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Decentralized Context Sharing in Vehicular Delay Tolerant Networks with Compressive Sensing

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***Abstract*—Vehicles equipped with various types of sensors can act as mobile sensors to monitor the road conditions. To speed up the information collection process, the monitoring data can be shared among vehicles upon their encounters to facilitate drivers to find a good route. The vehicular network experiences intermittent connectivity as a result of the mobility, which makes the inter-vehicle contact duration a scarce resource for data transmissions and the support of monitoring applications over vehicular networks a challenge.**

We propose a novel compressive sensing (CS)-based scheme to enable efficient decentralized context sharing in vehicular delay-tolerant networks, called CS-Sharing. To greatly reduce the data transmission overhead and speed up the monitoring processing, CS-sharing exploits two techniques: sending an aggregate message in each vehicle encounter, and quick collection of information taking advantage of data sharing and the sparsity of events in vehicle networks to significantly reduce the number of measurements needed for global information recovery. We propose a novel data structure, and an aggregation method that can take advantage of the random and opportunistic vehicle encounters to form the measurement matrix. We prove that the measurement matrix satisfies the Restricted Isometry Property (RIP) property required by the CS technique. Our results from extensive simulations demonstrate that CS-Sharing allows vehicles in a large network to quickly obtain the full context data with the successful recovery ratio larger than 90%.

***Index Terms*—Compressive Sensing, Vehicular Delay Tolerant Network, Context Sharing**

I. Introduction

In vehicular networks, more and more vehicles are equipped with sensors of different types, such as accelerators, pollution sensors and Global Positioning System (GPS) receivers. Therefore, vehicles are becoming powerful mobile sensors which can be exploited to gather data from the environment [1], [2], and vehicular networks can serve as promising new platforms to support a wide range of monitoring applications, such as road surface monitoring [3] and urban sensing [4].

The goal of this work is to develop an efficient algorithm that enables every vehicle in the network to quickly and efficiently collect the context data of all hot-spots with a vehicular network. As there often exist heavy and dynamic traffic as well as constant road repairs in the urban areas, we use the important road condition monitoring as an example to illustrate our algorithm in this paper.

Rather than letting each vehicle monitor all the hot spots itself, we take advantage of two features to speed up the monitoring process: 1) The mobility of vehicles, which allows encountering vehicles to exchange messages and share information collected; and 2) The rareness of the events to monitor, for example, the traffic congestions or road repairs, which enables the use of compressive sensing technique to recover the global context information with much smaller number of measurements.

Due to the mobility of vehicles, the vehicle network experiences intermittent connectivity, which makes inter-vehicle contact duration a scarce resource for data transmission. As it is difficult to find a connected path over vehicles at any time, road condition data may be exchanged during the opportunistic inter-vehicle contacts. Two vehicles can directly exchange the raw context data, however as the encountering duration is often short, the transmission of large amount of raw data is costly and subject to the packet loss. Therefore, it is critical to reduce the information to transmit in the vehicular Delay-Tolerant Networking (DTN) to well utilize scarce contact resources.

As a ground-breaking signal processing technique, recently compressive sensing (CS) has been applied in wireless sensor networks (WSNs) [5]–[16] and vehicle networks [17]–[23] to facilitate data gathering at low cost. According to the compressive sensing theory [24]–[27], sparse signals can be accurately reconstructed with a relatively small number of random measurements. Despite the large amount of effort, existing work on CS usually assumes that the sparsity level K of unknown data is known as a prior, based on which a pre-defined $M \times N$ measurement matrix ($M < N$) is usually applied to take M samples. With the need of exchanging M messages at a time, the transmission cost is still very high. In addition, as the sparsity level of the global road condition is often unknown, the use of pre-defined measurement matrix may either result in a failure of recovering the global information when the number of samples are insufficient or high measurement overhead.

As congestions in off-traffic time or road repair are rare events, the global context vector $\mathbf{x} \in R^N$ to capture the road condition is usually sparse, which provides the opportunity to recover the global context data from a significantly lower number of context measurements based on the CS technique.

Different from existing studies, in this paper, we propose a novel CS-enabled *decentralized context sharing* scheme in vehicular DTNs, called CS-Sharing. In our proposed system, vehicles act as the mobile sensors to monitor the road conditions. We propose an efficient algorithm to aggregate messages stored in the vehicle to reduce the communication cost for message exchanges among vehicles. Instead of monitoring all the hot-spots of interests directly or flooding the information throughout the network, each vehicle can obtain the global road context data through CS recovery based only on a small number of aggregate messages exchanged among vehicles.

Our CS-Sharing scheme takes advantage of the message sharing and sparse data feature to enable quick context data collection with a small number of on-site measurements, and reduces the number of messages to exchange each time exploiting novel message aggregation scheme. A vehicle driver can be quickly made aware of the road traffic conditions several miles ahead and find a route that allows for more smooth driving.

