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Compressive Sensing based Data Collection in Wireless Sensor Networks

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Abstract— **Compressive sensing originates in the field of signal processing and has recently become a topic of energy-efficient data gathering in wireless sensor networks. In this paper, we introduce a distributed compressive sensing approach, which utilizes spatial correlation among sensor nodes to group them into coalitions. The coalition formation method is represented by a block diagonal measurement matrix whose each diagonal entity corresponds to one of the coalitions. Then, a spatial-temporal correlation-based compressive sensing approach is used inside each coalition to schedule sensor nodes and encode their readings. Distributed data encoding over coalitions increases robustness and scalability of the approach. Simulation results verify that the proposed solution outperforms other compressive sensing approaches significantly in terms of data accuracy and energy efficiency.**

I. INTRODUCTION

Energy efficiency is a continuing concern within wireless sensor networks. Every sensor network is operational as long as they have enough energy resources. Therefore, to ensure the longevity of a network , energy efficient techniques are essential [1]. Compressive sensing is one of the new energy effecient compression based data gathering techniques which is introduced in recent years.

Compressive sensing is a concept originated from the field of signal processing. The promise of compressive sensing is that it can reconstruct sparse or compressible signals from a small number of measurements without having a priori knowledge about the signal structure. This technique utilizes information rate instead of sampling rate to sample and recover the signal [2].

Recent compressive sensing solutions proposed in wireless sensor networks have proven advantages in minimizing the number of measurements, but they are still not competitive with the existing data compression techniques [3]. Since transmission cost is the dominant energy consumption parameter, compressive sensing methods should consider minimizing the consumption by each measurement in terms of transmission cost. In some proposed solutions, each sensor node produces its measurements, aggregates these with the measurements of other nodes and transfers them to the base station. Since sensor nodes may be far from each other, the transmission cost is high enough to negate the advantages of compressive sensing-based data gathering [4]. Utilizing distributed compressive sensing could represent an important step towards improving existing compressive sensing methods in terms of energy consumption, bandwidth use and data quality [5].

This paper proposes a distributed compressive sensing solution that focuses on spatial-temporal correlation to minimize the number of active sensor nodes and their measurement rates. This approach leverages the sparsity distribution of signals in order to group spatially correlated sensor nodes into coalitions. A coalition formation method is represented by a block diagonal measurement matrix whose each diagonal entity corresponds to one of the coalitions. Upon forming coalitions, proposed spatial-temporal correlation based compressive sensing approach is used inside each coalition to collect sensor nodes' readings.

The remainder of this paper is organized as follows: Section II presents the related works while section III represents network architecture. Section IV introduces an overall overview of the proposed solution. Section V and VI explain collation formation algorithm and data gathering procedure inside coalitions, respectively. Data reconstruction procedure is mentioned in Section VII while Section VIII analyzes the performance of the proposed scheme. Finally, conclusions are drawn in Section IX.

II. RELATED WORKS

Luo et al [6] present a compressive data gathering (CDG) method, which combines data compression and routing for data collection in large-scale wireless sensor networks. The result of this combination is a balanced distribution of energy consumption over the network, which improves network lifetime. Furthermore, it shows a significant reduction in communication cost.

A further study [7] introduces a joint sparse signal recovery method which assumes sensor nodes have been distributed into different clusters, and uses a joint sparse signal recovery mechanism to recover the compressed data. The proposed solution reduces energy consumption in terms of data compression and transmission rate. However, it does not ensure that application-defined data accuracy requirements are met.

A hybrid network coding and compressive sensing-based solution in [8] represents a clustered spatial-temporal correlation-based compressive sensing method. Each sensor node utilizes a well-defined Gaussian code matrix to encode its reading and forwards it to the base station through the cluster head. Proper selection of the measurement matrix and network coding coefficients is utilized at the base station to implement a low-complexity data reconstruction algorithm that reconstructs data more accurately.

