A spatiotemporal compressive data gathering method combining block-wise compressed sensing with logical mapping

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Abstract. To fully exploit the spatiotemporal correlation of big sensory data towards transmission reduction, we propose a spatiotemporal compressive data gathering method combining block-wise compressed sensing (BCS) with logical mapping (LM). The method explores data correlation according to both the locations and contents of sensors and performs the dual compression of spatial and temporal domains. Specifically, temporal compression is achieved by random sampling at each sensor, as the temporal correlation of data is neglected by traditional BCS-based methods. Additionally, the spatial correlations caused by the contents of sensors and clusters have not been wholly exploited by the existing compressive data gathering methods yet, thus at edge devices, the temporal measurements of sensors are roughly sorted by the intra-cluster LM before the BCS-based spatial compression is performed; while at sink, the inter-cluster LM is used to coarsely order the data of clusters with joint reconstruction done afterward. The simulation results based on real-world data show that LM can effectively improve the compressibility of data. Our method not only guarantees the reconstruction quality but greatly reduces the transmissions and energy consumption of the sensor network.

1. Introduction

The real-world data generated by multiple devices that consecutively observe the same physical phenomena in a specified area are often spatiotemporally correlated. However, sensors at the bottom of the Internet of Things are usually cheap devices with limited resources while data transmission is the main source of their energy consumption [1]. Therefore, lots of data reduction strategies have been proposed to reduce the number of transmissions to lower energy consumption. The correlation of sensor readings results in a sparse or compressible representation in a proper basis, thus enabling the compressed sensing (CS) [2] technique which can reconstruct the original data from a small number of CS measurements. Therefore, the CS is capable of transmission reduction and has been widely used in the big sensory data collection applications marked by the wireless sensor network.

Currently, in most CS-based data gathering methods, only the temporal or spatial correlation of data has been concerned. The latter is the mainstream [3], a typical method of which includes the energy-efficient BCS-based method [4]. Since only the compression on spatial domain has been carried out, the number of transmissions of these methods is still large, thus the double compression of temporal and spatial domain has received more concern. In [3] and [5], random sampling (RS) is adopted to select temporal data while random walk like routings are utilized to select sensor nodes for spatial compression, hence reducing transmissions and energy consumption.
However, the spatial compression of existing CS-based methods is mostly based on the data correlation incurred only by the adjacency of sensors, i.e., sensor nodes belong to the same cluster, whereas that caused by the sensor readings themselves is neglected. Meanwhile, the DCT-based data collection schemes in [4] and [6] first use LM to smooth the signals inside each cluster based on sensor readings, and then apply DCT to extract vital components, thus reducing the transmissions. Although the number of vital components is fewer when the data are overall ordered, [4] and [6] only consider the LM within each cluster without adjusting the order of data between clusters.

Focusing on the aforementioned problem, we propose a spatiotemporal compressive data gathering method combining BCS with LM. Wherein RS and BCS cooperate to perform the dual compression in the temporal and spatial domains. Besides, the improved LM containing the intra-cluster LM and the inter-cluster LM is designed to enhance the information concentration of DCT coefficients. The further reduction on the number of transmissions is achieved by the combination of BCS and the improved LM.

2. System overview

2.1. Network model

According to the real scenario of the Internet of Things, the network model including the sensing layer, edge layer, and sink layer is considered here, as illustrated in figure 1. \( N \) sensor nodes of the sensing layer are randomly and uniformly distributed in the monitoring area, organized into \( h \) clusters, while \( h \) smart edge devices of the edge layer are deployed at the centroid of these clusters, acting as cluster heads. The number of sensor nodes in cluster \( i (1 \leq i \leq h) \) is \( N_i \). And the sink layer consists of an edge server with unlimited power consumption. First, we make the following reasonable assumptions:

1) Each device in the sensor network is relatively stationary and has a positioning module embedded to obtain its own location information. The devices interconnect through a wireless network and can adjust their own transmission power as per the required communication distance.

2) The sensor nodes need to sense the target phenomena periodically and transmit the sampled readings to the sink through edge devices.

