Spatial-Temporal Compressive Sensing for Cross-Layer Optimization Data Transmission in Wireless Sensor Networks

Chengtie Li, Jinkuan Wang, Mingwei Li

School of Information Science and Engineering, Northeastern University, China
neuqlct@hotmail.com, jk1wang@126.com, neuqlmw@126.com

Abstract

Inspired by the theory of compressive sensing (CS) and employing cross-layer optimization, we propose a cross-layer optimization data transmission scheme based on spatial-temporal compressive sensing (STCS-DT) in Wireless Sensor Networks (WSNs). The proposed scheme efficiently enhances transmission data efficiency in improving allocation of link capacity, power, transmission rate and channel access via Kronecker sparsifying bases. Specifically, we derive a joint CS reconstruction optimization method which not only consider the spatial and temporal of data streams, but also affiliate with each layer constraints. The optimization results improve the reconstruction accuracy of sensor data streams while reducing the necessary communications, and present the network protocols in physical, MAC, network and transport layers. Numerical results show that our proposed method achieves higher reconstruction accuracy with a smaller number of required transmissions, and with lower decoding delay and complexity as compared to those of the state of the art CS methods.

Keywords: Compressive sensing, Spatial temporal correlation, Cross-layer, Optimization, Wireless sensor networks

1 Introduction

In the past several years, Wireless Sensor Networks (WSNs) have received great interest in the disaster prevention, industrial automation and environmental monitoring, which are consisted of plenty of sensor nodes. Sensor nodes usually have the sensing, communication, and computing features. As the number of the readings in the sensor node, the performance bottleneck is the sensor node, which is severely limited in battery power, computing complex, wireless bandwidth and so on. Energy efficiency, reliability and robustness are the several more important properties.

In recent years, many schemes have been developed in the literature for enhancement various nature in WSNs [1-6]. For example, various sensor selection [2-4], communication schedule [5-6] and data collection [7] algorithms have been proposed to reduce the amount of redundant data transmitted in the network. Li et al. [3] proposed the distributed cross-layer optimization protocols, which attained global optimal control for signals and achieved fair channel allocation by the scheduling algorithm in WSNs. The scheme can effectively achieved load balancing, and considerable save network energy consumption. The resources can be allocated more and more to the channel in the case of not causing more severe congestion in the [6], which can avoid conservatively reducing resources allocation for eliminating congestion. Despite lots of schemes have been researched, they either be required rigorous network conditions or compromise part of network performance.

Compressive sensing [8-11] is more effective method to reduce the required number of measurements representing the original signal. Taking advantage of the relevance in network coding and CS, kind of schemes such as ECS [12], distributed sparse random projections (DSR) [13] and spatiotemporal compressive network coding for energy-efficient distributed data storage (ST-CNC) [14] have been investigated to improve mean square error (MSE) and decrease bandwidth. Due to the temporal correlation and spatial correlation of the data acquisition, effective data extraction can be optimized by the various distributed data storage (DDS) [15-17]. Duarte et al. [17] exploited temporal-signal and spatial-signal association, and proposed joint sparsity models, while [1] developed a sequential framework based on sliding window processing, in which the sink can efficiently reconstruct the current sensors' readings from a sequence of periodically delivered Kronecker CS (KCS).

Despite of being increasing network performance, the existing schemes have several drawbacks: (1) there is only considering the decrease of data transmission, and not giving considerable attention in data collision, insufficient link capacity and excessive energy consumption; (2) measurement matrix usually use Fourier or traditional matrix, which can not

*Corresponding Author: Mingwei Li; E-mail: neuqlmw@126.com
DOI: 10.3966/160792642018091905017

comprehensively regarding the other factors affected network performance; (3) power control is the significant case for battery power in sensors. In addition, the prior solutions is only discuss the energy consumption in the algorithms, not investigate the interaction between power cost and network utility.

To solve these problems, this paper explores the cross-layer spatial and temporal optimization of rate control, scheduling, channel access and power control via CS in WSNs. We develop a separable sensing matrix that is composed by Kronecker product of spatial and temporal sensing matrices. Spatial matrix is the function of channel access where compressed data is transmitted by only less channel and temporal matrix is the function of rate control, link capacity and power control. We formulate a new CS optimization problem that add the constraints of link capacity, power control and rate control, in which the original signal can be more efficiently recovers from periodically delivered CS measurements by exploiting the joint optimization solutions. The algorithm has the following benefits: (1) the spatial and temporal optimization can dynamically tradeoff between the CS recovery accuracy and decoding complexity. (2) Jointly CS reconstruction and each layer constraints, the reconstruction accuracy is significantly enhanced. (3) By solving CS construction, each protocols (rate control, channel access, link capacity, power control) are determined by the proposed cross-layer optimization algorithm with the simultaneous consideration of four layers (physical, MAC, network, transport).