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Another publication [9] proposes a novel compressive sensing-based data gathering solution for massive lossy data transmission scenarios. The proposed compressive sensing solution models environmental data dynamicity using an environmental matrix (EM) and then employs the spatial-temporal correlation observed in this matrix to reconstruct the encoded data.

III. NETWORK MODEL

Our heterogeneous network consists of N static sensor nodes regularly placed inside a region and utilizes multi-hop communication to forward the readings to the base station. Each sensor node is assigned an integer ID, i, which is in the range from 1 to N .

There are three types of sensor nodes in the network: normal nodes, coalition coordinator and base station. The normal sensor nodes have limited computational and storage capacity. Moreover, these sensor nodes are equipped with limited battery power, as replacing their batteries is difficult and expensive. There are a few powerful but also resource-restricted nodes, the coalition coordinators, which have more memory and computation capabilities. The base station is a powerful node with significant computational and storage resources.

IV. PROPOSED APPROACH OVERVIEW

In order to achieve an energy efficient and quality aware compressive sensing method, we introduce a distributed compressive sensing approach that utilizes spatial correlation among sensor nodes to group them into coalitions. Upon forming coalitions, the proposed spatial-temporal correlation-based compressive sensing approach is implemented inside each coalition in order to schedule sensor nodes and encode their readings. Temporal correlation among sensor node readings allows our approach to adjust the number of measurements with regard to the temporally changing sparsity level. The proposed coalition formation method is represented by a block diagonal measurement matrix in which each diagonal entity corresponds to one of the coalitions. The base station employs a two-step joint sparsity-based recovery algorithm to reconstruct the original signal.

V. COALITION FORMATION

The compressive sensing-based coalition formation introduced here is inspired by the fact that the subject signals are distributed in the environment and distribution of their signal elements is different for the sensor nodes based on their locations. Therefore, the sensor nodes observe the same signal with different resolution. On the other hand, the sparse representation of the signal can be shown in a sparsity base function. We utilize the base function distribution over the network to define a cover parameter. This cover metric shows the degree of the base function covered by the sensor nodes. This parameter helps sensor nodes inside each coalition produce informative measurements, which results in accurate data recovery by the base station.

To make a concrete and accurate coalition, we define a utility function U based on cover, transmission and sensor node correlations. This function is used to evaluate the efficiency of the coalitions produced. To do so, U makes a trade-off between reconstruction accuracy (correlation between sensor nodes and base function distribution pattern) and data transmission cost (distance between sensor nodes).

The following sections explain the prerequisites for the coalition formation algorithm and conclude by presenting the coalition formation procedure.

A. Measurement Matrix

Since we divide the network into different coalitions, the data is gathered through these different coalitions. Therefore, whole data may be divided into discrete blocks, in which each block is acquired via a local measurement operator. Assuming that we have divided the network into N_C coalitions and our signal X has being partitioned into N_C blocks $X_1, X_2, ..., X_{N_C} \in R^N$. Each block j which shows coalition j is assigned with a local measurement matrix $\Phi^j : R^N \rightarrow R^{N_j}$ collects the measurements. Each measurement sub-matrix Φ^j represents the measurement pattern inside each coalition j.

Each of our measurement matrix Φ^j is assigned one coalition matrix C which permutes the entities of original signal assigned for the specific coalition j. In order to assign each coalition j, through its measurement matrix Φ^j, with the permutated signal coefficients x_j^C, we multiply C by X which produces $CX = X^C = [x_1^C, x_2^C, ..., x_{N_C}^C]$ and finally we have:

$$Y = \Phi C X \tag{1}$$

where:

$$\Phi = \begin{pmatrix} \Phi^1 & & & \\ & \Phi^2 & & \mathbf{0} \\ & & \cdot & \\ & \mathbf{0} & & \cdot & \\ & & & & \Phi^{N_C} \end{pmatrix} \tag{2}$$

The resulting matrix ΦC represents the distribution of sensor nodes inside each coalition and C is a coalition matrix.