![Figure 1. The hierarchical structure of the sensor network and the data processing steps contained in each layer.](image)

2.2. Overview of the proposed method

In the BCS-based method, the spatial compression of sensor readings inside each clusters is performed independently at each cluster head (CH). The temporal correlation of data has been neglected. So we apply RS to execute the temporal compression of sensor readings at each sensor node. Besides, based on the nature of DCT transform, the smoothed data lead to a smaller number of vital components in the transform coefficients, which results in fewer number of measurements required for reconstruction according to CS. Thereby, an improved LM including intra-cluster LM and inter-cluster LM is proposed
for data arrangement inside and between clusters to roughly smooth temporal measurements in the spatial domain. And then we combine it with BCS to exploit the correlation caused by locations and contents simultaneously. Hence the data processing procedures involved in the equipment operation of each layer are depicted in figure 1, wherein the processes marked in red are the differences of our method when compared with other mainstream CS-based methods which mostly include only the steps marked in black. The complete workflow of a round of data gathering is outlined below. More technical details come in the next section.

1) Each sensor applies RS to its readings $x_{ij}$ and transmits the resulting temporal measurements $z_{ij}$ to CH$_i$, where $i$ and $j$ are virtual indexes of clusters and sensors inside cluster $i$, respectively.

2) After receiving $Z_i = \begin{bmatrix} z_{i1}, z_{i2}, \ldots, z_{iN_i} \end{bmatrix}$ from all sensors inside cluster $i$, the cluster head CH$_i$ calculates the mean value $\bar{z}_{ij}$ of $z_{ij}$ and $\bar{z}_i$ of $Z_i$. Then the roughly ordered $Z'_i$ is obtained by applying intra-cluster LM to $Z_i$ according to $\bar{z}_i = \begin{bmatrix} \bar{z}_{i1}, \bar{z}_{i2}, \ldots, \bar{z}_{iN_i} \end{bmatrix}$. Finally, $\bar{z}_i$ and the spatiotemporal measurements $Y_i$ obtained by applying spatial CS to $Z'_i$ are sent to the sink.

3) After receiving $Y = \begin{bmatrix} Y_1, Y_2, \ldots, Y_h \end{bmatrix}$ and $\bar{z} = \begin{bmatrix} \bar{z}_1, \bar{z}_2, \ldots, \bar{z}_h \end{bmatrix}$ from all clusters, the sink applies inter-cluster LM to $Y$ to obtain the adjusted $Y'$ according to $\bar{z}$ and generates the sensing matrix accordingly. Afterward, the joint reconstruction is performed on $Y'$.

3. Details of the proposed method

3.1. Spatiotemporal compressed sensing based on RS and BCS

The temporal compression of the readings $x_{ij} \in \mathbb{R}^T$ of sensor $(i, j)$ is computed via $z_{ij} = \Phi_x x_{ij}$ based on CS, where $\Phi_x \in \mathbb{R}^{K \times T}$ is an RS matrix, $T$ denotes the number of time slots in one sampling period, $1 \leq t < T$ represents the number of temporal measurements. Since the measurements obtained from multiple sensors using the same measurement matrix provides more spatial information about the original signal, identical $\Phi_x$ is applied to all sensor nodes. So the temporal compression results of cluster $i$ can be written as

$$Z_i = \Phi_x X_i = \Phi_x \begin{bmatrix} x_{i1}, x_{i2}, \ldots, x_{iN_i} \end{bmatrix}.$$  

(1)

Then the BCS is applied for spatial compression. So the ultimate spatiotemporal compression results $Y \in \mathbb{R}^{K \times M}$ ($1 \leq M < N$ is the number of spatial measurements) of the network can be organized as

$$Y^T = \begin{bmatrix} Y_1, Y_2, \ldots, Y_h \end{bmatrix}^T = \Phi_s \begin{bmatrix} Z_{i1}, Z_{i2}, \ldots, Z_{ih} \end{bmatrix}^T = \begin{bmatrix} Z_{i1} \Phi^T_{s1}, Z_{i2} \Phi^T_{s2}, \ldots, Z_{ih} \Phi^T_{sh} \end{bmatrix}^T.$$  

(2)