This paper is organized as follows. Section 2 provides the preliminaries and system model including CS background and spatial and temporal correlation of transmission data. In Section 3, we formulate the proposed STCS-DT Optimization. Performance of the proposed approaches is presented in the Section 4. Example results are provided in Section 5, followed by conclusions in Section 6.

2 Preliminaries and System Model

2.1 Compressive Sensing Background

The CS has investigated a fresh signal compressed-reconstruction theory which is suitable for correlated data gathering in multi-hop WSNs. The original signal is mapped into the low dimensional space obtained relatively small number of measurements, which includes valid information of the original signal. Basically, the rationale behind CS is focused on three main process as follows:

Sparsity: An original signal $v \in \Re^N$ is considered compressible and K-sparsity if $v = \Psi\theta$ where $\Psi \in \Re^{N\times N}$ is an orthogonal basis, and $\theta \in \Re^N$ is coefficient vector at most K ($K << N$) nonzero entries that the energy of coefficients in θ is concentrated in a relatively small set of entries. As the spatial and temporal correlation in WSNs, the sensor readings are usually compressible [14].

Sampling: Considering a K-sparsity signal v and measurement matrix $\Phi \in \Re^{M\times N}$, the linear projections of sensor readings can greatly reduce the number of transmissions and receptions through low-dimensional sampling

$$y = \Phi v = \Phi\Psi\theta = \Upsilon\theta \tag{1}$$

where $y \in \Re^M$ is measurement vector, and $\Upsilon \in \Re^{M\times N}$ is the sensing matrix [18-19].

Reconstruction: The CS decoder is capable of recovering original signal v from the measurement vector y through l_2-norm minimization

$$\begin{aligned} &\hat{\theta} := \arg\min \|\theta\|_2^2 \\ &\text{s.t. } y = \Phi v = \Phi\Psi\theta = \Upsilon\theta \end{aligned} \tag{2}$$

Φ and Ψ are required to satisfy for restricted isometry property (RIP) of Υ [20-21] and the mutual coherence between Φ and Ψ [20], which play an important role in terms of stable and accurate CS signal recovery.

2.2 System Model

We consider a single-sink multi-hop data gathering WSNs with N battery-powered sensor nodes jointly correlated sensor data streams. All sensor readings exhibit both spatial and temporal correlations. On this account, let $V(t) \in \Re^{N\times W}$ represent the sensor readings at W time slots in WSNs, $\Psi_S \in \Re^{N\times N}$ denote spatial basis and $\Psi_T \in \Re^{W\times W}$ is temporal basis. We assume that $V(t)$ has been transformed to compressible representation, such as

$$V(t) = \Psi_S \theta(t) \Psi_T^T \tag{3}$$

where $\theta(t) \in \Re^{N\times W}$ includes the spatial and temporal transform coefficients.

Jointly consider the relationship between CS and Kronecker sparsifying bases [22], we can integrate (1) and (3),

$$\begin{aligned} y(t) &= \Phi_S Vec(V(t))\Phi_T^T \\ &= \Phi_S Vec(\Psi_S\theta(t)\Psi_T^T)\Phi_T^T \\ &= (\Phi_T \otimes \Phi_S)(\Psi_T \otimes \Psi_S)Vec(\theta(t)) \\ &= (\Phi_T\Psi_T)\otimes(\Phi_S\Psi_S)Vec(\theta(t)) \\ &= (A_T \otimes A_S)\underline{\theta}(t) \end{aligned} \tag{4}$$

where $y(t) \in \Re^{MW}$ is the vector reshaped sensor readings, and $\underline{\theta}(t) \in \Re^{NW}$ is the vector reshaped spatial and temporal transform coefficients, $A_T \in \Re^{W\times N}$ is temporal sensing matrix, $A_S \in \Re^{M \times W}$ is spatial sensing matrix.

The sensors' readings are periodically delivered to the sink in the form of CS measurements, which are then used to sequentially reconstruct portions of the sensor data streams via exploiting the joint compressibility with Kronecker sparsifying bases. As main interests, the derived method produces estimates for the current sensors' readings via jointly restraining power, rate, link capacity allocation and channel access in spatial-temporal CS. The beneficial features of the proposed method will be comprehensively demonstrated in Section 3.