Our contributions in the CS-Sharing framework can be summarized as follows:

- To the best of our knowledge, CS-Sharing is the first work that applies the compressive sensing in vehicular DTN to learn the global environment information through *sparse context sharing* among vehicles. With vehicles driven around the network, CS-Sharing can exploit the large number of mobile vehicle sensors to efficiently collect the environment information over a vast area.
- We propose a novel message aggregation algorithm for each vehicle in the system to form an aggregate message from its sensory data stored. Rather than transmitting the raw context information upon vehicle encountering or M messages like other CS-related existing network, vehicles in our system opportunistically exchange an aggregate message upon each vehicle encounter, so that the message cost can be largely reduced.
- The proposed CS-Sharing scheme does not assume that the sparsity of the road condition data is known as a prior and uses a pre-defined measurement matrix as done in many CS-related studies. Instead, with our well designed data structure and the aggregation algorithm, the measurement matrix required for CS is naturally formed in each vehicle in a distributed way taking advantage of the random and opportunistic vehicle encounters.
- We prove that when a vehicle in the network gathers more than $M = cK \log N$ messages (where c is a constant, N is the number of hot-spots, K is the sparsity level of the global context vector with $K << N$), the vehicle can accurately recover the global urban context data of interest even when M is much smaller than N.
- To support efficient on-line message collection, we propose a data recovery algorithm along with a sufficient sampling principle so that a vehicle can identify whether the messages gathered contain enough information to recover the global context data without requiring the knowledge of the sparsity of unknown road condition data.

We have performed extensive simulations to demonstrate the effectiveness of our proposed CS-Sharing scheme. Although there are only a smaller number of aggregate message exchanged among vehicles, our results show that CS-Sharing allows vehicles in a large network to obtain the full context information within very short time period at high data estimation accuracy and low communication cost.

The rest of the paper is organized as follows. Section II and Section III briefly introduce the fundamentals of CS and related work. Section IV introduces the system model and the problem. Section V and Section VI present our aggregation algorithm and CS-based context recovery algorithm, respectively. Simulation results are given in Section VII. In Section VIII, we conclude the paper.

II. Fundamentals of Compressive Sensing

According to the CS theory [24]–[27], a sparse signal can be recovered with a high probability by solving an optimization problem from non-adaptive linear projections, which preserves the structure of sparse signals. Suppose $\mathbf{x} \in R^N$ is an unknown sparse vector where $\|\mathbf{x}\|_0 = K$ and $K \ll N$. We call K the sparsity level of $\mathbf{x}$. Then $\mathbf{x}$ can be reconstructed by a small number of measurements from the acquisition system by solving the following problem

$$\begin{aligned} &\min_{\mathbf{x}} \|\mathbf{x}\|_0 \\ &\text{subject to} \quad \mathbf{y} = \mathbf{\Phi x} \end{aligned} \tag{1}$$

where $\mathbf{\Phi}$ is an $M \times N$ measurement matrix and the number of measurements M satisfies:

$$M \geq cK \log \frac{N}{K} \tag{2}$$

where c is a constant value.

However, Eq.(1) is intractable because it is an NP-hard problem [28]. In recent research work [29], [30], it has been proven that the signal $\mathbf{x}$ can be recovered by solving the following minimum l_1-norm optimization problem with a very high probability

$$\begin{aligned} &\min_{\mathbf{x}} \|\mathbf{x}\|_1 \\ &\text{subject to} \quad \mathbf{y} = \mathbf{\Phi x} \end{aligned} \tag{3}$$

with the measurement matrix $\mathbf{\Phi}$ satisfying the Restricted Isometry Property (RIP) [31], expressed as

$$(1 - \delta_s) \|\mathbf{x}\|^2 \leq \|\mathbf{\Phi x}\|^2 \leq (1 + \delta_s) \|\mathbf{x}\|^2 \tag{4}$$

where δ_s is a constant and $\delta_s \in [0, 1)$.

The RIP condition quantifies how well the measurement matrix $\mathbf{\Phi}$ preserves the norm of sparse vectors. In Section VI, we will show that the measurement matrix is naturally formed during the message exchange process in our CS-Sharing scheme and the matrix satisfies the RIP condition.

III. RELATED WORK

With the recent advances in inter-vehicular communications via Dedicated Short-Range Communication (DSRC) [32] and Wireless Access in the Vehicular Environment (WAVE) [33], vehicular networks are drawing growing attentions from both research and industrial fields. Equipped with various types of sensor, vehicles can serve as mobile sensors for many monitoring applications [3], [4]. In [1], a good survey on urban vehicular sensing platforms is given. Despite the large amount of effort, there are only very limited studies on applying compressive sensing to vehicular networks.

The work in [17]–[21] estimates the mobility trajectories via a small number measurements from mobility traces, and proposes a trajectory compression algorithm based on compressive sensing to avoid network congestion in vehicular networks. In [17], the proposed scheme AACAT can achieve an accuracy in the order of meters for the reconstructed trajectories, and an improved compression scheme SimpleTrack [18] can achieve the sub-meter accuracy. In these schemes, the measurement matrix required for CS is maintained by both the vehicle itself and the receiver. The vehicle transmits its own compressed trajectory messages to the receiver, while the receiver recovers the original trajectory information with the aid of the measurement matrix. Different from these studies, the goal of our work is to enable every vehicle in the network to quickly and efficiently collect the context data of all hot-spots. To achieve this, this paper considers vehicles as mobile sensors to collaboratively collect information on the road conditions. Therefore, the problem and main solution of our work are very different from those of the existing studies.