Based on equation 2 and sparse representation of the signal $X = \widetilde{\Psi} a$, we obtain:

$$Y = \Phi C X = \Phi(C\widetilde{\Psi})a = \Phi\Psi a \tag{3}$$

where $\Psi = C\widetilde{\Psi}$ is a permutated version of $\widetilde{\Psi}$. As we have seen, our coalition matrix permutates the base functions. Through this permutation, each row in Ψ is a permutated row of $\widetilde{\Psi}$ as follows:

$$\psi_i^T = \sum_{j=1}^{N} P(i,j)\widetilde{\psi}_j^T \tag{4}$$

where ψ_i^T and $\widetilde{\psi}_j^T$ are the row vectors of Ψ and $\widetilde{\Psi}$, respectively. if $P(i,j) = 1$, then the i^{th} row of Ψ is replaced with j^{th} row of $\widetilde{\Psi}$.

After permutation with coalition matrix, we have a proper pattern for each Φ^j to measure data from sensor node inside each coalition j.

The coalition formation mechanism proposed here leads to a block diagonal measurement matrix with the appropriate coalition matrix C, relative to the location of the sensor nodes. This provides a distributed data measurement pattern.

B. Utility Function

The proposed coalition matrix C can be assigned to any coalition formation method. During the coalition formation procedure, we aim to make the best trade-off between energy savings and reconstruction accuracy. To do so, we introduce a utility function to evaluate the efficiency of the coalition formation process. This utility function is defined based on the energy, correlation and cover degree parameters. The following sections explain these parameters in more detail and conclude by introducing the utility function.

1) Energy: We define the energy parameter for coalition formation scenarios based on transmission and measurement costs. Energy consumption is described as:

$$E_i = E_{comm} + E_{pro} + E_{meas} \tag{5}$$

where $E_{comm}, E_{pro}, E_{meas}$ are communication, processing and measurement energy parameters, respectively. In this section, we focus on data transmission and measurement cost. We normalize these costs and replace energy requirements for processing and measurement with measurement cost. The transmission cost relates directly to the distance, while the measurement cost is influenced by the number of measurements. We replace the energy parameter with the normalized parameters of distance between two nodes inside the coalition and the number of measurements is represented as:

$$ECo(i,j) = \frac{Dist(i,j)}{Dist_{max}} + \frac{M_i}{M_{max}} \tag{6}$$

where ECo_i is the energy cost in terms of normalized distance between node i,j $Dist(i,j)$ and the normalized number of measurements taken by node i, M_i.

2) Correlation Degree: Since sensor nodes are located close to each other and they sense the same signal with different resolutions, we were able to find different levels of spatial correlation among them. Existing compressive techniques usually ignore this correlation and transfer redundant compressed data, which costs energy. Our approach tries to remove the redundancy among compressed data, thus leveraging this spatial correlation. To do so, in the coalition formation phase we force the algorithm to consider this correlation along with other parameters. When we have correlated sensors in the same coalitions, we remove redundancy in the compressed data using the algorithm described in the next section. The correlation metric among sensor nodes is defined as $Corr$.

$$Corr(i,j) = \frac{Cov(y_i, y_j)}{\sigma(y_i)\sigma(y_j)} \tag{7}$$

According to this formula, we define a binary variable CR which indicates whether two sensor nodes are sufficiently correlated. For this purpose, we utilize a user-defined correlation threshold $TH1$.

$$CR(i,j) = \begin{cases} 1 & ifCorr(i,j) > TH1; \\ 0 & ifCorr(i,j) \leq TH1. \end{cases}$$

3) Cover Degree: Measured signals can be represented by a sparsity function distribution over the networks. These functions can also be grouped into one or more coalitions. The performance of our coalition mechanism in terms of recovered data accuracy greatly depends on the nature of the sparsity base functions. To evaluate this performance, we define a sparsity base cover degree (SCD) metric which measures the degree of the overlap between each coalition with the base functions Ψ. Essentially, the SCD shows the energy overlap between base functions and coalitions.

