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Efficient sampling and compressive sensing for urban monitoring vehicular sensor networks

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Abstract: Vehicular sensor network (VSN) using vehicle-based sensors is an emerging technology that can provide an inexpensive solution for surveillance and urban monitoring applications. For the constantly moving vehicles, resulting in unpredictable network topology, data transmission in VSN is vulnerable to packet losses, thus deteriorating the surveillance quality. To resolve this problem, a cooperative data sampling and compression approach is proposed. Based on compressive sensing, this approach does not require inter-sensor communication and adopts sparse random projections to remove redundancy in spatially neighbouring measurements. It is experimentally shown that the proposed algorithm provides fairly accurate reconstruction of the field under surveillance, and incurs much less communication traffic load compared to conventional sampling strategies. Practical data sets, including the temperature distribution in Beijing and the global position system (GPS) tracking data of over 6000 taxis in the city, are used in our experiments to verify the reconstruction accuracy and energy efficiency of the scheme. Different vehicular mobility models are also employed to study the impact of movement behavior. Simulation results show that our proposed approach outperforms the conventional sampling and interpolation strategy, which propagates data in uncompressed format, by 5 dB in reconstruction quality and by 50% in communication complexity reduction for the same sampling rate.

1 Introduction

Successful city management that promotes the habitability and sustainability of the community relies on urban environmental monitoring to provide essential information for decision making. With the emergence of low-power and inexpensive sensing and wireless communication devices, the wireless sensor network (WSN) becomes a promising technology for urban environmental surveillance [1–3]. WSN for environmental monitoring uses distributed sensors to acquire physical conditions, such as temperature, pressure, noise and pollution levels, at different locations. However, fine-grained environmental data acquisition needs a large number of sensor nodes to be deployed, which is economically infeasible. Recent advances [4, 5] in vehicular communications facilitate the use of vehicular sensor network (VSN) as more effective, flexible and affordable solutions for fine-grained urban sensing. Compared to static sensors, vehicular sensor nodes take advantage of their mobility to extend their coverage. On the other hand, the movements of the vehicles and hence of the sensors are unpredictable, potentially resulting in non-uniform sampling and sub-optimal resource allocation in the monitored area. In addition, the highly dynamic VSN topology may potentially impede the successful transmission of large volume of data sampled by multiple sensors to the aggregator. The above issues motivate the development of a data compression technology for VSN to reduce the overall communication traffic load.

The properties of environmental data suggest that the samples are temporally and spatially correlated [3, 6]. This can be employed to improve the compression efficiency and reconstruction accuracy. Specifically, we present herein a cooperative data sampling and compression approach, first reported in the conference paper [7], where environmental data of interest are considered as an ensemble to be sampled and reconstructed. The proposed algorithm applies compressive sensing (CS) [8–13] that provides an efficient signal acquisition scheme to exploit the inherent correlation of the signal so as to reconstruct it from any small fraction of random linear projections, in the context of vehicular/mobile sensor network, to effectively code the ensembles. Prior related research on employing CS in sensor networks includes [14–17], where the sensor locations are assumed known and static.

The merits of our proposed approach are multifold. First, the algorithm is computationally asymmetric, that is, simple implementation of encoding at sensor nodes and relatively complicated decoding at the aggregator [18]. This is particularly suitable for the common sensor networks where the sensors are of low-complexity, although the constraints imposed on the aggregator are flexible. Second, sensor nodes can execute their respective compression processes independently without incurring extra inter-sensor

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collaboration overhead; thus the communication traffic is significantly reduced. Third, every node samples the field independently and randomly, hence relaxing the sensitivity on the movement pattern of sensors, and allowing flexibility in the deployment of the system. Moreover, environmental data ensemble can be reconstructed with fairly high quality at the aggregator, when all compressed data are used simultaneously for the joint reconstruction. In the conference paper [7], two mobility models were used to test the approach. However, only using theoretical models does not suffice to prove its validity in the real world. In order to further evaluate the efficacy of the approach in urban environment, in this paper, we collect the real GPS tracking data of over 6000 taxis in Beijing, and combine them with Beijing temperature distribution to examine the efficacy of the proposed algorithm in VSNs for urban monitoring applications. The results demonstrate that our approach achieves higher monitoring accuracy with less overall traffic load, compared with conventional sensing schemes. Furthermore, we study the relationship between recovery quality and total traffic load under the same setting of number of sensors and sampling period. It is shown that given a small error tolerance of recovery quality, total traffic load could be decreased significantly.

The rest of the paper is organised as follows. In Section 2, we discuss some related work. Section 3 briefly reviews CS basics. A model for environmental monitoring with mobile sensor networks (MSNs) is presented in Section 4, serving as the problem formulation. We describe the proposed cooperative sensing and compression strategy and the mathematical analysis in Section 5. Section 6 shows the simulation results and demonstrates the performance of the proposed approach in comparison with conventional sensing scheme based on practical data sets. We conclude in Section 7.