Li *et al.* [22] investigate the use of probing vehicles for traffic sensing, where each vehicle senses its speed and position periodically. The authors propose a CS-based method based on the principal component analysis of data traces of taxies in an urban environment and reveal the existence of the hidden structures of the traffic data. In [23], the authors addressed two issues: tradeoff between the communication cost and the estimation accuracy, and guaranteeing the estimation accuracy in the highly dynamic network. The work also demonstrates that the number of vehicles and Access Points (APs) have impact on the estimation accuracy. Instead of depending on the deployment of APs on the side of the road to recover the raw data, every participating vehicle in our system would like to know the global set of hot-spot data by benefiting from the context sharing.

Besides above studies, compressive sensing is becoming a new paradigm for data gathering in WSNs as it can greatly improve the communication efficiency [5]–[16], [34], [35]. CS-based data gathering in WSNs often relies on a sink node to perform CS data reconstruction, which requires the knowledge of the packet transmission paths to derive the measurement matrix structure and collect the data at each intermediate node. This makes the solutions developed for WSNs difficult to apply in vehicular networks where the network topology constantly changes as a result of movement of vehicles. Also, different from WSNs, nodes in our proposed system would like to share the information and learn the global context information at low cost. This would require each vehicle rather than the fusion center to recover the complete set of data of interest, which makes the context sharing problem much harder to solve than the conventional data gathering problem in WSNs.

Despite the large amount of effort on CS (in WSNs and in vehicular networks), existing studies usually apply a pre-defined $M \times N$ measurement matrix, with M determined based on the sparsity level K assumed to be known and M messages to transmit from a node. In contrast, our CS-Sharing scheme does not rely on the knowledge of the sparsity level of the road condition data and any pre-defined measurement matrix. With our well designed data structure and the aggregation algorithm, the measurement matrix required for CS is naturally formed at each vehicle in a distributed way by taking advantage of the random and opportunistic vehicle encounters. Moreover, only one aggregate message is exchanged upon a vehicle encounter. Therefore, the message cost can be largely reduced compared with other CS-related work.

IV. SYSTEM MODEL AND PROBLEM DESCRIPTION

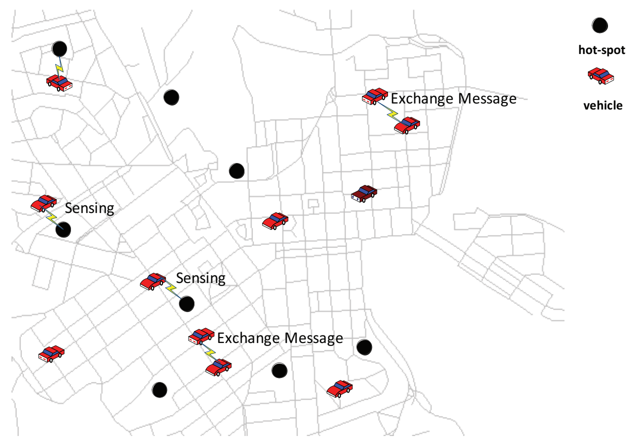

Fig. 1. System model

Fig. 1 shows the system model. A set of vehicles, $V = \{v_1, v_2, \ldots, v_C\}$, can communicate with each other when they are within the communication range through inter-vehicle radio technologies such as Dedicated Short-Range Communication (DSRC) [32]. The vehicles collaboratively monitor N hot-spot locations in a set $H = \{h_1, h_2, \ldots, h_N\}$.

A vehicle can be considered as a mobile node in the vehicular network, whose moving path is usually determined by the driver and/or the passengers. When a vehicle passes by a hot-spot location, the vehicle can collect the road conditions (such as traffic congestion or road surface repair) and store the corresponding context information in its storage. The sensing can be performed by a roadside unit and the data can be carried away by a passing vehicle; alternatively, vehicles equipped with sensors can gather information on the location and road conditions of the nearby hot-spots directly. How to sense the road condition is not our focus. Our goal is to propose an efficient scheme to facilitate in-network data processing and data transmission for vehicles to more quickly gather the global context data.

The mobility of vehicles on the one hand provides the opportunity for vehicles to exchange data upon their encounter, and on the other hand leads the network connectivity to be intermittent which further makes inter-vehicle contacts scarce resources for data transmissions. To allow every vehicle to be aware of the context information of all the hot-spots of a target monitoring environment so it can determine the best path, we propose to leverage the vehicle encountering opportunity to enable efficient and opportunistic context sharing among vehicles.

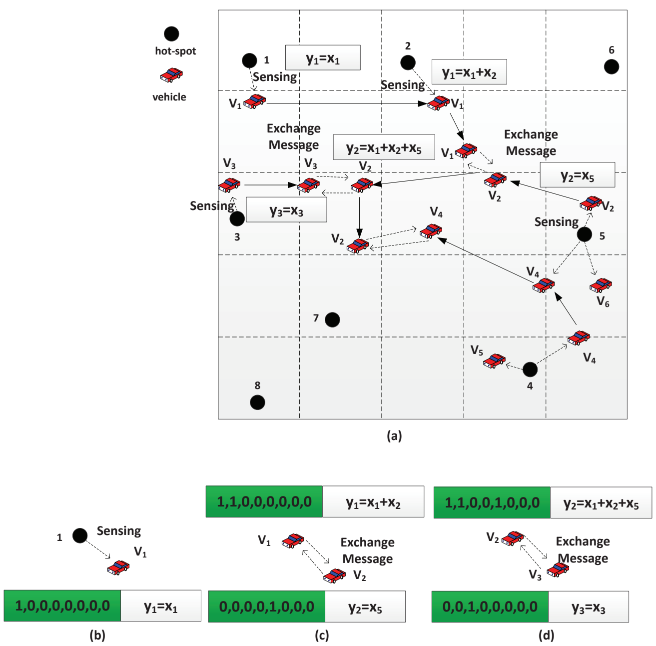

Fig. 2. Exchanging context information by leveraging the opportunity encounter.