We define the SCD metric between each base function i and coalition Col_j as follows:

$$SCD(j,i) = \sum_{m \in Col_j} \psi^2(i,m) \tag{8}$$

where m is a sensor node located in coalition j. This metric $SCD(j,i)$ indicates that measurements collected from coalition j contain information about the measurements of other coalitions that cover the same base function i. Taking into account this coverage degree among different coalitions, we use a joint sparse signal recovery approach to recover the original signal. However, there are situations in which Ψ is covered only by one coalition. This means that for a K-sparse signal, the sparsity bases are contained in one coalition. Since this coalition is not known beforehand, we need to gather data from all coalitions, which is not energy efficient. Meanwhile, for accurate data recovery we must have $O(K \log N)$ measurements, meaning that we need $O(KN_C \log N)$ measurements from all coalitions. On the other hand, the redundant measurements from other coalitions that do not overlap with the base, do not contribute to improving data accuracy. If Ψ has even overlap among different coalitions, our data recovery accuracy is increased. To quantify the cover level of Ψ over coalitions, we define the maximum SCD as follows:

$$SCD_{max}(\Psi) = SCD_{max}(C\overline{\Psi}) = max_{j,u} \sum_{w} {\Psi^{j}}^2(w,u), \quad SCD(\Psi) \in [0,1] \tag{9}$$

SCD_{max} shows the maximum cover level of each coalition with the sparsity base, while Ψ^j is the base sub-matrix assigned to coalition j.

Forming coalitions such that the sparsity function can be recovered with several coalitions increases the quality of the recovered data. On the other hand, we must minimize the number of correlated coalitions and the number of measurements to minimize energy consumption. To find this balance, we must define a utility function as described in the next section. We discuss the number of coalitions and measurements and how SCD_{max} makes a trade-off between energy and quality in terms of the minimum number of measurements and data recovery accuracy.

4) Utility Function Formulation: In this section, we calculate a utility function U to evaluate the candidate coalition structures.

In the coalition formation phase, we aim to build N_C coalitions to achieve minimum energy consumption while meeting data quality requirements. Minimizing transmission and measurement cost, which is the main energy consumption parameter here, depends on SCD_{max}, $M_i$and $Dist_{ij}$. The proposed utility function should evaluate adding a new sensor node to any coalition in terms of the trade-off between energy and quality. To do so, we define the utility function U for each combination of (n_i, Col_r) as follows:

$$\begin{aligned} U(n_i, Col_r) = CR(n_i) \times (ECo(n_i, Col_r) \\ +\alpha SCD_{max}(n_i, Col_r)), \quad \alpha > 0 \end{aligned} \tag{10}$$

where $CR(n_i)$ defines the correlation level of sensor node i with other sensor nodes in Col_r . Regarding the $SCD_{max}(n_i, Col_r)$ parameter, adding a sensor node to different coalitions may change the value of SCD_{max}.

C. Coalition Formation Algorithm

In the model introduced in this paper, the network consists of N sensor nodes $SN = \{n_1, n_2, ..., n_N\}$ and $L = \{l_{n_i,n_j}\}$ is the set of all possible connections between sensor nodes. Two sensor nodes are considered to be connected if they are placed in communication range of each other. We assume that Ψ is known and all sparsity bases are normalized to 1 so that $SCD \in [0, 1]$. This algorithm aims to minimize energy consumption, provided that the data quality requirement is met. Adding a new sensor node to the coalition is a selection procedure that evaluates which coalition is the best candidate for adding a sensor node. To make a good selection we run an optimization algorithm on U.