The $\Phi_{si}$ here denotes the $i$-th block of the corresponding block diagonal matrix $\Phi_s \in \mathbb{R}^{M \times N}$ and is a $m_i \times N_i$ ($1 \leq m_i < N_i$ is the spatial measurement times of CH$_i$) Gaussian random submatrix generated by CH$_i$. Let $X \in \mathbb{R}^{T \times N}$ denote the original readings of all sensors. Due to the existence of spatiotemporal correlation, the spatial and temporal sections of $X$ are sparse or compressible in sparsiﬁying bases $\Psi_x \in \mathbb{R}^{T \times T}$ and $\Psi_s \in \mathbb{R}^{N \times N}$, respectively. Let $x \in \mathbb{R}^N$ and $y \in \mathbb{R}^M$ be the vector-shaped representations of $X$ and $Y$, then $x = (\Psi_x \otimes \Psi_s) \theta$, where $\theta$ is the coefficient vector of $x$ in the basis $\Psi = \Psi_s \otimes \Psi_t$. Then according to Kronecker compressive sensing [7], we have

$$y = (\Phi_s \otimes \Phi_t) x = (\Phi_s \otimes \Phi_t)(\Psi_s \otimes \Psi_t) \theta.$$  

(3)
Thus, the sensing matrix for spatiotemporal CS can be calculated via \( A = (\Phi_s \otimes \Phi_t)(\Psi_s \otimes \Psi_t) \) and afterward \( X \) can be recovered using traditional CS reconstruction algorithms.

### 3.2. The improved logical mapping

The aim of the improved LM is to roughly smooth the sensor readings in spatial domain not only inside clusters but also between clusters.

Assume that \( I \in R^{1 \times n} \) denotes the sub-block ID sequence of the data \( B = [B_1, B_2, \ldots, B_n] \) whose mean vector is \( b = [b_1, b_2, \ldots, b_n] \), where \( n \) is the number of the sub-blocks. The basic process of LM is to sort \( b \) and rearrange the ID positions in \( I \) accordingly to get the updated sequence \( I' \), so that if reading \( B \) following the ID sequence \( I' \) is equivalent to directly reading the \( B' \) after the arrangement according to \( b \) but no actual physical movement of data blocks is required. This means that the virtual index \( [1, 2, \ldots, n] \) of sub-blocks is always associated with the latest ID sequence \( I' \).

So in the improved LM, the intra-cluster LM is to update the old sensor ID sequence \( S_i \) to the new version \( S'_i \) according to \( \bar{z}_i = [\bar{z}_{i1}, \bar{z}_{i2}, \ldots, \bar{z}_{in}] \) at each CH, and get the roughly ordered \( Z'_i \) by reading \( Z_i \) in the order of \( S'_i \). While the inter-cluster LM is to get the updated cluster ID sequence \( C' \) from the last \( C \) based on \( \bar{z} = [\bar{z}_1, \bar{z}_2, \ldots, \bar{z}_h] \), and then obtain the arranged \( Y' \) from \( Y \) using \( C' \). Subsequently, the sink generates the sensing matrix according to \( C' \) and applies it to \( Z' \) to get the recovered data \( \hat{X}' \) organized by the updated ID sequences of clusters and sensors.

These previous operations reflect the adjustments implicitly imposed on the original sensor readings \( X \), which are first a rough local ordering based on the sensor readings \( [x_{i1}, x_{i2}, \ldots, x_{in}] \) inside each cluster and then a rough global ordering based on the data blocks \( [X_1, X_2, \ldots, X_h] \) of clusters. Thus the \( X' \) implicitly adjusted by LM relates to \( X \) by \( X' = PX \), where \( P \) is an \( N \times N \) block-wise permutation matrix obtained from the ID sequences. The aforementioned \( \hat{X}' \) corresponds to \( X' \).

### 4. Experiments and discussions

The daily sea surface temperature data collected by a remote sensing system [8] are used for experiments, in which we choose an area with size of \( 100 \times 100 \) units, from which the sensory data are sampled. Assume that \( N = 400 \) sensor nodes are randomly and uniformly distributed in a square monitoring area with length \( L = 300 \text{m} \). The sampling period \( T \) is set to 32 time slots. Besides, we choose DCT transform matrices as the sparsifying bases for both temporal and spatial domains.

#### 4.1. Compressibility of DCT coefficients

Three mapping schemes are considered here: no LM, intra-cluster LM and the improved LM. The residual energy ratio \( \rho_{res} \) is used as the metric of coefficient compressibility, defined as the ratio of \( \| \theta_k \|^2 \) to \( \| \theta_t \|^2 \), where \( \theta \) is the DCT coefficient vector of the spatial data \( x' \in \mathbb{R}^N \) obtained in the time slot \( t \), \( \theta_k \) denotes the \( \theta \) of which the \( K \) elements with the largest absolute amplitude are zeroed. The smaller \( \rho_{res} \), the more concentrated the information of \( \theta \), thus the higher its compressibility.