2 Related work

In recent years, the problem of sampling data while performing compression before transmission has been receiving increasing interest in the area of sensor networks. Much work has focused on exploiting relaxed precision requirements to compress data and reduce communication load in the network. Deligiannakis *et al.* [19] exploit the correlations of data collected by the same node in different time periods, use historical measurements to build a base signal, and then approximate the collected data by means of linear projections of the base signal. Guitton *et al.* [3] study the temporal and spatial correlations of car-flow data, and propose two Fourier-based compression algorithms utilising single node temporal correlations and spatial correlations separately. These approaches aim to exploit correlations in the data which has been collected by sensor nodes.

Recent results in CS provide radically different approaches for distributed sensing and compression to solve the problem. Shen *et al.* [14] establish an early model for WSN with CS, but previous knowledge of the sensor field must be obtained at a considerable cost. Masiero *et al.* [15] use principal component analysis to derive transformations that sparsify signals for CS. In [16, 17, 20], multi-hop routing has been integrated with data compression using normal random projections. However, sensors are stationary, and dense deployment is required to maintain good coverage and network connectivity.

Different from the aforementioned work, we address the joint sampling and compression problem by exploiting spatial correlations of the sensing field in an MSN context. Our approach exploits mobile sensors to guarantee high coverage rate and hence the reconstruction quality, and employs CS with sparse random projections to significantly reduce the data transmission load, thus providing an energy-efficient sensing and transmission scheme.

3 CS with random projections

CS is a promising sampling technique to retrieve sparse signals accurately and sometimes even exactly from a reduced number of random projections, without global coordination or previous knowledge about the signals. Reconstruction of the original data is possible through dedicated algorithms including matching Pursuit with excellent accuracy either in the absence of noise [8, 9] or even with noise [10].

3.1 CS basics

Based on the work mentioned [8, 9], consider the real-valued signal $\boldsymbol{x} \in \mathbb{R}^N$, indexed as x_i where $i \in \{1,2, \ldots, N\}$. Suppose that $\boldsymbol{x}$ has a K-sparse ($K \ll N$) representation in a specific domain with basis $\Psi = [\psi_1 \psi_2 \ldots \psi_N]$; that is

$$\boldsymbol{x} = \Psi \tilde{\boldsymbol{x}} = \sum_{i=1}^{N} \psi_i \tilde{x}_i = \sum_{k=1}^{K} \psi_{i_k} \tilde{x}_{i_k}, \quad \tilde{x}_{i_k} \neq 0 \tag{1}$$

where $\boldsymbol{x}$ is represented as a linear combination of K vectors chosen from Ψ, i_k are the indices of those vectors, and $\{\tilde{x}_{i_k}\}$ are the coefficients. $\tilde{\boldsymbol{x}}$ is an $N \times 1$ column vector with K non-zero elements, we say that $\tilde{\boldsymbol{x}}$ is K-sparse when $K \ll N$ is satisfied.

$\boldsymbol{x}$ can be compressed by left multiplying by an $M \times N$ measurement matrix of Φ, with $M \ll N$. The compressed measurement of vector $\boldsymbol{x}$ is thus obtained as

$$\boldsymbol{y} = \Phi \boldsymbol{x} = \Phi \Psi \tilde{\boldsymbol{x}} \tag{2}$$

where $\boldsymbol{y} \in \mathbb{R}^M$.

We assume that $\boldsymbol{x}$ contains N recordings of sensors. Since the environmental parameters of interest are always highly spatially correlated, we may safely further assume that $\boldsymbol{x}$ has a sparse representation $\tilde{\boldsymbol{x}}$ under some basis. $\boldsymbol{y}$ is the data transmitted back to the aggregator node; the data collection load could be significantly reduced, since $M \ll N$.

Given that $\tilde{\boldsymbol{x}}$ is K-sparse, the original signal can be recovered by solving the following convex optimisation problem with $M \sim O(K \log N)$ measurements [8, 9, 11]

$$\min ||\tilde{\boldsymbol{x}}||_{\ell_1}, \quad \text{subject to}\, \Phi\, \Psi\, \tilde{\boldsymbol{x}} = \boldsymbol{y} \tag{3}$$

The measurement matrix $\boldsymbol{\Phi}$ must satisfy the uniform uncertainty principle (UUP) condition [12] to guarantee the reliability of the reconstruction. Random Gaussian matrices and ± 1 Bernoulli matrices are proved to satisfy UUP condition with high probability [21]. They are easy to be implemented in practice.

While the sparse signal can be exactly reconstructed with high probability, in reality signals may rarely be sparse. Most natural signals, however, will be compressible, which means that their coefficients decay very fast under some orthogonal basis [12]. Moreover, the measurements $\boldsymbol{y}$ may be obtained in noisy conditions. Even so, compressible

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signals can still be accurately recovered from noisy random projections [10].