Before describing the optimization algorithm, the SCD parameter must be redefined. During coalition formation, when we add a new sensor node to the coalition, SCD evaluates the effect of adding this node by assigning a weight for the link between existing node in the coalition and the new sensor node. Our coalition formation method, in order to examine the effect of adding a sensor node to each coalition, defines the SCD factor as $SCD_{max}(l_{n_i,n_j}, Col_r)$ by considering the link, $l_{n_i,n_j} \in L$ and a given coalition Col_r. This link does not connect two nodes in the same coalition, which means $n_i \in Col_r$ and $n_j \ni C_r$.

Now we redefine the utility function U for each combination of (l_{n_i,n_j}, Col_r):

$$\begin{aligned} U(n_i, Col_r) = CR(n_i, n_j) \times (ECo(l_{n_i,n_j}) \\ +\alpha SCD_{max}(l_{n_i,n_j}, Col_r)), \qquad \alpha > 0 \end{aligned} \tag{11}$$

$SCD_{max}(l_{n_i,n_j}, Col_r)$ here represents the maximum cover level when a new node is added to coalition Col_r using the link l_{n_i,n_j}.

Now we can formalize our optimization algorithm. The main goal in the optimization procedure is to minimize the energy consumption and data recovery error by adding new sensor nodes to the coalitions. When selecting an appropriate coalition for a new sensor node, the optimization algorithm examines the utility of adding the new sensor node to each coalition. For each coalition, this utility is defined based on the link connecting the new sensor node to an existing node in the coalition. Running the optimization algorithm finds the coalitions that minimize the utility function in terms of link cost. We formulate this optimization as follows:

$$\begin{aligned} U(n_i, l_{min}, Col_{r_{min}}) = \\ \arg\min U(n_i, Col_r) = \arg\min[CR(n_i, n_j) \times \\ (ECo(l_{n_i,n_j}) + \alpha SCD_{max}(l_{n_i,n_j}, Col_r))] \\ subject\ to\ n_i \in SN,\ n_j \in Col_r,\ CR(n_i, n_j) \in \{0, 1\} \end{aligned} \tag{12}$$

Now let us describe the algorithm according to the optimization equations. To find a set of sensor nodes for each coalition, this algorithm uses equation 12 to find a set of links such that the total U of the links is minimized. In the initialization step, we assume a set of candidate nodes and candidate links to be added to the coalitions defined by a set of SN and L. The algorithm then assigns each coalition coordinator node CC to one of the N_C coalitions. In addition, it defines SN_{Col_r} and L_{Col_r} as a set of sensor nodes and connections of coalition r, respectively. Along with the initialization step, the algorithm runs an iterative procedure where in each iteration it allocates one sensor node to one of the coalitions. To do so, it first finds the utility function for all possible connections defined in L. It then runs the optimization function defined in 12 and finds the minimum utility. However, it finds the utility for sensor nodes which satisfy the minimum correlation requirements. The output of this optimization is a connection link with minimum utility l_{min}. This link connecting (n_i, n_j), adds sensor node n_i to the coalition of which node n_j is a member. Upon adding a new sensor node, the SCD parameter of the all links connected to the coalitions changes so that the link utility of the sensor nodes may change. It then removes this link and sensor node n_i from the list of candidate links and nodes. This procedure continues until all sensor nodes are assigned to the coalitions. Algotithm 1 represents this algorithm.

VI. COMPRESSIVE SENSING BASED DATA GATHERING

After Grouping sensor nodes inside coalitions, sensor nodes transfer their readings to the base station. We now construct a block diagonal measurement matrix using the spatial-temporal correlation among sensor nodes.