3 Proposed STCS-DT Optimization

In this section, we will respectively provide restrictions on link capacity, power allocation, channel access, and rate allocation in each layer. The restrictions in each layer, assimilated into the signal reconstruction optimization, significantly enhance reconstruction accuracy. On this account, we assume that temporal sensing matrix A_T is the linearly function of link capacity matrix $f^T(t-1) \in \Re^{N \times N}$, measurement vector $\underline{y}^T(t-1) = \left(y(t-1) \quad 0 \quad \cdots \quad 0\right)^T \in \Re^N$ and power of sensor $P(t) \in \Re^N$,

$$\begin{aligned} A_T = \alpha(t-1) f^T(t-1) + \beta(t-1)\underline{y}^T(t-1) \\ + \gamma(t-1)P^T(t-1) + \omega(t-1) \end{aligned} \tag{5}$$

where $\alpha(t-1) \in \Re^{W \times N}$, $\beta(t-1), \gamma(t-1) \in \Re^W$ are the parameters, $\omega(t-1) \in \Re^{W \times N}$ is the noise.

Note that the temporal sensing matrix is transformed along with link capacity, measurement vector, and power at prior time, which can achieve data transmission synchronization. Block diagram of the STCS-DT as shown in Figure 1.

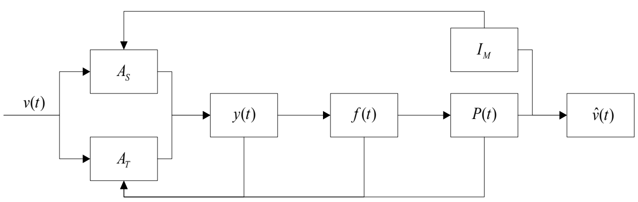


Figure 1. Block diagram of the STCS-DT

3.1 Each Layer Restriction

Link capacity. Let $f_{ij}(t)$ denote the link capacity from sensor i to sensor j at time instant t. Since bidirectional data broadcast, $f_{ij}(t)$ is satisfied restriction as follow:

$$y_i(t) + y_j(t) \le f_{ij}(t) \le \overline{f}(t) \tag{6}$$

where $\overline{f}(t)$ is the supremum of link capacity at time instant t.

Power control. Let $P_i(t)\left(i = 1, 2, \cdots, N\right)$ represent power allocation for sensor i at time instant t, $\overline{P}_i$ is the supremum of power allocation for sensor i.

$$\overline{P}_i^{rs} + \overline{P}_i^{ts} \le P_i(t) \le \overline{P}_i \tag{7}$$

where $\overline{P}_i^{rs}, \overline{P}_i^{ts}$ are received and transmitted power at sensor i.

Consider the relationship between transmission rate, channel access and power allocation, we suppose

$$P_i(t) = \zeta I_M \log_2\left(1 + y_i(t-1)\right) \tag{8}$$

where ζ is a regularization parameter and, I_M is channel access function. According to (8), if the sensor is occupied, the power allocation is logarithmic with measurement vector; if the sensor is sleeping, the power is zero, which can significantly save unnecessary energy allocation.

Channel access. Similar to A_T, we assume spatial sensing matrix A_S is the linear function of channel access.

$$A_S = I_M \xi + \eta \tag{9}$$

where $\xi \in \Re^{M \times W}$ is a regularization parameter matrix, and $I_M \in \Re^{M \times M}$ is the channel access matrix. Since transmission data is only M via compressive procedure, thus the dimension of I_M is $M \times M$, and which can be defined as

$$I_M = \begin{cases} 1, \textit{sensor i is occupied} \\ 0, \textit{sensor i is sleeping} \end{cases} \tag{10}$$

3.2 Optimization Model

To explore the reconstruction of original signal, we need to minimize the sparse parameter. By exploiting the joint spatial, temporal compressibility (4), and each layer restrictions, measurement vector can be recovered by solving the l_2-minimization problem

$$\min \left\|\theta(t)\right\|_2^2 \tag{11}$$

$$\begin{cases} y(t) = \left(A_T \otimes A_S\right)\underline{\theta}(t) \\ y_i(t) + y_j(t) \le f_{ij}(t) \le \overline{f}(t) \\ \overline{P}_i^{rs} + \overline{P}_i^{ts} \le P_i(t) \le \overline{P}_i \\ P_i(t) = \zeta I_M \log_2\left(1 + y_i(t-1)\right) \end{cases} \tag{12}$$

where $A_T \otimes A_S$ is the jointly spatial and temporal sensing matrix.