In the example of Fig. 2, before vehicles v_1 and v_2 meet each other, vehicle v_1 collects the context information at the location h_1 first and then the location h_2, while vehicle v_2 collects the information at h_5. Instead of sending raw sensing data, a vehicle in our proposed system will exchange an aggregate message to another vehicle encountered to reduce the message cost. When vehicles v_1 and v_2 meet, v_1 will combine context messages at locations h_1 and h_2 and send an aggregate message to v_2. Similarly, vehicle v_2 also sends an aggregate message to v_1.

The road conditions such as traffic congestion and road report will not change instantly. Vehicles passing by the same hot-spot within a short time period will obtain similar context data. Through a small number of random aggregations of the sensory data and message exchanges among vehicles, each vehicle in our proposed network system can achieve a shared view of some aggregate measurements of the global context after several opportunistic encounters. We will apply a CS-based recovery algorithm to recover the global context information based on the aggregate measurement data, so that each vehicle in the network can obtain the full context information in the network.

V. Measurement Aggregation

One of the key issues in the proposed CS-Sharing scheme is to generate the aggregate message to reduce the data exchanged in vehicle networks. We first introduce the structure of the context message, and then our aggregation algorithm.

A. Message structure

Two types of context messages are stored in each vehicle, the *atomic* message containing the context data of only one hot-spot location, and the *aggregate* message summarizing the context of multiple hot-spot locations for a vehicle to exchange with others at low cost.

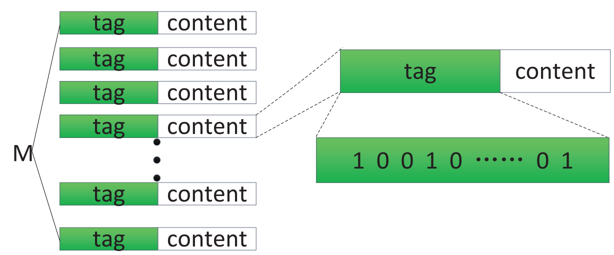

Fig. 3. Format of the context information

In Fig.3, each context message includes two parts, a tag and the corresponding message content. A tag is represented with an N-bit binary vector, and $tag[i] = 1$ indicates the context at h_i ($1 \leq i \leq N$) is included in the message. An atomic context message has one bit set to 1, but an aggregate message generated with n atomic messages will have n corresponding bits set to 1.

B. Message Aggregation

As the vehicle encounter duration is short and a valuable resource which can be exploited for wireless communications, rather than directly transmitting raw context data, we propose to exchange aggregate messages to dramatically reduce the total number of messages and thus the communication cost.

When a vehicle obtains a new message, which can be a new atomic context message collected by itself when passing by a hot-spot or an aggregate context message transmitted from another vehicle, the vehicle will generate a new aggregate message for the future message exchange. Thus, the aggregate message is generated as a random measurement of the global context based on either type of messages. In the next section, we will provide a CS recovery algorithm to reconstruct the individual context data for all locations of interest based on a set of aggregate messages the vehicles obtains. The performance of the CS recovery depends on the properties of the measurement matrix Φ, which is required to meet conditions such as Restricted Isometry Property (RIP) and uniform uncertainty principle (UUP) [26].

Different from the conventional CS work where the measurement matrix is known as a priori, in the next section, we will show that a row of the measurement matrix Φ in the CS-Sharing scheme is generated naturally following the message aggregation process. Thus the message aggregation process directly impacts the properties of the matrix Φ. According to the RIP requirement, the aggregate message should be generated as a random projection of the global context data, so an aggregation algorithm should follow the principles below:

Principle 1. For vehicles in the network to quickly obtain enough information of the global context, an aggregate message should contain as much information as possible.

Principle 2. To make Φ a Bernoulli random measurement matrix to satisfy the RIP property, the corresponding $\boldsymbol{\Phi}$ will not have values larger than 1. Thus when generating an aggregate message, there is a need to avoid including the context data of the same location multiple times, i.e., causing the problem of *redundant context*.

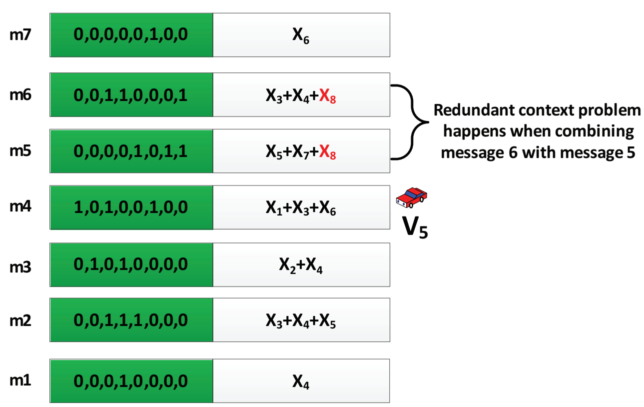

Fig. 4. An illustration of the redundant context problem

In Fig. 4, both messages m_5 and m_6 include the information of the location h_8, which would lead to information redundancy if the two messages are aggregated.