Let $SN_{Col_j} = \{1, 2, ..., N_j\}$ denote the set of sensor nodes for the j^{th} coalition where P_j of these sensor nodes

Algorithm 1 Coalition formation

$SN = n_1, n_2, .., n_N$
Define $L = l_{ij}$ as a set of all possible links
Define N_C coalitions with one coalition coordinator
Define set of nodes N_{col_k} and links for each coalitions L_{col_k}
for $(P = 1; P \leq (N - N_C); P++)$ **do**
    for $(Q = 1; Q \leq |L|; Q++)$ **do**
        $Find\ L_{poss} = l_{ij} i \in N_{col_k}, j \in SN$
    end for
    Cacluate $U(I_{ij}, Col_k)$
    Add n_j to $Col_{k_{min}}$
    Add l_{min} to $L_{Col_{min}}$
    $(n_j, l_{min}, Col_{k_{min}})$
    Remove n_j from SN
    Remove l_{min} from L
end for

are randomly scheduled to be active. In contrast to existing compressive sensing methods, we define a new structure for the measurement matrix that is compatible with our coalition formation method. We use a temporal block diagonal measurement matrix, Φ_t, to gather data. During each sampling instance, we gather spatial observations of all sensor nodes at time t and produce a discrete spatial signal X_t at this time. The temporal observation of all active sensor nodes together is a spatial-temporal signal $[X_1^{tr}, X_2^{tr}, ..., X_{ST}^{tr}]$, where ST is a parameter representing the number of samples in each sampling round T . Each sampling period consists of T sampling instances equal to the Shannon-Nyquist rate. To reduce this number of sampling times, the base station adjusts the number of sampling times according to the signal sparsity level and defines a number of sampling points ST for each sampling period.

For each sampling period t, we consider Φ_t as a measurement matrix; Φ_t is $P_j \times SN_{Col_j}$. The measurement vector Y_{Col_j} is consists of ST_j sub-vectors of ST_j sampling times such that $Y^{Col_j} = [Y_1^{tr}, Y_2^{tr}, ..., Y_{ST_j}^{tr}]$ where each Y_i is a $P_j \times 1$ vector.

As indicated above, for the distributed compressive sensing techniques, inside each coalition we utilize a block diagram measurement matrix that compactly represents several temporal measurement sub-matrices. Combining these spatial-temporal measurements together yields:

$$Y^j = Y_{Col_j} = \Phi^j X^j \tag{13}$$

$$Y^J = \begin{bmatrix} Y_1 \\ Y_2 \\ . \\ . \\ . \\ Y_{ST_j} \end{bmatrix} = \begin{pmatrix} \Phi_1 & & \mathbf{0} \\ & \Phi_2 & \\ & & . \\ \mathbf{0} & & . \\ & & & \Phi_{ST_j} \end{pmatrix} \begin{bmatrix} X_1 \\ X_2 \\ . \\ . \\ . \\ X_{ST_j} \end{bmatrix} \tag{14}$$

where for each $1 \leq t \leq ST$, Φ_t has P_j rows and SN_{Col_j} columns.

At the end of each sampling round, every sensor node transfers its measurement vector Y_j to its neighbor node. The neighbor node receives the data and forwards it to the coalition coordinator. Introducing this temporal block diagonal measurement inside each coalition provides energy-balanced data aggregation within the coalitions

VII. SIGNAL RECOVERY PROCEDURE

Upon collecting sensor node readings, base station employs a belief propagation based signal recovery algprithm to reconstruct the original data. This recovery procedure is already introduced in our previous work [17]. We will not explain the reconstruction procedure in this paper again. For more details you can refer to [17].

VIII. PERFORMANCE EVALUATION

A. Assumption

We use a real dataset collected at the campus of University of Surrey, UK for the REDUCE projects [10][11]. We compare the proposed spatial-temporal compressive sensing approach with the existing data compression techniques. The approaches used in the comparison are Bayesian compressive sensing (BCS) [12], clustered spatial-temporal Bayesian compressive sensing (STBCS) [13], temporal belief propagation-based compressive sensing (TBCS) [14], OMP-based compressive sensing [15] and spatial Bayesian compressive sensing (SBCS) [16].

Our simulation is implemented on Matlab environment and we have utilized the toolbox provided for Bayesian Compressive sensing in [17].

