we concentrate on data gathering underwater sensor network that collects information of interest for applications such as geographical and environmental monitoring. We consider that only a portion of active sensors are selected during the monitoring cycle and simultaneously communicate their sensory data in uplink transmission, i.e., direct random access. This partial sensor selection method makes the sensory measurements of physical phenomenon which is sparse in frequency domain, are sparse in the spatial domain. In this paper, we innovatively introduce multi-user detection based on compressed sensing into data gathering networks, and propose a dual-dimensional compressed sensing (DCS) for underwater wireless data gathering networks by successively utilizing sparsity of frequency and spatial domain. The proposed scheme guarantees high-performance data measurements collection and allows for the most energy-efficient data gathering networks at the same time.

2 Preliminaries and Problem Formulation

2.1 Compressed Sensing Theory

Originated as a method for acquiring sparse solutions even for under-determined linear systems, compressed sensing provides a new paradigm for signal processing and data acquisition, with which the network data or signals can be efficiently sampled and accurately reconstructed from much fewer measurements than Nyquist sampling theory.

Consider an original signal $\boldsymbol{x} = (x_1, x_2, \ldots, x_n)^T$, which is an n-dimensional vector. Supposing that $\boldsymbol{x}$ is sparse itself or can be represented over a certain appropriate basis $\Psi = \{\boldsymbol{\varphi}_i\}_{i=1}^{n}$, where $\boldsymbol{\varphi}_i \in \mathbb{R}^n$. As shown in (1), $\boldsymbol{x}$ can be sparse expressed as the linear combination of a subset of basis vector:

$$\boldsymbol{x} = \sum_{i=1}^{n} \boldsymbol{\theta_i \varphi_i} \quad \text{or} \quad \boldsymbol{\theta} = \Psi^T \boldsymbol{x}, \tag{1}$$

where $\boldsymbol{\theta_i}$ is an $n \times 1$ vector which denotes the weights vector, $\boldsymbol{\theta_i} = <\boldsymbol{x}, \boldsymbol{\varphi_i}>$ and Ψ is the basis matrix. Ψ is an identity matrix when $\boldsymbol{x}$ is sparse vector. We say that vector $\boldsymbol{\theta}$ is perfectly s-sparse if it has at most $s (s \ll n)$ non-zero elements. In addition, vector $\boldsymbol{\theta}$ is approximately s-sparse means that it has at most s large coefficients while the remaining coefficients are small. For simplicity and without of generality, s-sparse signal vector include perfect sparse and approximately sparse in this paper.

According to CS theory, the original vector $\boldsymbol{x}$ can be reduced-dimensional measured by taking a smaller number (m) of samples by using a linear/convex programming operator Φ; hence the reduced-dimensional measurement vector $\boldsymbol{y}$ can be written as

$$\boldsymbol{y} = \Phi \boldsymbol{x} = \Phi \Psi \boldsymbol{\theta} = \mathrm{A} \boldsymbol{\theta}, \tag{2}$$

where $\Phi = \{\varphi_1, \varphi_2, \ldots, \varphi_m\}^T$, $\mathrm{A} = \Phi\Psi$, $s \le m \le n$, and the original vector $\boldsymbol{x}$ is compressed into an $m \times 1$ vector $\boldsymbol{y}$. Several imposing conditions on measurement matrix Φ guarantee the uniqueness of the solution, such as restricted isometry property (RIP), incoherence and so on [12].

The problem of recovering original vector $\boldsymbol{x}$ from the compressed m-length measurement vector $\boldsymbol{y}$ is equivalent to finding sparsest solution of (2), which can be expressed as an optimization problem:

$$\min_{\boldsymbol{\theta}} \|\boldsymbol{\theta}\|_p \text{ s.t. } \boldsymbol{y} = \Phi \Psi \boldsymbol{\theta}, \tag{3}$$

where $\|\bullet\|_p = \left(\sum_{i=1}^{n} |\bullet|\right)^{1/p}$ denotes the l_p-norm. $l_p(0 < p \le 1)$ guarantees the RIP condition, and hence original vector $\mathbf{x}$ can be accurately reconstructed in highly probability.