Principle 3. The aggregate message exchange during each encounter corresponds to one measurement in the CS algorithm. As repetitive aggregate messages bring no extra information, to efficiently utilize the inter-vehicle contact opportunities for more information, the aggregate messages exchanged should vary in different encounters with each independently generated.

According to the above principles, we design our aggregation algorithm below.

On line 1 of the Algorithm 1, the vehicle will append the new message at the end of the message list to be used for generating the aggregate message. The maximum length of the message list is set based on the number of measurement messages needed to recover data at a desired accuracy, beyond which the outdated data will be removed from the list.

To generate the aggregate message as a random combination of the sensory data, we first randomly generate a starting location i, and then combine all the messages in the order of m_i, m_{i+1}, $\cdots$, m_n, m_1, $\cdots$, m_{i-1}. Obviously, starting from

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Algorithm 1 Message Aggregation (Executed at each vehicle when a new message is obtained)

Input: The message list stored in a vehicle, $M_{List} = \{m_1, m_2, \cdots, m_n\}$, which contains n messages.
The newly obtained message M_{new};
Output: The aggregate message M_{agg}

1: Append M_{new} to M_{List};
2: Update the total message number, $n = n + 1$;
3: $M_{agg} = NULL$;
4: i = random$[1, n]$, $L_i = i$;
5: **while** $i < L_i + n$ **do**
6: $\quad j = \begin{cases} i \bmod n & i \neq n \\ n & i = n \end{cases}$;
7: $\quad M_{agg}$=Redundancy-Avoidance-Aggregation(M_{agg}, m_j);
8: $\quad i++$;
9: **end while**
10: Return M_{agg}.

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different locations will allow for a higher probability of forming different aggregate messages at a vehicle.

On line 7, two messages are combined into an aggregate message through the function Redundancy-Avoidance-Aggregation in Algorithm 2 to avoid including the redundant information.

Algorithm 2 Redundancy Avoidance Aggregation

Input: Messages m_1 and m_2
Output: The aggregate message M_{agg}

1: $M_{agg} = m_1$;
2: **for** $i = 1$ to N **do**
3: $\quad$ **if** m_1.tag[i] = m_2.tag[i] **then**
4: $\quad\quad$ Message m_1 and m_2 have redundant information;
5: $\quad\quad$ Return M_{agg}
6: $\quad$ **end if**
7: **end for**
8: M_{agg}.tag = m_1.tag + m_2.tag;
9: M_{agg}.content = m_1.content + m_2.content;

In Algorithm 2, CS-sharing compares the tags of two messages to determine whether they contain the information of the same location. If there is no redundant context, the aggregate message is generated by setting its content to the summation of the content value of each message, and the tag is set to indicate all hot-spot locations corresponding to the summation.

As vehicles serve as the mobile nodes to opportunistically collect the context information of the hot-spot locations passed by, to prevent losing the sensed information of a hot-spot, the raw context information collected by a vehicle should be included in the aggregate message to spread across the network. Thus, wherever the starting location is chosen to combine the messages, our algorithm ensures that the atom context data collected by this vehicle are included in the aggregate message to transmit for other vehicles to more accurately recover the global context information.

Fig. 5 shows the messages stored in vehicles v_5 and v_6 before and after their encounter. Figs. 5 (a) and (b) show the messages stored before the encountering. Vehicle v_5 randomly selects its starting location at m_3 to generate the aggregate message, and

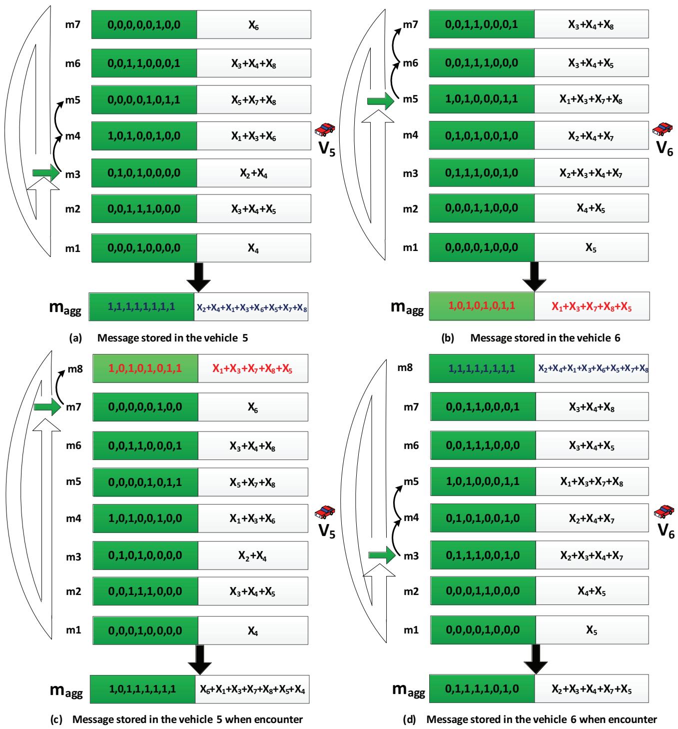


Fig. 5. Messages stored before and after vehicle v_5 and v_6 encounter

v_6 takes the similar operation. The atom messages m_1 and m_7 are included in the aggregate message of vehicle v_5, while the atom message m_1 is included in the aggregate message of vehicle v_6.