3.2 CS with sparse random projections

CS has great potential for fully distributed compression in sensor networks. However, the dense projections of traditional CS are not cost-effective since each sensor is required to transmit its data once for each measurement, and the cumulative traffic load can potentially be equal to that of a raw data gathering scheme. A more efficient sensing strategy has been proposed by Wang *et al.* [13]. The work shows that CS recovery algorithms can also apply to sparse random projections, where the measurement matrix $\boldsymbol{\Phi}$ is defined as

$$\phi_{ij} = \begin{cases} +1, & \text{with probability } \dfrac{1}{2p} \\ -1, & \text{with probability } \dfrac{1}{2p} \\ 0, & \text{with probability } 1 - \dfrac{1}{p} \end{cases} \tag{4}$$

where p determines the sparseness of the measurement matrix. It has been proved that with $p \sim (N \log N)$ and $M \sim O(K \log N)$, reconstruction quality is as good as that obtained with the K largest transform coefficients. The key procedure in the proof shows that sparse random projections of vectors preserve the inner product in expectation as in the case of dense random projections.

Our goal in this paper is to propose a specific data sampling and compression scheme that constructs a measurement matrix similar to (4). The merit of the scheme is that the distributed sampling and compression procedure is conducted in conjunction with CS using sparse random projections, thereby reducing data transmission load.

4 System model and problem formulation

Consider a group of vehicles equipped with sensors roaming around a certain area in the metropolitan area. A fixed data aggregator is deployed at the centre of this area. The cars adopt vehicular short range communication technology that provides car-to-car and car-to-aggregator connection if the receiver is within range. The data sampled by sensors spread among cars until they arrive at the aggregator. When the aggregator collects enough such data, it can integrate them and rebuild the whole area.

In this section, we first introduce the map model and the properties of environmental signals. Based on such modelling, we describe the proposed VSN scheme. The problem of interest is then defined. In this paper, we use the urban heat island monitoring application as an example. Therefore we assume that taxis equipped with temperature sensors roam around the metropolitan area.

4.1 Map and monitored sensing field settings

Different from typical MSNs, VSNs have a unique constraint, that is, the movement of sensors is restricted to the roads and streets. Therefore sampling can be done only at the positions that vehicles have access. Hence, the topology of VSN is modelled on the basis of the distribution of roads and speed limits in the monitored area.

We adopt Manhattan grid map [22] to model roads and streets of a metropolitan area denoted by G. G is basically composed of a number of horizontal and vertical streets. Each street has two lanes of different directions. The mobile sensors move along the streets, change their speeds, and choose new directions at intersections with a certain probability. Assume the set of intersections in G is denoted by I. The parameter of the model is the size of G, which is set to $n \times n$ in our scenario, that is, the cardinality of I is $|I| = n \times n$.

Information about the environment, such as temperature, air pollution and wind speed, can be described as a dynamic spatial scalar field [23]. The indexes and their variations are always scalar properties over a region and the scalar property fluctuates over time. In this paper, we focus on the temperature, which is a dynamic spatial scalar field defined as a function on a temporal domain and over a spatial field. The temporal domain and the spatial field can either be continuous or discrete, depending on the applications. According to the Manhattan grid map model, the spatial field can be divided into $n \times n$ uniform discrete grids. The average temperature value of each grid is assigned to the corresponding intersection in G. Furthermore, since temperature of cities varies slowly, we may safely assume that a snapshot of the field can represent the data over a period of time T, that is, the temperature variations during the time interval T in the same location is assumed to be negligible. In this way, we can denote the thermal signals of a city during a certain period of time T by a signal matrix

$$\boldsymbol{X}_{2\text{D}} = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{nn} \end{pmatrix} \tag{5}$$

where x_{ij} is the temperature value of intersection $I_{ij} \in I$. It can be rewritten in vector form in such a way that each column of the matrix is stacked up; that is

$$\begin{aligned} \boldsymbol{x} &= \text{Vec}(\boldsymbol{X}_{2\text{D}}) \\ &= (x_{11}, \ldots, x_{n1}, x_{12}, \ldots, x_{n2}, \ldots, x_{1n}, \ldots, x_{nn})^{\text{T}} \\ &= (x(1), x(2), \ldots, x(N))^{\text{T}} \end{aligned} \tag{6}$$

with $\boldsymbol{x} \in \mathbb{R}^N$ and $N = |I| = n \times n$. The thermal signals during a certain period of time are expected to exhibit strong spatial correlations. Moreover, the temperature distribution of a city is likely to be sparse in the frequency domain, because, intuitively, the temperature is largely distributed near the average, and the fluctuation is caused by local heat sources that are spatially distributed in repeated spatial patterns because of the block structure of the city, resulting in concentrated distribution in the frequency domain. Therefore we make the assumption that the temperature field is compressible in discrete cosine transform (DCT) domain; that is

$$\boldsymbol{x} = \boldsymbol{\Psi}\tilde{\boldsymbol{x}} = \sum_{i=1}^{N} \psi_i \tilde{x}_i \tag{7}$$

where $\boldsymbol{\Psi}$ is the $n \times n$ DCT transformation matrix and $\tilde{\boldsymbol{x}}$ is an $N \times 1$ column vector. We say $\tilde{\boldsymbol{x}}$ is a compressible signal when its entries obey the power law

$$|\tilde{\boldsymbol{x}}|_{(k)} \le C \cdot k^{-r} \tag{8}$$

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for some $r \geq 1$, where $|\tilde{x}|_{(k)}$ is the kth entry of $\tilde{\boldsymbol{x}}$, and C is a constant. The compressibility assumption is validated based on real urban temperature data analysis in Section 5.