In this paper, we take a unique approach to recovering the original signal in that we solving the optimization in (2) appended the each layer restriction (11). By this method, there exists two benefits: (1) Optimization solutions will be more perfect than the prior optimization, that is because we add power, link capacity, rate, channel access into the CS signal reconstruction optimization. The spatial and temporal of these parameters effectively guarantee sensing matrix synchronism. (2) The optimal power control, rate control, link capacity allocation and channel access are obtained through solving optimization problem (11).

3.3 Algorithm Design

At this point, the proposed spatial-temporal compressive sensing data transmission scheme based on l_2-norm regularization is summarized in Algorithm 1. At each time instant $t \geq W$, the sink periodically gathers the CS measurements.

Algorithm 1. spatial-temporal compressive sensing data transmission algorithm

Require: $y^*(t)$, $f^*(t)$ and $P^*(t)$

for $t = t_0$ till end do

(1) Initialize parameters $\alpha(t_0)$, $\beta(t_0)$, $\gamma(t_0)$, $\omega(t_0)$, ξ,η.

(2) Evaluate measurement vector $y(t_0)$, link capacity $f(t_0)$, and power $P(t_0)$ using (4)-(9)

(3) Obtain the optimal solution $y^*(t)$, $f^*(t)$ and $P^*(t)$ by solving the LP problem defined in (11)-(12).

(4) Decide optimal channel policy I_M^*, and obtain the optimal A_T, A_S.

It is observed from the optimization analysis above that the objective function (11) can be optimized by non-linear optimization techniques with multiple constraints. From algorithm, it is obvious that power, link capacity, rate, channel access are fed into the cross-layer optimization formulation, which can be adopted by the physical layer, network layer, transport layer and MAC layer, respectively. Meanwhile, the developed modified CS reconstruction method and further decrease the amount of necessary sensor communications for acquiring jointly correlated sensor data stream in a WSNs monitoring framework.

4 Performance Analysis

To obtain the performance of the STCS-DT, we provide some necessary but practical boundaries assumptions in this section. We then formally derive the performance on reconstruction accuracy and data transmission stability.

Assumption 1. For any time instant $t \in \{0,\cdots,W\}$, and any sensor node $i \in \{1,2,\cdots,N\}$, any measurement vector $y(t)$, we assume that

$$E\left(Tr\left(\left(A_T \otimes A_S\right)^T \left(A_T \otimes A_S\right)\right)\right) \leq Thr_1 \tag{13}$$

where Thr_1 is the finite threshold. Since the power, rate, link capacity are bounded in realistic WSNs, the assumption (13) is fairly reasonable.

Assumption 2. For any time instant $t_m, t_k \in \{0,\cdots,W\}$, $y(t_m), y(t_k)$ satisfy the inequality as follows:

$$E\left(\left\|\frac{y(t_m)-y(t_k)}{y(t_m)}\right\|_2^2\right) \leq Thr_2 \tag{14}$$

where Thr_2 is the finite threshold.

Theorem 1. (Reconstruction Accuracy)

Suppose $\hat{\underline{\theta}}(t)$ is reconstruction vector of $\underline{\theta}(t)$ and the expectation of reconstruction accurate ratio is $\mu(t) = E\left(\left\|\frac{\hat{\underline{\theta}}(t)-\underline{\theta}(t)}{\underline{\theta}(t)}\right\|_2^2\right)$. If $A_T \in \Re^{W\times N}$ and $A_S \in \Re^{M\times W}$ are temporal and spatial sensing matrix, which satisfies the constraint (13), then $\mu(t) \leq Thr_1$.