When vehicles v_5 and v_6 encounter, they exchange the aggregate message generated individually. Figs. 5 (c) and (d) show the different messages stored after the two vehicles encounter. Generated independently from different starting locations each time, there is a high probability for the aggregated message to be different to follow the Principle 3.

VI. Global Context Recovery

After a short period of time, a vehicle in the network may store M messages, $M_{List} = \{m_1, m_2, \ldots, m_M\}$, and the number of messages stored in different vehicles may be different.

The goal of the vehicle is to recover the raw context information of N monitoring locations using the M messages stored. That is, given a vector $\mathbf{y} \in R^M$ containing M measurement values and the measurement matrix $\mathbf{\Phi}$, a vehicle will solve the recovery problem $\mathbf{y} = \mathbf{\Phi x}$ to recover the global context vector $\mathbf{x} \in R^N$, with $\mathbf{x} = \{x_1, x_2, \cdots, x_i, \cdots, x_N\}^T$, where x_i represents the context data on the hot-spot h_i. That is

$$\mathbf{y} = \mathbf{\Phi x} \Leftrightarrow \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{pmatrix} = \begin{pmatrix} \phi_{11} & \phi_{12} & \cdots & \phi_{1N} \\ \phi_{21} & \phi_{22} & \cdots & \phi_{1N} \\ \vdots & \vdots & \vdots & \vdots \\ \phi_{M1} & \phi_{M2} & \cdots & \phi_{MN} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{pmatrix} \tag{5}$$

where y_i is the content value of message m_i, with $y_i = m_i.content$. The i_{th} row of matrix $\mathbf{\Phi}$ corresponds to the tag of message m_i, with $\phi_{(i)} = m_i.tag$. The entry of matrix $\mathbf{\Phi}$ is

$$\phi_{ij} = m_i.tag[j] = \begin{cases} 1 & m_i \text{ includes the context at } h_j \\ 0 & otherwise \end{cases}$$

Obviously, if $M < N$, Eq.(5) is an under-determined equation and cannot be solved using the conventional matrix theory. Fortunately, in vehicle DTNs, $\mathbf{x} \in R^N$ is usually sparse because events such as congestions in off-traffic time or road repair usually seldom happen. In the traffic hour, the congestion levels can be differentiated, so the number of heavy traffic places is still small. Recent research shows that CS can reconstruct a sparse signal with a lower sampling rate (smaller number of measurements in this paper). Therefore, the sparse context data provides the possibility for us to apply CS theory to recover the global context information in the whole network.

A. RIP property

As stated in CS theory, a sufficient condition for the successful recovery of the event information by CS is that the measurement matrix $\mathbf{\Phi}$ satisfies some conditions (RIP, UUP) to preserve the norm of sparse vectors. In Theorem 1, we will show that our proposed CS-Sharing scheme can yield a random and binary matrix, which provides the vehicle the capability of accurately recovering the global context data with a set of messages gathered by solving the optimization problem defined in (5).

Before providing the proof, we first normalize the measurement matrix $\mathbf{\Phi}$ in (5) to $\mathbf{\Theta}$, where

$$\mathbf{\Theta} = \begin{pmatrix} \theta_{11} & \theta_{12} & \cdots & \theta_{1N} \\ \theta_{21} & \theta_{22} & \cdots & \theta_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{M1} & \theta_{M2} & \cdots & \theta_{MN} \end{pmatrix} \tag{6}$$

with the entry of $\mathbf{\Theta}$ defined as

$$\theta_{ij} = \frac{1}{\sqrt{N}}\phi_{ij} = \begin{cases} \frac{1}{\sqrt{N}} & m_i \text{ includes the context at } h_j \\ 0 & \text{otherwise} \end{cases}$$

After the normalization, we can define another optimization problem $\mathbf{z} = \mathbf{\Theta x}$, where $\mathbf{z} \in R^M$ and $\mathbf{z} = \frac{\mathbf{y}}{\sqrt{N}}$. This problem has the same solution as that defined in (5).

Theorem 1. *According to the CS theory, the global context* $\mathbf{x}$ *can be accurately reconstructed from* $\mathbf{z} = \mathbf{\Theta x}$ *if* $M \geq cK \log N$ *where* c *is a constant,* K $(K << N)$ *is the sparsity level of the context vector* $\mathbf{x}$.

Proof: Obviously, $\mathbf{z} = \mathbf{\Theta x}$ can also be expressed as

$$\begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_M \end{pmatrix} = \begin{pmatrix} \theta_{11} & \theta_{12} & \cdots & \theta_{1N} \\ \theta_{21} & \theta_{22} & \cdots & \theta_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ \theta_{M1} & \theta_{M2} & \cdots & \theta_{MN} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{pmatrix}$$
$$= \begin{pmatrix} \theta_1 & \theta_2 & \cdots & \theta_N \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{pmatrix} = \sum_{i=1}^{N} x_i \theta_i \ ;$$
$$where\ column\ vector\ \theta_i = \begin{pmatrix} \theta_{1i} \\ \theta_{2i} \\ \vdots \\ \theta_{Mi} \end{pmatrix}$$