We vary \( h \) from 1 to 60 and observe the average \( \rho_{res} \) under 50 random network topology, incurring a total of \( 50T = 1600 \) time slots for each parameter settings, wherein \( K = 30 \). As shown in Figure 2, the intra-cluster LM can improve the compressibility of spatial data, but its performance degrades as \( h \) increases due to the random positions of the cluster data blocks. Thus its curve gradually increases and
tends to coincide with that of no LM. In the improved LM, when the number of clusters is small, the global ordering of the data is affected to some extent. Even so, its $\rho_{\text{res}}$ is still lower than the previous two. As $h$ continues to increase, the inter-cluster LM gradually offsets the impact and makes the data generally orderly. Therefore, the curve of the improved LM first increases slightly, then gradually decreases and stabilizes. So our proposed improved LM results in higher compressibility of DCT coefficients compared with no LM and intra-cluster LM, especially for bigger $h$.

4.2. Reconstruction quality
We measure the reconstruction quality using the normalized reconstruction error defined as the ratio of $\|X' - \hat{X}\|_2$ to $\|X'\|_2$. The comparison of the results of our method with the spatial CS-based method is presented in figure 3. The values in different parameter settings are obtained by averaging the results of 300 repeated experiments under the same network topology. Also, we set the number of clusters $h$ to 17 to make the no LM scheme get its best compressibility. As figure 3 shows, the improved LM can enhance the reconstruction quality for both the spatiotemporal CS in this paper and the spatial CS. For the former, the improvement is especially obvious when the number of temporal measurements is small (about 46% for $t = 6$, $M = 220$). Moreover, the normalized reconstruction error decreases as $t$ and $M$ increase. The reconstruction quality of our method is gradually approaching or even better than that of the spatial CS-based data gathering method under the same $M$.

Combining the results of the previous experiment, we can conclude that our method with less number of measurements can obtain an approximate or even better reconstruction accuracy than spatial CS with the help of compressibility improvement, thus reducing the number of transmissions.

4.3. Transmissions and energy consumption
Assume that the sink is located at the left bottom corner of the square monitoring area and sensors send their measurements to the corresponding CHs via direct transmission while CHs communicate with each other by multi-hop relaying based on the minimum spanning tree. We compare our method with other known ones, i.e., the one in [1] and the one in [4], on the number of transmissions and energy consumption. These methods are referred to as ST-CDG, H-CDG and B-CDG later, respectively. The first order radio model [9] is adopted for energy dissipation analysis and only the power consumed by data transmission is considered. The energy consumption of the transceiver circuit and the amplifying circuit are set to 50nJ/bit and 0.1nJ/bit/m², respectively.

Figure 4 and figure 5 separately present the number of transmissions and energy consumption averaged under 50 random network topology with varying $N$, where $M = 0.2N$, $t = 16$, and the length of the data packet is set to 64 bit. With the number of sensors in the area increasing, the
transmission quantity and energy consumption of the three methods grow almost linearly. B-CDG has better performance than H-CDG since the number of data packets sent by each CHs in B-CDG is always less than or equal to that required by H-CDG. As ST-CDG adopts duel compression in the temporal and spatial domain, i.e., RS is applied in the temporal domain and BCS is performed in the spatial domain, it gains lower transmission number and energy consumption in a single time slot, and leads to a smaller growth factor. Consequently, ST-CDG is more suitable for data gathering in large-scale sensor networks.

5. Conclusions
A transmission-efficient scheme for big sensory data gathering of the Internet of Things was proposed. We made use of the compression in both spatial and temporal domains and the spatial correlation resulting from both the locations and contents of sensors. In the proposed method, random sampling and block-wise compressive sensing are utilized in temporal and spatial domains, respectively. Logical mapping according to the mean of temporally compressed data is applied to adjust the reading order of data at the edge and sink to smooth the data in spatial domain. Experiment results verify that our proposed method can improve the reconstruction performance at the sink while greatly reduce the transmissions and energy consumption of the sensor network.

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