Proof: According to (4), the reconstruction vector of $\underline{\theta}(t)$ is

$$\begin{aligned}\hat{\underline{\theta}}(t) &= \left(\left(A_T \otimes A_S\right)^T \left(A_T \otimes A_S\right)\right)^{-1} \left(A_T \otimes A_S\right)^T y(t) \\ &= \left(\left(A_T \otimes A_S\right)^T \left(A_T \otimes A_S\right)\right)^{-1} \left(A_T \otimes A_S\right)^T \\ &\quad \times \left(A_T \otimes A_S\right)\underline{\theta}(t)\end{aligned} \tag{15}$$

Based on [15],

$$\begin{aligned}&E\left(\left\|\frac{\hat{\underline{\theta}}(t)-\underline{\theta}(t)}{\underline{\theta}(t)}\right\|_2^2\right) = \\ &E\left(\left\|\frac{\left(\left(\left(A_T \otimes A_S\right)^T \left(A_T \otimes A_S\right)\right)^{-1} \left(A_T \otimes A_S\right)^T \left(A_T \otimes A_S\right) - I\right)\underline{\theta}(t)}{\underline{\theta}(t)}\right\|_2^2\right) \\ &= E\left(\left\|\left(\left(A_T \otimes A_S\right)^T \left(A_T \otimes A_S\right)\right)^{-1} \left(A_T \otimes A_S\right)^T \left(A_T \otimes A_S\right) - I\right\|_2^2\right) \\ &= E\left(Tr\left(\left(A_T \otimes A_S\right)^T \left(A_T \otimes A_S\right)\right)\right) \leq Thr_1\end{aligned} \tag{16}$$

Note 1: It exits several reasons for increased reconstruction accuracy. (1) Available transmission information is extracted from the spatial and temporal data, which can advance the reconstruction accuracy.

(2) Each layer constrains are embodied into the restrains of optimization problem, which primarily promotes the reconstruction accuracy.

Theorem 2. (Data Transmission Stability)

Suppose $\varphi(t)=E\left(\frac{\left\|Vec(V(t))-Vec(V(t-1))\right\|_2^2}{\left\|Vec(V(t))\right\|_2^2}\right)$ as stability parameter. If measurement vector $y(t)$ is deemed as data transmission stream, which satisfies the constraint (14), then data transmission stream is asymptotically stable.

Proof: For (4), we can formulate

$$Vec(V(t))=\left(\Phi_S^T\Phi_S\right)^{-1}\Phi_S^T y(t)\Phi_T^T\left(\Phi_T^T\Phi_T\right)^{-1} \quad \textbf{(17)}$$

And, we can easily derive

$$Vec(V(t-1))=\left(\Phi_S^T\Phi_S\right)^{-1}\Phi_S^T y(t-1)\Phi_T^T\left(\Phi_T^T\Phi_T\right)^{-1} \quad \textbf{(18)}$$

Thus, the stability parameter

$$\begin{aligned}\varphi(t)&=E\left(\frac{\left\|Vec(V(t))-Vec(V(t-1))\right\|_2^2}{\left\|Vec(V(t))\right\|_2^2}\right)\\&=E\left(\frac{\left\|y(t)-y(t-1)\right\|_2^2}{\left\|y(t)\right\|_2^2}\right)\end{aligned} \quad \textbf{(19)}$$

On the basis of the assumption 2,

$$\varphi(t)=E\left(\frac{\left\|y(t)-y(t-1)\right\|_2^2}{\left\|y(t)\right\|_2^2}\right)\le Thr_2\,. \quad \textbf{(20)}$$

Note 2: The data transmission streams stability is used to depict and control the average delay. Theorem 2 shows that network stability is guaranteed if the Assumption 2 is satisfied. From the proof, we can conclude that the transmission streams are stable. That because the optimization results guarantee the link capacity, power, transmission rate stability.

5 Simulation Results

In this section, we present numerical results compared the throughput, average delay, signal transmission accuracy, network lifetime, and network utilization with other algorithms. On the basis of analysis in previous sections, the simulation environment is built via NS-2. We consider WSNs topologies with $N=9$ sensors, in which there is one sensor as sink node. All sensors monitor a phenomenon over 20s sampling instants, in which every time slot is 2s. The sensors are randomly deployed in a 100×100 square field. The network lifetime is defined as the time instant when the first sensor node dies. As a comparison, we also present the performance of the approach in [1, 4].

Figure 2 displays the evolution of throughput with eGuard-out [1] and CLO [4]. We can distinctly discover that the throughput of the STCS-DT is higher than others. That is because the spatial and temporal features of data stream are simultaneously considered. To avoid transmission redundancy, we compressed the data along each sensor and each transmission time slot. Transmission data decreased will advance throughput extremely enhance.