According to our aggregation algorithm and the random opportunistic encounters, the matrix $\mathbf{\Theta}$ is a $\{0, +1\}$ Bernoulli measurement matrix with $P(\theta_{ij} = \frac{1}{\sqrt{N}}) = P(\theta_{ij} = 0) = \frac{1}{2}$:

$$\theta_{ij} = \begin{cases} \frac{1}{\sqrt{N}} & P(\theta_{ij} = \frac{1}{\sqrt{N}}) = \frac{1}{2} \\ 0 & P(\theta_{ij} = 0) = \frac{1}{2} \end{cases} \tag{7}$$

Let $\hat{\mathbf{z}} = \hat{\mathbf{\Theta}}\mathbf{x}$, where

$$\hat{\mathbf{\Theta}} = \begin{pmatrix} \hat{\theta}_{11} & \hat{\theta}_{12} & \cdots & \hat{\theta}_{1N} \\ \hat{\theta}_{21} & \hat{\theta}_{22} & \cdots & \hat{\theta}_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ \hat{\theta}_{M1} & \hat{\theta}_{M2} & \cdots & \hat{\theta}_{MN} \end{pmatrix} \tag{8}$$

with

$$\hat{\theta}_{ij} = 2\theta_{ij} - \frac{1}{\sqrt{N}} = \begin{cases} \frac{1}{\sqrt{N}} & m_i \text{ includes the context at } h_j \\ \frac{-1}{\sqrt{N}} & otherwise \end{cases} \tag{9}$$

We can rewrite $\hat{\mathbf{z}}$ as follows

$$\hat{\mathbf{z}} = \begin{pmatrix} \hat{\theta}_{11} & \hat{\theta}_{12} & \cdots & \hat{\theta}_{1N} \\ \hat{\theta}_{21} & \hat{\theta}_{22} & \cdots & \hat{\theta}_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ \hat{\theta}_{M1} & \hat{\theta}_{M2} & \cdots & \hat{\theta}_{MN} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{pmatrix}$$
$$= \begin{pmatrix} 2\theta_{11} - \frac{1}{\sqrt{N}} & 2\theta_{12} - \frac{1}{\sqrt{N}} & \cdots & 2\theta_{1N} - \frac{1}{\sqrt{N}} \\ 2\theta_{21} - \frac{1}{\sqrt{N}} & 2\theta_{22} - \frac{1}{\sqrt{N}} & \cdots & 2\theta_{2N} - \frac{1}{\sqrt{N}} \\ \vdots & \vdots & \vdots & \vdots \\ 2\theta_{M1} - \frac{1}{\sqrt{N}} & 2\theta_{M2} - \frac{1}{\sqrt{N}} & \cdots & 2\theta_{MN} - \frac{1}{\sqrt{N}} \end{pmatrix} \times \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{pmatrix}$$
$$= 2\mathbf{z} - \mathbf{C} \tag{10}$$

where $\mathbf{C}$ is defined as

$$\mathbf{C} = \begin{pmatrix} \frac{1}{\sqrt{N}} & \frac{1}{\sqrt{N}} & \cdots & \frac{1}{\sqrt{N}} \\ \frac{1}{\sqrt{N}} & \frac{1}{\sqrt{N}} & \cdots & \frac{1}{\sqrt{N}} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{1}{\sqrt{N}} & \frac{1}{\sqrt{N}} & \cdots & \frac{1}{\sqrt{N}} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_N \end{pmatrix} = \frac{1}{\sqrt{N}} \begin{pmatrix} S_{\mathbf{x}} \\ S_{\mathbf{x}} \\ \vdots \\ S_{\mathbf{x}} \end{pmatrix} \tag{11}$$

where $S_{\mathbf{x}} = \sum_{i=1}^{N} x_i$.

According to Eq.(9), we obtain that $\hat{\mathbf{\Theta}}$ is the $\{-1, +1\}$ Bernoulli measurement matrix with $P(\hat{\theta}_{ij} = \frac{1}{\sqrt{N}}) = P(\hat{\theta}_{ij} = -\frac{1}{\sqrt{N}}) = \frac{1}{2}$. The work in [26] proves that for the $\{-1, +1\}$ Bernoulli measurement matrix, if $M \geq cK \log N$ measurements are collected, according to the uniform uncertainty principle (UUP) condition defined in [26] (and UUP can be refined as Restricted isometry property (RIP) in [31]), then $\mathbf{x}$ can be recovered accurately from $\hat{\mathbf{z}} = \hat{\mathbf{\Theta}}\mathbf{x}$ if $\mathbf{x}$ is K-sparse.

Denote the solution of $\hat{\mathbf{z}} = \hat{\mathbf{\Theta}}\mathbf{x}$ as $\mathbf{x}'$. We further define $\Omega_K(\mathbf{x}')$ as the set of the K sparse location of $\mathbf{x}'$. Obviously, when $i \in \Omega_K(\mathbf{x}')$ we can obtain that

$$\left\langle \hat{\mathbf{z}}, \hat{\theta}_i \right\rangle \in \left\langle \hat{\mathbf{z}}, \hat{\mathbf{\Theta}} \right\rangle_{TOPK} \tag{12}$$

where $\hat{\theta}_i$ is the i-th column vector of matrix $\hat{\mathbf{\Theta}}$, $\left\langle \hat{\mathbf{z}}, \hat{\mathbf{\Theta}} \right\rangle_{TOPK}$ is the set of the largest K Inner product between $\hat{\mathbf{z}}$ and each column of $\hat{\mathbf{\Theta}}$.