2.2 Problem Formulation

Consider a typical UWSN architecture for oceanic data gathering with N sensor nodes deployed in a two-dimensional plane and a fusion center (FC) as shown in Fig. 1. Specifically, the sensor nodes are uniformly distributed to collect some kinds of ocean monitoring elements (e.g. temperature, salinity, and ocean current) and report data to the FC via uplink multiple access channel by one hop. Generally speaking, all sensors transmit collected information with low cost and low-energy consumption, whereas the FC can support more complex computational consumption, such as advanced signal processing. Typically the readings of sensor nodes have spatial correlation due to the closeness of sensors, and hence the reconstruction of network data can be accomplished by collecting a portion of sensory data at the FC according to CS theory. The resource-constraint underwater network necessitates an efficient data transmission between SNs and FC. Channelization access schemes (e.g. time division multiple access, code division multiple access) for selected sensors' communication would produce a significant coordination overhead and increase the time latency. In view of the facts, this paper aims to find an efficient data gathering approach for the large-scale ocean monitoring underwater sensor networks as shown in Fig. 1.

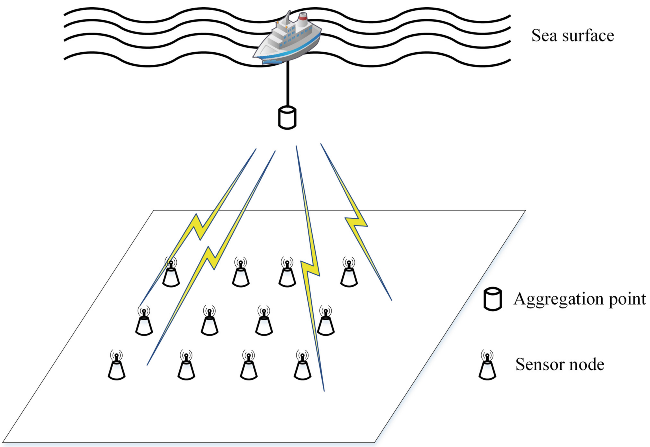


Fig. 1. Two-dimension underwater wireless sensor network for ocean monitoring

3 Dual-Domain Compressed Sensing

In this section, the dual-domain compressed sensing for data gathering scheme is proposed and illustrated for the large-scale ocean monitoring underwater sensor networks. The framework of the proposed scheme is simple and clear. The proposed scheme consists of four components: (1) random sensing with probability p_a. (2) multiple access over noisy channels. (3) activity and data detection based on CS (4) network data recovery based on CS, as shown in As shown in Fig. 2.

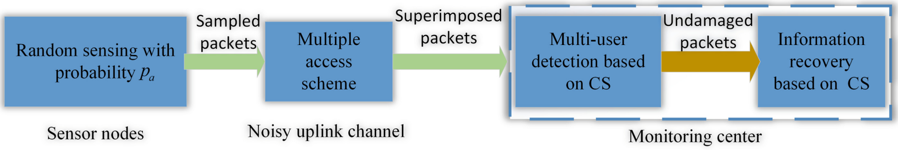


Fig. 2. Framework of data gathering based on dual-domain compressed sensing.

3.1 Random Sensing at Sensor Nodes

Due to the fact that most natural phenomenon has a compressible/sparse representation in an appropriate basis, random sensing is considered in this paper to conserve power of the sensor nodes, in which case only a portion of sensors participates in sensing. To model sensor node activity, we adopt a statistical approach, where each sensor node equips with a simple Bernoulli random generator with a probability p_a denoted as *sensing probability*. Those sensors who are engaged in data transmission are referred to as being *active*, while the other sensors are kept silent and overhearing state to conserve power energy. This activity probability, that determines the total number of active sensors N_{act} in a statistical sense, is assumed to be identical for all deployed sensor nodes. Since not all sensors signaling in a given time, that is, only a few sensors are only active on occasion and we call this *sporadic transmission* [13].