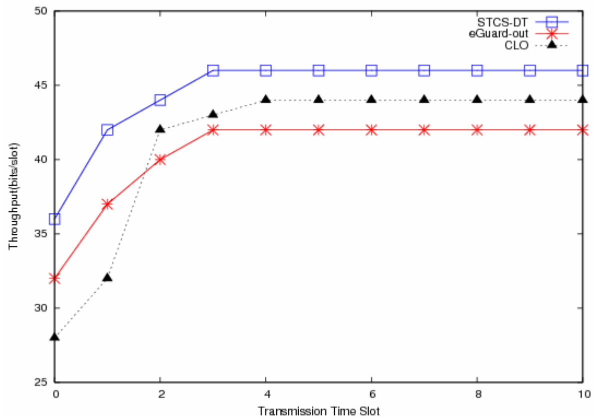


Figure 2. Throughput for different problems along with transmission time slot

Figure 3 provides a significant guideline for delay to dynamically adjust link capacity, rate and channel access. The delay jump is because the numbers of procedure are injected along 0 to 1 time slot. In generally, STCS-DT improves the delay compared with other schemes, which is the significantly important performance in WSNs.

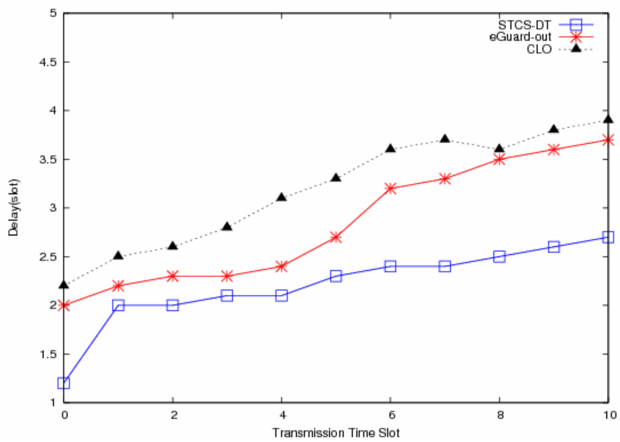


Figure 3. Delay for different problems along with transmission time slot

Figure 4 presents the transmission accuracy along with transmission time slot usage for different approaches. For detrimental CS, the proposed STCS-DT, exploited the spatial and temporal correlations at distinct time in CS, achieves the better reconstruction performance in comparison to both the other approaches.

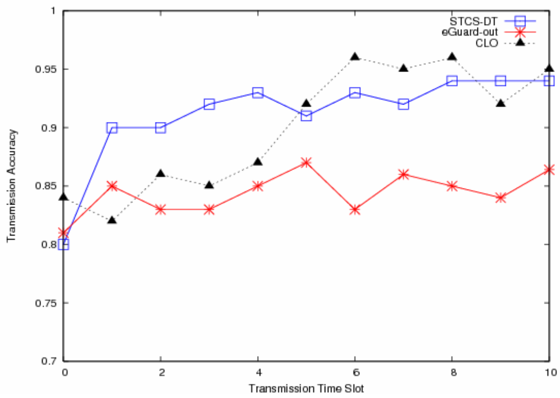


Figure 4. Transmission accuracy for different problems along with transmission time slot

Figure 5 shows the network utilization comparison against transmission time slot. The distribution of link capacity and channel access according to WSNs's needs makes the network utilization higher than other approaches.

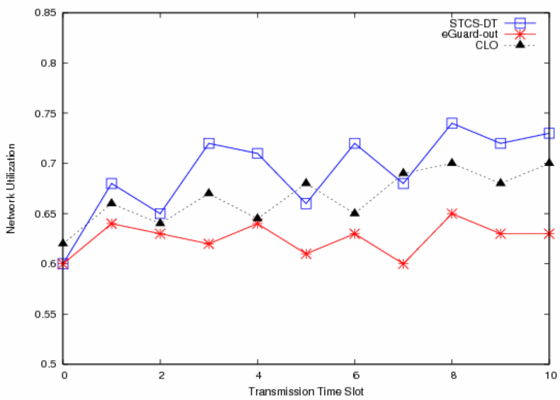


Figure 5. Network utilization for different problems along with transmission time slot

Figure 6 compares the network lifetime against the average relative error for different approaches. The proposed STCS-DT achieves the longest lifetime for various values of the average relative error. The results attribute the success to the decreased numbers of transmission flow through CS and reasonable allocation of link capacity and power.