B. Data Accuracy

In order to measure the data accuracy, we compare the accurate reconstruction percentage for the different data compression values. As shown in figure 1, our approach provides accurate data reconstruction with a minimum number of measurements. The main reason for this performance is the value of information gained using the coalition formation method. Our approach tries to group sensor nodes based on their sparsity similarity, which leads to transmitting more information with a lower number of measurements. However, increasing the compression ratio decreases the gap between our approach and other methods. On the other hand, our approach adjusts the number of measurements based on the signal sparsity level, which removes redundant data transmission.

C. Energy Consumption

In this section we compare energy consumption parameters among the different methods. As shown in figure 2, our approach provides the best energy resource consumption performance among the approaches compared. STBCS and SBCS are the second and third best approaches, which provide performance somewhat more comparable to our method than do the other methods. The main common feature

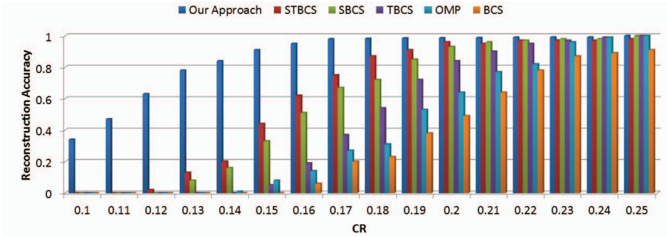

Fig. 1. Reconstruction accuracy percentage for different CRs

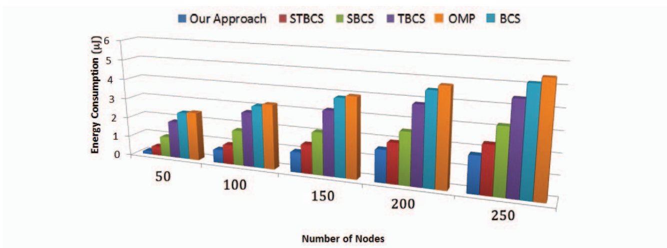

Fig. 2. Energy consumption

of these three approaches is grouping sensor nodes and localizing sensor node measurements. The means of grouping sensor nodes and gathering measurements from each group are the main difference among these methods. Since our approach utilizes sparsity similarity to group the sensor nodes, the number of active nodes is minimized. Moreover, it adjusts the number of measurements to the sparsity level, which removes the redundancy in data gathering.

D. Energy accuracy trade-off

We study the trade-off between network energy consumption and data accuracy. To do so, we investigate energy consumption in terms of normalized network lifetime, while for accuracy we consider the error between the reconstructed data and real data. Our approach provides approximately 40% network lifetime at a minimum error level, while with less accurate data it provides higher percentages of lifetime. Adapting both the number of measurements and the number of active sensor nodes to the signal sparsity level is the main contribution of our approach to prolong network lifetime. In addition, spatial-temporal correlation-based coalition formation provides sufficient similarity among sensor node measurements, which leads to less error in recovered data.

IX. CONCLUSION

This paper has proposed a spatial-temporal compressive sensing technique that improves data gathering performance in terms of data accuracy and energy consumption. We introduced coalition-based compressive sensing that uses the spatial correlation among sensor nodes to localize compressive sensing data gathering. Upon forming a coalition, the proposed approach is used within each coalition to schedule the sensor nodes. Simulation results shows that our approach enhances network performance by minimizing the energy consumption and increasing the data accuracy.

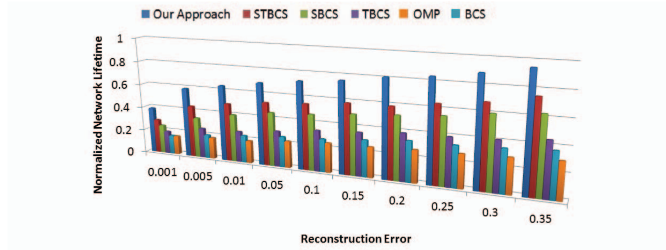

Fig. 3. Normalized network lifetime versus reconstruction error trade-Off

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