At the beginning of the monitoring cycle, each sensor node performs one independent Bernoulli trial to determine which sensors participating sensing. It is noteworthy that active sensors report data in a time frame which is assumed to be less than the coherence time of nature phenomenon. According to CS theory, a simple and efficient measurement matrix, random extractive matrix Φ, is considered in this paper to reflect the process of random sensing. Φ is easily formed by randomly selecting N_{act} rows from the $N \times N$ identity matrix. The elements in the random extractive matrix have the following property:

$$\begin{aligned} &\sum_{i=1}^{N_{act}} \phi_{ij} \leq 1, j = 1, 2, \ldots, N \\ &\sum_{j=1}^{N} \phi_{ij} = 1, i = 1, 2, \ldots, N_{act} \end{aligned} \tag{4}$$

3.2 Multiple Access Over Noisy Channel

IDMA is a relatively novel multiple access method, which can be considered as a special case of CDMA due to use low rate code as spreading and separating users from specific interleavers [14]. Such a multiple access inherits many distinguished features of the well-studied CDMA, and further improvement in terms of performance and spectrum efficiency in UWSN. Therefore, IDMA is attractive for underwater wireless communication.

All sensors are equipped with IDMA transmitter. In prior to access channel, multiple access techniques are adopted in processing the symbol frame to implement multi-user transmission. Neither access reservation protocols for node coordination or signing the activity of sensor nodes are assumed in order to avoiding significant additional transmission. Further, we assume slotted random access for data transmission and one frame of data are transmitted per slot.

After that, all transmitted symbols are superimposed in the receiver, and the receiver signal $\boldsymbol{y}$ is modeled as

$$\begin{aligned}\mathbf{y} &= \sum_{k=1}^{K} \mathbf{H}_k \boldsymbol{\Pi}_k \mathbf{S} \mathbf{d}_k + \mathbf{n} \\ &= \mathbf{A}\mathbf{d} + \mathbf{n}.\end{aligned} \tag{5}$$

For the kth sensor, $\mathbf{d}_k \in \mathcal{A}_0^M$ is the vector including the transmitted symbols, Each column of $\mathbf{S} \in \mathbb{R}^{F \times M}$ contains the spreading sequence $\mathbf{s}_k$, $\boldsymbol{\Pi}_k \in \mathbb{R}^{F \times F}$ describes the matrix form of user specific interleaver φ_k, and $\mathbf{H}_k \in \mathbb{R}^{F' \times F}$ is channel matrix for the node-specific block-fading channel $\mathbf{h}_k$. Then, the total influence of transmission can be represented as $\mathbf{A} \in \mathbb{R}^{F' \times M}$, and vector $\mathbf{d} \in \mathcal{A}_0^L$ is the stacked vector of all $\mathbf{d}_k$, where $L = KM$. Further, the noise vector $\mathbf{n} \in \mathbb{R}^{F'}$ is i.i.d. zero-mean Gaussian distributed, i.e., $\mathbf{n} \sim \mathcal{N}(0, \sigma_{\mathbf{n}}^2 \mathbf{I})$. Herein, the symbols of $\mathbf{d}$ are taken from the discrete augmented alphabet $\mathcal{A}_0$.

Synchronous reception and perfect channel state information are assumed in system model (5).

3.3 Activity and Data Detection Based on CS by Utilizing Sparsity of Spatial Domain

IDMA allows a low-cost chip-by-chip (CBC) iterative multi-user detection strategy to implement multi-user detection. However, it assumes that active sensors are exactly known at the receiver, which is challenging in practice.

Due to the fact that each sensor is activated to transmitting measurements with a sensing probability p_a in one time frame, the number of active SNs at one time instance, K_{act}, is small, resulting in a sparse signal $\mathbf{d}$ in the process of multiple access. Furthermore, as to sporadic wireless communication, the connected nodes transmit signals continuously on a frame basis by a low probability. Since sensors are active or inactive for a whole frame, the non-zeros symbols of the sparse vector $\mathbf{d}$ appear in groups or blocks form in a fixed length. Therefore, this feature is also known as *block sparsity* or *group sparsity* [15]. For the sake of uniform expression in this paper, we choose *block sparsity* in the following. The multi-user detection problem can be treated as a block sparse signal recovery inherently, which naturally incorporate the powerful tool CS into the joint sensor activity and data detection problem. Therefore, the greedy group orthogonal matching pursuit (GOMP) [16] is a good choice for CS detection.