4.2 VSN scheme

Suppose S cars mounted with sensors roam in the area G. Let $\Lambda := \{1, 2, \ldots, S\}$ denote the set of indices of S sensors. During the period T, they perform samplings at each intersection they pass through. Since every vehicle has different routes and speeds, the number of intersections which they pass in the same period T is possibly different. Each sensor $s \in S$ makes L_s samples at the end of T, denoted by $\boldsymbol{x}_s = (x_s(1), x_s(2), \ldots, x_s(L_s))^{\mathrm{T}} \in \mathbb{R}^{L_s}$, with $x_s(i) \in \{x(1), x(2), \ldots, x(N)\}$. Each sample sequence $\boldsymbol{x}_s$ is directly related to the trajectory of the sensor s, that is, vehicular mobility pattern determines the sampling scheme. In order to reduce redundant information, we assume that a sensor does not repeat sampling if it goes through the same intersection many times. However, each intersection might be sampled by several sensors during T because of the lack of inter-sensor collaboration.

Considering the constraints of the city streets, we use two different mobility models for the vehicular movements in the metropolitan area. They will be set as control groups to compare with real taxi track data in our simulations to evaluate the sampling and compression approach in Section 5.

1. *Manhattan mobility (MM) model* [22]*:* Assuming that intially sensors are uniformly distributed in a Manhattan grid, each node has equal chance of choosing any direction from its starting location. A node moves in a chosen direction first and then is switched into a subsequent, randomly selected street when it reaches the next intersection. Suppose that a node has 50% chance of going straight ahead, 25% chance of turning right and 25% of turning left as shown in Fig. 1. In order to eliminate the impact of the edge effect, we assume a node will rejoin the grid from the opposite side when it moves beyond the grid.
2. *City section mobility (CSM) model* [24]*:* The CSM model provides realistic movement pattern of taxis in cities since it severely restricts the travelling behaviour of mobile nodes. Nodes must follow predefined paths and traffic rules (e.g. speed limits). To start with, each node is randomly put at a point on the grid. Then the node randomly chooses a destination, also represented by a point on some grid. The path from the current location to the destination is randomly chosen from all paths of the shortest travelling time between these two points; in addition, some driving rules such as speed limits exist. Upon reaching the destination, the node may stay there for a specified time and again choose another random destination to repeat the process. In Fig. 2, two nodes' movements according to CSM have been illustrated.

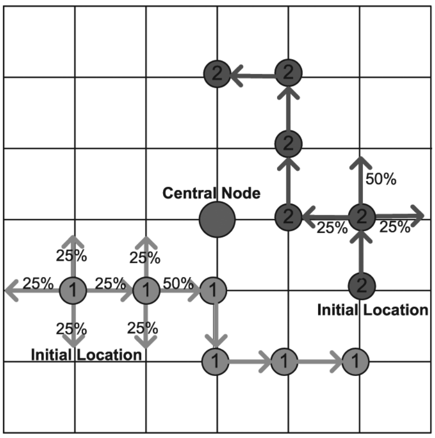

Fig. 1 *MM model*

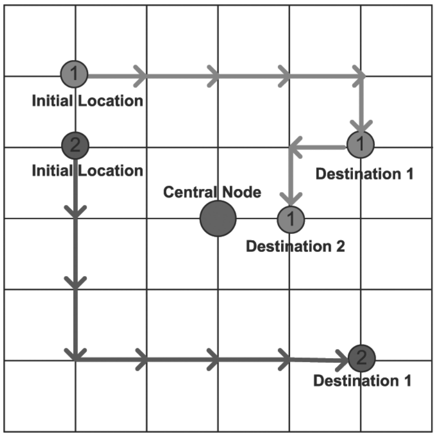

Fig. 2 *CSM model*

4.3 Problem definition

Urban monitoring requires complete environmental information in the area of interest, that is, we need to estimate the environmental signal ensemble $\hat{\boldsymbol{x}}$ at the aggregator, not just the signals sampled by each sensor. Obviously, the more information the sensor acquires, the better the estimation. At the same time, the amount of data transmitted to the aggregator increases. The objective here is to consider spatial correlation of environmental signals and movement patterns of participating vehicles and accordingly design compression and reconstruction algorithm such that we can minimise the distortion between the estimation $\hat{\boldsymbol{x}}$ and the real signal $\boldsymbol{x}$ with an affordable transmission cost.