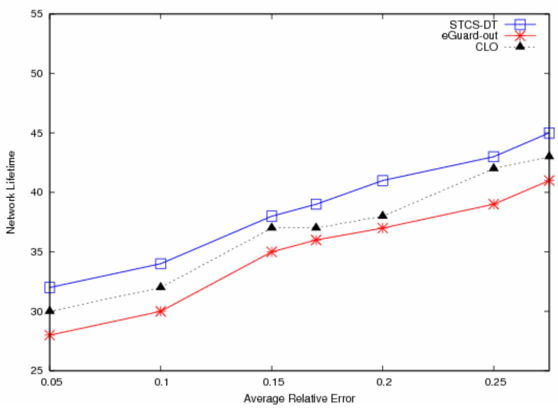


Figure 6. Network lifetime for different problems along with average relative error

6 Conclusion

In this paper, we propose a novel cross-layer data transmission optimization framework in order to improve the performance of data reconstruction accuracy, network lifetime, and link resource utilization, which can minimize the collision in the WSNs. In addition, the jointly cross-layer optimization and spatial temporal CS heighten the reconstruction accuracy and improve the power, channel access, link capacity and transmission rate allocations, respectively in physical layer, MAC layer, network layer and transport layer. The proposed scheme significantly reduces energy consumption, and efficiently enhances network effectiveness. The superiority of our proposed approach in relation to the other approaches is revealed by our experimental study.

Acknowledgements

This work has been supported by the Natural Science Foundation of China No. 61374097; Fundamental Research Funds for the Central Universities of China No. N142303013; Program of Science and Technology Research of Hebei University No. QN2014326; The school funds for Northeastern University at Qinhuangdao of China No. XNB2015004.

References

[1] Y. Li, M. Sheng, C.-X. Wang, X. Wang, Y. Shi, J. Li, Throughput-Delay Tradeoff in Interference-Free Wireless Networks With Guaranteed Energy Efficiency, *IEEE Transactions on Wireless Communications*, Vol. 14, No. 3, pp. 1608-1621, March, 2015.

[2] N. Michelusi, M. Zorzi, Optimal Adaptive Random Multiaccess in Energy Harvesting Wireless Sensor Networks, *IEEE Transactions on Communications*, Vol. 63, No. 4, pp. 1355-1372, Apirl, 2015.

[3] M. Li, Y. Jing, C. Li, A Class of Cross-Layer Optimization Design for Congestion and Energy Efficiency with Compressed Sensing in Wireless Sensing Networks, *Asian Journal of Control*, Vol. 16, No. 2, pp. 565-573, March, 2014.

[4] D. Liao, A. K. Elhakeem, A Cross-layer Joint Optimization Approach for Multihop Routing in TDD-CDMA Wireless Mesh Networks, *Transactions on Emerging Telecommunications Technologies*, Vol. 23, No. 1, pp. 6-15, January, 2012.

[5] K. Hou, B. Wang, Z. Wang, C. Zhu, A Review of Recent Developments about Secure Data Aggregation in Wireless Sensor Networks, *Journal of Internet Technology*, Vol. 17, No. 7, pp. 1511-1519, December, 2016.

[6] J.-S. Wu, R.-S. Huey, Improved Joint Radio Resource Management Usage Grey Fuzzy Control in Heterogeneous Wireless Networks, *Journal of Internet Technology*, Vol. 16, No. 5, pp. 777-788, September, 2015.

[7] R. Velmani, B. Kaarthick, An Efficient Cluster-Tree Based

Data Collection Scheme for Large Mobile Wireless Sensor Networks, *IEEE Sensors Journal*, Vol. 15, No. 4, pp. 2377-2390, April, 2015.

[8] F. Fazel, M. Fazel, M. Stojanovic, Random Access Compressed Sensing for Energy-Efficient Underwater Sensor Networks, *IEEE Journal on Selected Areas in Communications*, Vol. 29, No. 8, pp. 1660-1670, September, 2011.

[9] M. Leinonen, M. Codreanu, M. Juntti, Compressed Acquisition and Progressive Reconstruction of Multi-dimensional Correlated Data in Wireless Sensor Networks, *2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Florence, Italy, 2014, pp. 6449-6453.

[10] H. Zheng, S. Xiao, X. Wang, X. Tian, M. Guizani, Capacity and Delay Analysis for Data Gathering with Compressive Sensing in Wireless Sensor Networks, *IEEE Transactions on Wireless Communications*, Vol. 12, No. 2, pp. 917-927, February, 2013.

[11] E. Candés, J. Romberg, T. Tao, Robust Uncertainty Principles: Exact Signal Reconstruction from Highly Incomplete Frequency Information, *IEEE Transactions on Information Theory*, Vol. 52, No. 2, pp. 489-509, February, 2006.