In order to enhance the robustness of uplink sporadic IDMA transmission, we propose a CS-CBC multi-user detector that can accurately detect the sensor activity and efficiently implement data detection. It should be noted, while classical CS could provide jointly recovery the activity and data detection, CS-CBC only need CS detection to accurately detect positions of nonzero elements of sparse signal $\mathbf{d}$, rather than the values of non-zero elements.

After the user activity information obtained above, the received signal $\mathbf{y}$, which compose of the active sensor transmitted symbols modulated by the interleaved spreading sequences, can be expressed as

$$\begin{aligned} \mathbf{y} &= \sum_{n=1}^{N_{act}} \mathbf{H}_n \mathbf{\Pi}_n \mathbf{S} \mathbf{d}_n + \mathbf{n} \\ &= \mathbf{A}_2 \mathbf{d}_{active} + \mathbf{n}, \end{aligned} \tag{6}$$

where $\mathbf{d}_{active}$ only contains the transmitted symbols of active sensors, $\mathbf{A}_2$ has the same form as $\mathbf{A}$ in system model (5) except that it only includes interleaved spreading sequences and channel influence for active sensors. Then, CBC algorithm can be implemented to realize active data detection.

Differing from the typical application of CS, the goal of detection based on CS is capable of determining the activity of sensors and recovering the symbol data packets of active sensors. Activity information of all SNs enables the construction of measurement matrix $\mathbf{\Phi}$, while symbol data packets of active SNs contain the successfully collected packets utilized for network recovery. Therefore, implementing multi-user detection based on CS at the FC simultaneously provide two prerequisite information for network data recovery.

3.4 Network Data Recovery Based on CS by Utilizing Sparsity of Frequency Domain

In view of the fact the network data acquired from the monitored underwater characteristics are usually are compressible or sparse representation in the frequency domain (such as sea currents, temperature and salinity), CS theory further enables the possibility of reconstruction a high-resolution information map of the monitoring network by utilizing sparsity of frequency domain.

Supposed by the end of monitoring, the data measurement vector from the active sensor nodes $\mathbf{d}_\Gamma$ has been successfully acquired via MUD, which is given by

$$\mathbf{d}_\Gamma = \Phi \mathbf{f} = \mathbf{\Phi \Psi \theta}, \tag{7}$$

where $\mathbf{\Phi}$ is the random extractive matrix that can be received from the recovered sparse vector $\mathbf{d}$, $\boldsymbol{\theta}$ is the sparse representation of original network data $\mathbf{f}$. Therefore, the network data recovery can be solved by the following optimization problem

$$\min_{\mathbf{d}} \|\boldsymbol{\theta}\|_1 \text{ s.t. } \mathbf{d}_\Gamma = \mathbf{\Phi \Psi \theta}. \tag{8}$$

CS theory indicates that if the number of measurements exceeds a certain threshold r_s, the original network data $\mathbf{f}$ can be reconstructed in high probability by solving the problem of (8).

4 Simulation Results

4.1 Performance of the Proposed CS-CBC

We will discuss simulation results for the reliability of the detection in terms of Symbol Error Rate (SER), define as

$$SER = p(\hat{\mathbf{d}} \neq \mathbf{d}). \quad (9)$$

Here, the SER is given by the probability that the symbol frames of all sensors are detected incorrectly at the FC and therefore it summarizes both activity and data detection errors.

We consider an overloaded IDMA system, which result in under-determined equation system for CS detection. The main simulation parameters are set as follows. The total number of sensor nodes is $N = 100$ and the frame length M is set to 50 symbols. In order to separate users, random interleavers are adopted. All sensor nodes use the same spreading sequence, which is generated based on repetition coding multiplied by a mask sequence with alternant signs, i.e., [+1, −1, +1, −1, …]. The spreading length N_s is 64. Therefore, the overloading factor is 156%. BPSK signaling is always considered.