In the next section, we present an efficient distributed compression and reconstruction algorithm which decides how to (i) easily compress data without extra inter-sensor collaboration overhead, and (ii) precisely construct a complete signal of the environment using all of the compression data at the same time.

5 Cooperative sensing and compression approach

Sensor s gets a series of samples, $\boldsymbol{x}_s$ of dimension L_s during the sampling period T. We encode $\boldsymbol{x}_s$ to an M-dimensional vector $\boldsymbol{y}_s$ as

$$\boldsymbol{y}_s = \Phi_s \boldsymbol{x}_s \tag{9}$$

where $\boldsymbol{\Phi}_s$ is considered as an $M \times L_s$ random ± 1 Bernoulli measurement matrix, with i.i.d. entries

$$\phi_{ml} = \begin{cases} +1, & \text{with probablity } \dfrac{1}{2} \\ -1, & \text{with probablity } \dfrac{1}{2} \end{cases} \tag{10}$$

where $1 \leq m \leq M$, $1 \leq l \leq L_s$, $M < L_s$.

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In general, Φ_s is different for each sensor, and could be generated by a pseudo-random number generator at the sensors or pre-allocated to them. As such the dimension reduction by random projection can be easily done on mobile sensor nodes in a distributed manner, and only an M-dimensional vector is transmitted to the aggregator from each sensor for signal reconstruction, thus reducing the traffic load. The dimension M of vector $\boldsymbol{y}_s$ is a key parameter in the algorithm in the sense that it affects the traffic load and the signal recovery quality. We evaluate the impact of M on the system performance experimentally in Section 5. The data routing algorithm is beyond the scope of this paper, and we simply assume that the aggregator receives each sensor node's data $\boldsymbol{y}_s$ after the sampling period T, and then try to recover the signal $\boldsymbol{x}$ which is the one-dimensional version of the thermal field ensemble $\boldsymbol{X}_{2\text{D}}$ of the $n \times n$ metropolitan area. The random measurement matrix $\boldsymbol{\Phi}_s$ can be generated at each mobile sensor for compressed sensing, and at the aggregator for signal reconstruction, since we are really using the same pseudo-random number generator and synchronisation seeds at both the sensors and the aggregator. Therefore when stacking up all of signals from sensors, we have

$$\boldsymbol{y} = \Phi^* \boldsymbol{x}^* \tag{11}$$

where

$$\boldsymbol{x}^* = \begin{bmatrix} \boldsymbol{x}_1 \\ \boldsymbol{x}_2 \\ \vdots \\ \boldsymbol{x}_S \end{bmatrix}, \quad \boldsymbol{y} = \begin{bmatrix} \boldsymbol{y}_1 \\ \boldsymbol{y}_2 \\ \vdots \\ \boldsymbol{y}_S \end{bmatrix},$$

$$\Phi^* = \begin{bmatrix} \Phi_1 & 0 & \cdots & 0 \\ 0 & \Phi_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \vdots & \Phi_S \end{bmatrix}$$

Φ^* is a $P \times Q$ sparse Bernoulli measurement matrix ($P = M \times S$, $Q = \Sigma_{s=1}^{S} L_s$) and $\boldsymbol{x}^*$ is the stack of $\boldsymbol{x}_s$. For the purpose of recovering the complete thermal signal $\boldsymbol{x}$ instead of $\boldsymbol{x}^*$, we rearrange and combine some columns of Φ^* in accordance with the order of the element index of $\boldsymbol{x}$, so that

$$\boldsymbol{y} = \Phi \boldsymbol{x} = \Phi \Psi \tilde{\boldsymbol{x}} \tag{12}$$

where $\boldsymbol{x} = (x(1), x(2), \ldots, x(N))^{\text{T}}$ and $\tilde{\boldsymbol{x}}$ is its compressible representation under DCT transformation Ψ.

Fig. 3 demonstrates the compression scheme and matrix rearrangement. Since usually the paths of different vehicles will cover the entire area with some overlapping, the length of vector $\boldsymbol{x}^*$ may be different from that of vector $\boldsymbol{x}$, and the number of columns (Q) in Φ^* may not be equal to the number of columns (N) in Φ. During the matrix rearrangement process, several columns of Φ^* would be combined to one column in Φ when the samples made by different vehicles is overlapping, as shown in Fig. 3*b*. The rows, corresponding to the entries of $\boldsymbol{x}$ which are not sampled, would be set to zeros in Φ. Therefore the final measurement matrix $\boldsymbol{\Phi}$ is a sparse random matrix, which is determined by vehicular movements.