[12] Z. Zou, Y. Bao, H. Li, B. F. Spencer, J. Ou, Embedding Compressive Sensing-Based Data Loss Recovery Algorithm Into Wireless Smart Sensors for Structural Health Monitoring, *IEEE Sensors Journal*, Vol. 15, No. 2, pp. 797-808, February, 2015.

[13] T. Wimalajeewa, P. K. Varshney, Wireless Compressive Sensing Over Fading Channels With Distributed Sparse Random Projections, *IEEE Transactions on Signal and Information Processing over Networks*, Vol. 1, No. 1, pp. 33-44, March, 2015.

[14] B. Gong, P. Cheng, Z. Chen, N. Liu, L. Gui, F. de Hoog, Spatiotemporal Compressive Network Coding for Energy-Efficient Distributed Data Storage in Wireless Sensor Networks, *IEEE Communications Letters*, Vol. 19, No. 5, pp. 803-806, May, 2015.

[15] R. Zeng, Y. Jiang, C. Lin, Y. Fan, X. Shen, A Distributed Fault/ Intrusion-Tolerant Sensor Data Storage Scheme Based on Network Coding and Homomorphic Fingerprinting, *IEEE Transactions on Parallel and Distributed Systems*, Vol. 23, No. 10, pp. 1819-1830, October, 2012.

[16] Z. Kong, S. Aly, E. Soljanin, Decentralized Coding Algorithms for Distributed Storage in Wireless Sensor Networks, *IEEE Journal on Selected Areas in Communications*, Vol. 28, No. 2, pp. 261-267, February, 2010.

[17] M. Duarte, Y. Eldar, Structured Compressed Sensing: From Theory to Applications, *IEEE Transactions on Signal Processing*, Vol. 59, No. 9, pp. 4053-4085, September, 2011.

[18] E. Candes, J. Romberg, T. Tao, Stable Signal Recovery from Incomplete and Inaccurate Measurements, *Communications On Pure and Applied Mathematics*, Vol. 59, No. 8, pp. 1207-1223, August, 2006.

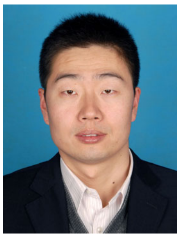
[19] E. Candes, M. Wakin, An Introduction to Compressive Sampling, *IEEE Signal Processing Magazine*, Vol. 25, No. 2, pp. 21-30, March, 2008.

[20] M. Duarte, R. Baraniuk, Kronecker Compressive Sensing, *IEEE Transactions on Image Processing*, Vol. 21, No. 2, pp. 494-504, February, 2012.

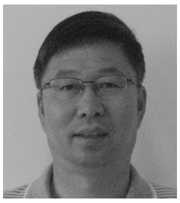
[21] E. Candes, The Restricted Isometry Property and Its Implications for Compressed Sensing, *Comptes Rendus Mathematique*, Vol. 346, No. 9-10, pp. 589-592, May, 2008.

[22] G. Yu, G. Sapiro. Statistical Compressed Sensing of Gaussian Mixture Models, *IEEE Transactions on Signal Processing,* Vol. 59, No. 12, pp. 5842-5852, December, 2011.

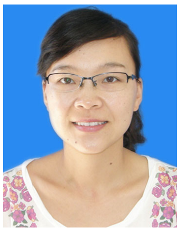
Biographies



Chengtie Li received his B.S. degree in Automation from the Northeastern University, China, in 2005 and M.S. degree in Control Theory and Control Engineering from the Northeastern University, China, in 2011. His research interests include wireless communication and compressive sensing.



Jinkuan Wang received M.S. degree from Northeastern University, Shenyang, China, in 1985 and the Ph.D. degree from University of Electro-Communication, Tokyo, Japan, in 1993. As a special member, he joined the Institute of Space Astronautical Science, Japan, in 1990. And he worked as an Engineer in the Research Department, COSEL, Japan, in 1994. He is currently a Professor in the Institute of Information and Engineering at Northeastern University, China, since 1998. His main interests are in the area of adaptive signal processing, mobile communication and intelligent control.



Mingwei Li received B.S. degree in Information and Computing Science from the Northeastern University, China, in 2006 and M.S. degree in Operations Research and Control Theory from the Northeastern University, China, in 2008 and Ph.D. in Control Theory and Control Engineering from the Northeastern University in 2014. Her research interests include wireless sensor networks and compressive sensing.