Figure 3 compare the SER performance of the following four detectors: Conventional CBC, CS detection, CS-CBC and Genie-knowledge CBC assuming the perfect knowledge of active sensors, where the active probabilities is $p_a = 0.2$. Herein, the Genie-knowledge CBC algorithm plays a lower bound of the algorithm for sensor activity detection and data recovery. CS-CBC is superior to CS detection and CBC-AD and their gaps become larger with higher E_b/N_0. Furthermore, it can achieve the performance of Genie-knowledge CBC under high E_b/N_0. This means that CS-CBC

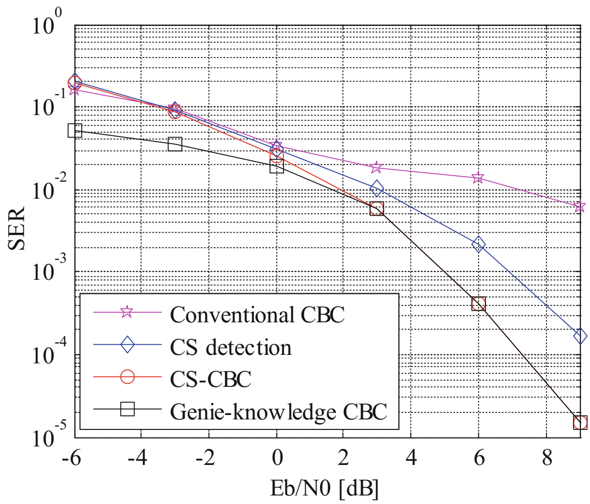


Fig. 3. SER performance comparison against SNR, where active probability $p_a = 0.2$.

has perfect knowledge of active sensors due to the reliable performance of CS detection to positioning non-zeros items and CS-CBC do better data recovery than CS detection.

4.2 Performance of Data Gathering Based on DCS

We consider a UWSN consisting of N sensor nodes in a simple single-path multiple access underwater channel model with ideal power control. Real ocean meridional current data of Monterey Bay is experiment subject, which is obtained by the Regional Ocean Modeling System (ROMS) at 3GMT 05/13/2012. The monitored region is 100 m below the sea surface and ranged over $[-122.8°\text{E}, -122.6°\text{E}]$ in longitude and $[36.6°\text{N}, 36.8°\text{N}]$ in latitude. Considering that the number of active sensors is usually large in the ocean monitoring sensor networks, the uplink frame will be split into several subframes and IDMA scheme is operated in each subframe. The main procedure is as following: Firstly, downlink control information included subframe index and interleaver is broadcasted to all sensor nodes. Secondly, the selected nodes transmit subframes separated by a guard time to FC. Finally, the FC implement CS-CBC and OMP algorithm to recovery the network data. The main simulation parameters are summarized in Table 1.

Table 1. Simulation parameters

Parameters	Value
Data packet length	50 bit
Spreading length	64
Noise power spectral density	−100 dBm
Underwater depth	100 m
Carrier frequency	10 kHz

Ideal power control for each sensor node is adopted and the required power of each sensor at the FC is P_0, the distance between the sensor node and the FC is d (km), and the carrier frequency is f (kHz). In order to achieve the required BER, the transmitted power should be $P_0 \cdot A(d,f)$, where

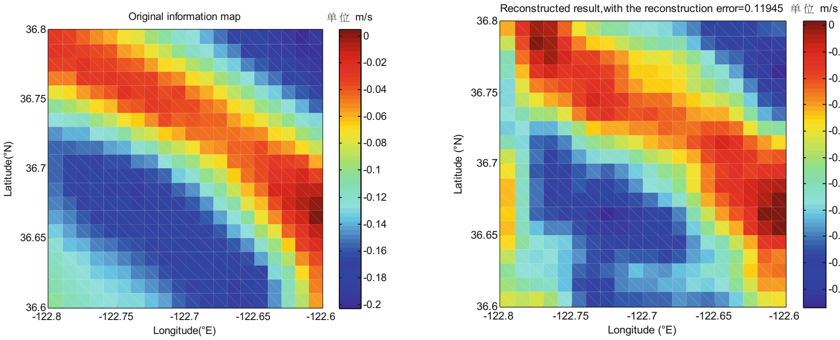
$$A(d,f) = d^c \cdot a(f)^d. \tag{10}$$

The constant c is usually set as 1.5, and

$$a(f) = 10^{\alpha(f)/10}, \tag{11}$$

where $\alpha(f)$ is the absorption coefficient, with an experiential formula as follows:

$$a(f) = \frac{0.11f^2}{1+f^2} + \frac{44f^2}{4100+f^2} + \frac{2.75f^2}{10^4} + 0.003. \tag{12}$$



(a) (b)

Fig. 4. Information map about ocean meridional current of the given area. (a) Original information map. (b) Reconstructed information map.