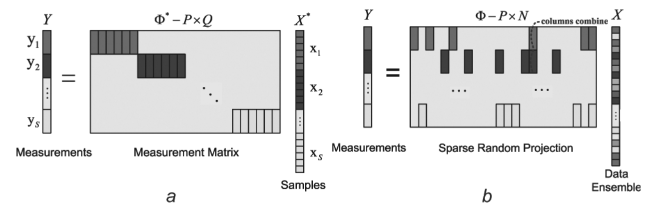

Fig. 3 *Illustration of compression scheme based on sparse random projections*

a Sampling and compression
b Measurement matrix rearrangement

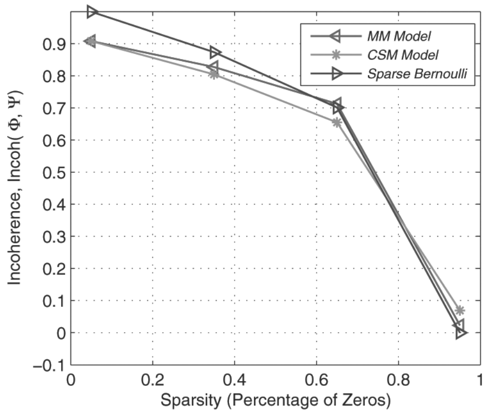

Fig. 4 *Incoherence between measurements*

To reconstruct the signal field, the aggregator needs to estimate the N-dimensional vector $\boldsymbol{x}$, based on the P-dimensional vector $\boldsymbol{y}$ and the $P \times N$ matrix $\boldsymbol{\Phi}$, where $N \ll P$. The problem can be solved approximately by ℓ_1-norm minimisation algorithms since vector $\boldsymbol{x}$ has a sparse representation $\tilde{\boldsymbol{x}}$ under the basis Ψ as described in Section 3, and measurement matrix $\boldsymbol{\Phi}$ must satisfy UUP. As mentioned in Section 2, ideally sparse random Bernoulli projections guarantee reliable recovery. In our settings, however, the condition is somewhat different: zeros in the measurement matrix are distributed block by block, instead of being randomly distributed as the sparse projection assumed in prior work. Numerical experiments are conducted to verify that the measurement matrix satisfies the UUP condition.

In Fig. 4, we show the normalised incoherence [17] between the DCT transform matrix Ψ and three different measurement matrices Φ as follows: $\boldsymbol{M}1$ is the standard sparse Bernoulli projection matrix defined by (4), $\boldsymbol{M}2$ is built according to the MM model, and $M3$ is determined by the CSM model. It is clear that the incoherent property of the measurement matrix obtained from the real application scenarios are very close to standard sparse random projections for the same sparsity, providing evidence that the measurement matrix satisfies the CS condition and similar performance gains could be expected.

6 Performance evaluation

6.1 Experiment setup

In order to precisely evaluate the performance of the sampling and compression approach, we conduct our experiments using real dataset of thermal signals and taxis' tracks in addition to MM and CSM in the city of Beijing. The thermal data was originally captured by the satellite NOAA-18 [25], and analysed to build low surface temperature map by the Beijing climate centre, as shown in Fig. 5. We choose a

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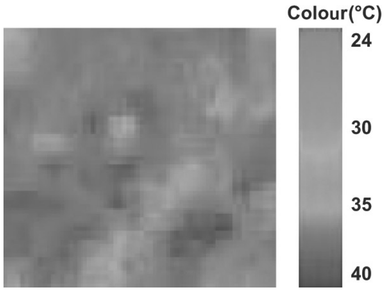

Fig. 5 *Temperature distribution in fourth ring area of Beijing*

snapshot of the temperature distribution of the metropolitan area of Beijing as the testing data set, with latitude ranging from N39.842286° to N39.990970° and longitude ranging from E116.477051° to E116.270313°, which is a 42×44 thermal signal matrix covering about 300 km^2 of the fourth ring area. Fig. 6*a* shows the original thermal signal which is rearranged in vector form from the signal matrix, and Fig. 6*b* gives its representation in DCT domain. We can see that most coefficients of the representation are small except for a few large values. Therefore it can be approximately regarded as a compressible signal and our assumptions hold.

The vehicle tracks contain the daily operation information (e.g. time, location and speed) of 6591 taxis in Beijing. Each vehicle has its information recorded every 60 s. We choose some of the most active cars in the selected area and perform the simulation on the data collected between 8:00am and 6:00pm.

The sensing map, with an actual size of 17–18 km, is rescaled to 42×44 Manhattan grids. The aggregator is placed at the centre of the map. For MM and CSM, mobile nodes are deployed uniformly in the map as initialised. We set the velocity of cars to 1 grid/min (24.3 km/h) in these two models, whereas in the real taxi traces vehicles move at their actual speeds.

Since coverage rate is an important parameter of vehicular movement pattern and it greatly influences the sampling efficiency, we compare the coverage rate of the two mobility models, MM and CSM, with the real taxis' tracks first before evaluating the field sensing approach performance. Fig. 7 further shows the coverage rate of the three movement patterns as number of mobile nodes and sampling time increase. There exist non-negligible gaps between the real tracks and the two mobility models, especially for large number of nodes and long sampling time. The difference is mainly because of the characteristics of the taxis' movement patterns. For example, taxis tend to cluster around popular areas, such as commercial districts and tourist attractions, and they always choose to travel on highways and main streets. Hence the trajectories of different cars would partially overlap. Such characteristics make the coverage rate grow less rapidly than the mobility models.