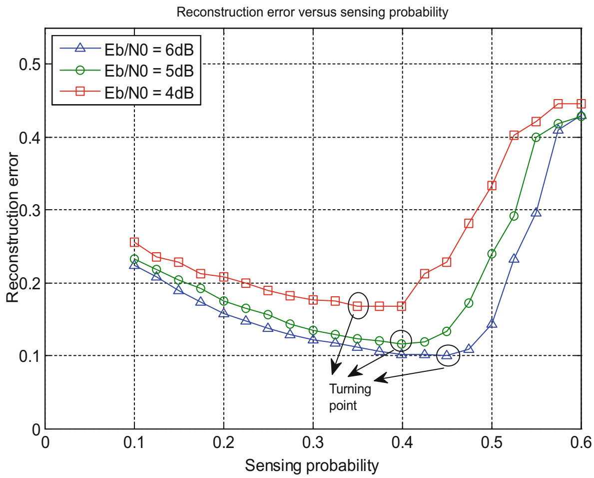


Fig. 5. Reconstruction error versus sensing probability.

The reconstruction error P_e is defined as $\left\|\hat{\mathbf{f}} - \mathbf{f}\right\|_2 / \|\mathbf{f}\|_2$ to evaluate the quality of network data recovery.

To visually illustrate the DCS scheme for data gathering network, the simulations for real data are shown in Fig. 4. E_b/N_0 is 6 dB at the FC and the sensing probability p_a is 0.3. The simulation result of PER is 0.0913 and hence about of 110 of the 120 random measurements are successfully collected for the network data recovery, leading to a reconstruction error $P_e = 0.11945$.

The relationship between reconstruction error P_e and the sensing probability p_a is illustrated in Fig. 5. An interesting phenomenon that the relationship curve presents downward bending and an optimal sensing probability exists in the turning point is

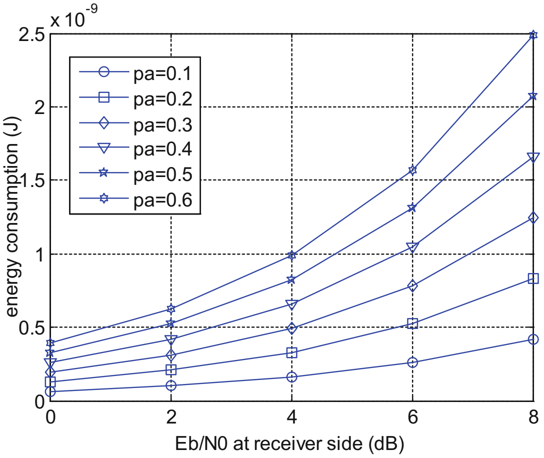


Fig. 6. Average energy consumption per sensor vs E_b/N_0 at receiver side.

observed. Further, the turning point varies with different channel conditions and appears latter with the increasing E_b/N_0. As mentioned above, the sensing probability p_a is negatively correlated with p_{suc}, and positively correlated with N_{act}. Consequently, the optimal sensing probability reaches a balance between two influence factor related to reconstruction error P_e in a given channel condition. The increasing E_b/N_0 improves the p_{suc}, which breaks the original balance and push sensing probability to increase in order to build a new balance. In addition, the reconstruction evidently deteriorates with the increase of E_b/N_0 because of the high PER. However, higher E_b/N_0 consume more energy, and the average energy consumption per sensor versus E_b/N_0 at FC is shown in Fig. 6. The performance tradeoff between resource requirement and quality of reconstruction should be taken into consideration in system design.

5 Conclusion

In this paper, we have elaborated the role of activity and data detection based on CS in data gathering networks in terms of symbol data recovery. The DCS scheme for data gathering that exploits the spatial sparsity of active sensors' data and the frequency sparsity that exists in most natural signals is proposed. The proposed CS-CBC that combines the benefits of CBC and conventional CS detection guarantees an efficient data transmission in DCS. Moreover, the influence of the activity and data detection on network recovery has been illustrated and the performance of proposed DCS scheme has been simulated in terms of reconstruction error and energy consumption. The optimal sensing probability problem related to minimum reconstruction error is illustrated and should be considered in system design.

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