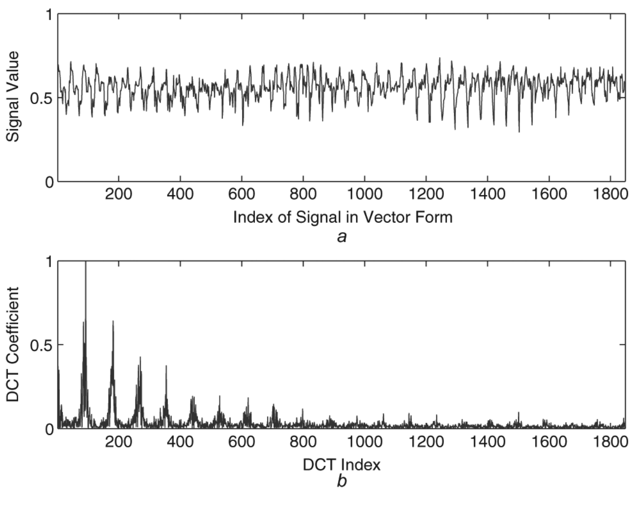

Fig. 6 *Temperature signal and its DCT transformation*

a Original signal
b Representation in DCT domain

6.2 Evaluation results

In our simulations, we use the primal-dual log-barrier algorithm obtained from SparseLab [26] to minimise ℓ_1-norm and recover the sensing field. Our cooperative compression and reconstruction scheme is compared with the conventional sensing schemes, in which sensors simply sample the sensing field and transmit raw data in an uncompressed form, and a bilinear interpolation algorithm is used to reconstruct the sensing field. We measure the reconstruction quality and traffic load of the two sensing schemes as we vary (i) sensor node movement patterns, (ii) the number of sensor nodes' and (iii) the sampling period.

Fig. 8 shows the impact of the number of nodes and the total sampling period on the SNR performance. We can see that more sensor nodes and longer sampling period improves the SNR performance of the three sensing schemes. For CSM and real taxi dataset, the reconstruction quality of our proposed compression approach is better than conventional sensing, regardless of the number of nodes and the total sampling period. For MM, the compression approach gains better SNR performance compared to the conventional approach at small number of sampling times and sensor nodes. However, as the number of sensor nodes and the sampling period increase, the compression approach gradually loses its advantage. We can conclude that, considering SNR performance, our compression and reconstruction approach is better than the conventional approach, and CSM model represents reality better than MM model. Furthermore, although as coverage rate changes the SNR performance of the conventional approach varies greatly, the coverage rate does not have great influence on the compression approach as shown in the figures.

Fig. 9 shows the total communication cost of the two sensing schemes under three different movement patterns. The total communication cost is calculated by $\Sigma(\text{Bit}) \times (\text{distance})^2$ [16]. When very few nodes are deployed to sample the field during a short period, total

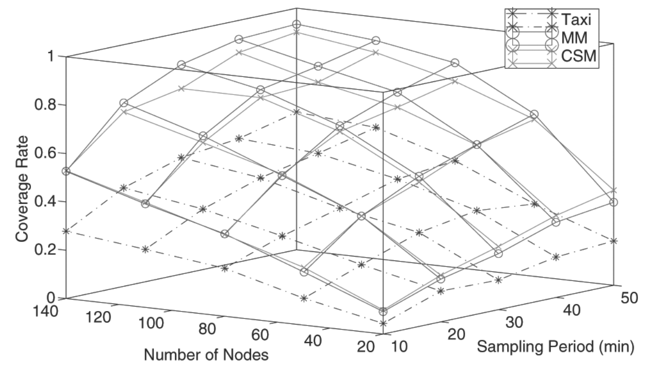

Fig. 7 *Coverage rate of different movement patterns*

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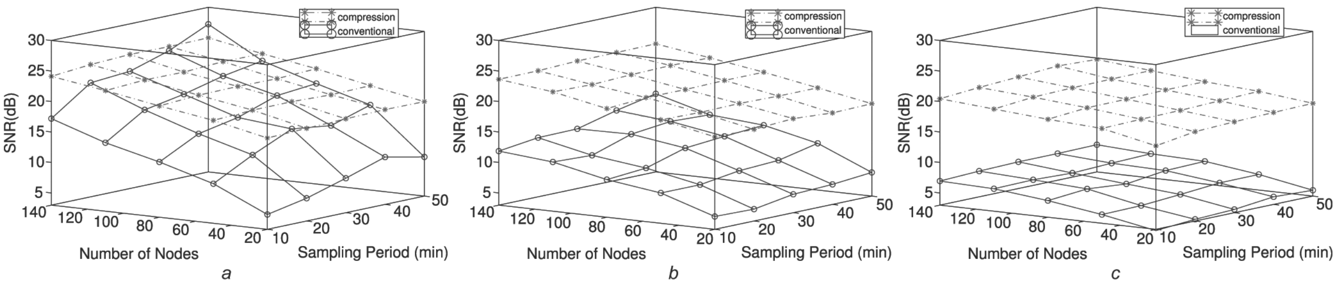

Fig. 8 *Comparison of reconstruction quality between the compression approach and conventional sampling approach using three different movement patterns*

a MM model
b CSM model
c Taxi tracks

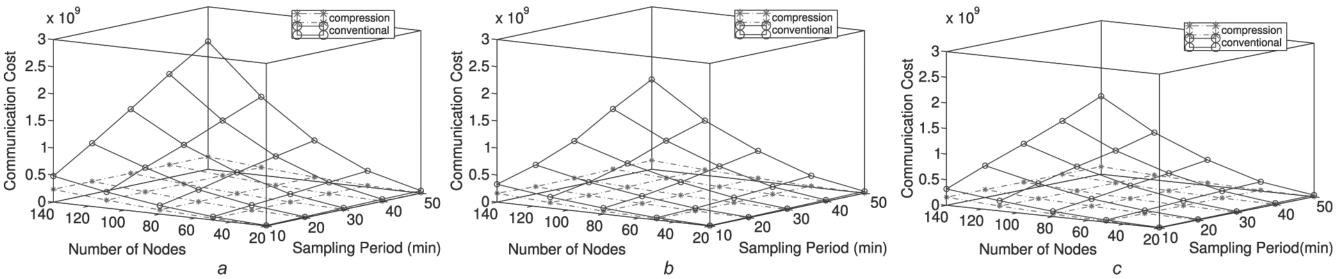

Fig. 9 *Comparison of communication cost between the compression approach and conventional sampling approach using three different movement patterns*

a MM model
b CSM model
c Taxi tracks

traffic loads generated by both the compression and conventional schemes are similar. However, the compression scheme continues to yield significant communication savings compared to the conventional scheme as we increase the number of nodes and the sampling period. Moreover, if we fix the number of nodes and only increase the total sampling period, the communication cost of the compression scheme hardly changes, whereas in the conventional scheme it rises dramatically. In addition, we find that the communication cost of the CSM model is smaller than that of the MM model and real taxi data sets. This is because in the CSM model, the movement algorithm from the current location to the destination makes a path according to the shortest travelling time between these two points. So sensor nodes are more likely to pass the central area of the sensing map rather than the marginal area, and they can transmit data to the aggregator at a shorter distance.

Finally, we examine the relationship between the recovery quality and the total traffic load, with the number of nodes set to 100 and the sampling period to 10 min (or approximately 10 min when we use taxi data sets). Different from Fig. 9, increase of traffic load in Fig. 10 comes from increment of parameter L_s (dimensionality of vector $\boldsymbol{y}_s$). As Fig. 10 shows, given a small error tolerance from 20 to 19 dB in the reconstruction, our compression strategy yields 37.75% traffic load savings. Although the reconstruction quality decreases, it is still much higher than the conventional scheme. When data were propagated in an uncompressed form, it would generate almost 50% more traffic load, but the Avg. SNR is less than 15 dB by the bilinear interpolation algorithm. It is worth noting that the recovery

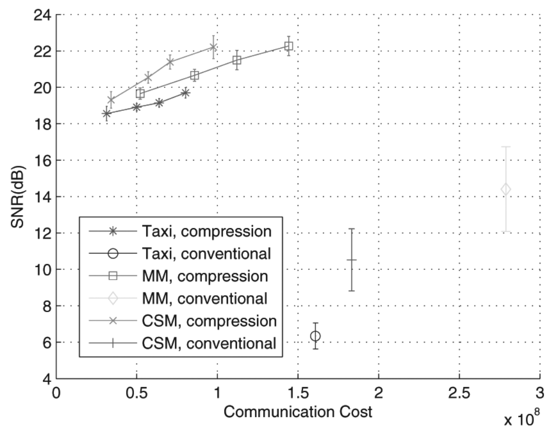

Fig. 10 *Relationship between total communication cost and reconstruction quality of the two sensing approaches*

quality based on real taxi data sets is very close to the MM model and the CSM model using compression approach. This gives strong support on the feasibility of the proposed approach in vehicular sensor networks for urban monitoring.

7 Conclusion

In this work, we present a cooperative data sensing and compression approach to monitor an urban environment using vehicular sensor networks. The proposed sampling and compression algorithm installed on every node does not incur additional inter sensor communication cost and can be implemented with low complexity. The compressed data from these sensors are collected by the aggregator, where

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they are jointly decoded to restore the samples across the entire monitoring area. The proposed approach, based on sparse random projections, exploits the erratic movements of vehicles and the spatial correlation of samples. Simulation results demonstrate dynamic performance gain under the proposed scheme, in comparison with conventional sensor networks, including 50% reduction in communication cost and 5 dB improvement in the reconstruction quality for the same sampling rate. Future directions involve optimising the sampling and recovery strategies through exploiting the temporal – spatial properties of environmental data and investigating real-time data transmission scheme for accurate and timely information.

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