Insert $\hat{\mathbf{z}} = 2\mathbf{z} - \mathbf{C}$ into $\left\langle \hat{\mathbf{z}}, \hat{\theta}_i \right\rangle$, we have

$$\left\langle \hat{\mathbf{z}}, \hat{\theta}_i \right\rangle = \left\langle 2\mathbf{z} - \mathbf{C}, \hat{\theta}_i \right\rangle = \begin{pmatrix} 2z_1 - \frac{S_{\mathbf{x}}}{\sqrt{N}} \\ 2z_2 - \frac{S_{\mathbf{x}}}{\sqrt{N}} \\ \vdots \\ 2z_M - \frac{S_{\mathbf{x}}}{\sqrt{N}} \end{pmatrix}^T \begin{pmatrix} \hat{\theta}_{1i} \\ \hat{\theta}_{2i} \\ \vdots \\ \hat{\theta}_{Mi} \end{pmatrix}$$
$$= 2 \begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_M \end{pmatrix}^T \begin{pmatrix} 2\left(\theta_{1i} - \frac{1}{\sqrt{N}}\right) \\ 2\left(\theta_{2i} - \frac{1}{\sqrt{N}}\right) \\ \vdots \\ 2\left(\theta_{Mi} - \frac{1}{\sqrt{N}}\right) \end{pmatrix} - \begin{pmatrix} \frac{S_{\mathbf{x}}}{\sqrt{N}} \\ \frac{S_{\mathbf{x}}}{\sqrt{N}} \\ \vdots \\ \frac{S_{\mathbf{x}}}{\sqrt{N}} \end{pmatrix}^T \begin{pmatrix} \hat{\theta}_{1i} \\ \hat{\theta}_{2i} \\ \vdots \\ \hat{\theta}_{Mi} \end{pmatrix}$$
$$= 4\left\langle \mathbf{z}, \theta_i \right\rangle - \left(\frac{2S_{\mathbf{z}}}{\sqrt{N}} + \frac{S_{\mathbf{x}} S_{\hat{\theta}_i}}{\sqrt{N}} \right) \tag{13}$$

where $S_{\mathbf{z}} = \sum_{i=1}^{M} z_i$, and $S_{\hat{\theta}_i} = \sum_{j=1}^{M} \hat{\theta}_{ji}$.

We can easily obtain that $\lim\limits_{K<<M<<N\to\infty} \frac{2S_{\mathbf{z}}}{\sqrt{N}} = 0$ and $\lim\limits_{K<<M<<N\to\infty} \frac{S_{\mathbf{x}} S_{\hat{\theta}_i}}{\sqrt{N}} = 0$, based on which, we obtain $\lim\limits_{K<<M<<N\to\infty} \left\langle \hat{\mathbf{z}}, \hat{\theta}_i \right\rangle = 4\left\langle \mathbf{z}, \theta_i \right\rangle$. Therefore, we obtain when $i \in \Omega_K(\mathbf{x}')$ both $\left\langle \hat{\mathbf{z}}, \hat{\theta}_i \right\rangle \in \left\langle \hat{\mathbf{z}}, \hat{\mathbf{\Theta}} \right\rangle_{TOPK}$ and $\left\langle \mathbf{z}, \theta_i \right\rangle \in \left\langle \mathbf{z}, \mathbf{\Theta} \right\rangle_{TOPK}$ hold.

Even though different measurement matrixes are adopted in the optimization problems ($\hat{\mathbf{z}} = \hat{\mathbf{\Theta}}\mathbf{x}$, $\mathbf{z} = \mathbf{\Theta}\mathbf{x}$), when $M \geq cK \log N$, the sparsity locations of originally $\mathbf{x}$ can be identified in both $\hat{\mathbf{z}} = \hat{\mathbf{\Theta}}\mathbf{x}$ and $\mathbf{z} = \mathbf{\Theta}\mathbf{x}$. According to greedy pursuit algorithm, if the sparsity locations can be identified, $\mathbf{x}$ can be accurately reconstructed. That is, when $M \geq cK \log N$, $\mathbf{x}$ can be accurately reconstructed from $\mathbf{z} = \mathbf{\Theta}\mathbf{x}$.

■

Denote K as the sparsity level. According to Theorem 1, when the number of messages gathered by a vehicle meets $M \geq cK \log N$, the vehicle can apply the CS recovery algorithm to accurately recover the global context data of all the N hotspots. Our CS-Sharing does not depend on the CS-recovery algorithm, in this paper, we adopt Large-Scale l_1-Regularized Least Squares (l_1-l_s) algorithm [36].

Obviously, the measurement matrix Φ varies in different vehicles because each row in matrix Φ corresponds to an independent aggregate-message generation process. In the simulation part, we will show that despite the difference in the measurement matrices, vehicles in the network can obtain all the global context information in very short time.

VII. Performance Evaluation

We evaluate the proposed CS-sharing scheme through extensive simulations using the Opportunistic Network Environment simulator (ONEs) [37]. As shown in Fig.6, we use the map of Helsinki, Finland as the simulation reference, and the simulations are performed within a $4500m \times 3400m$ area. $N = 64$ hot-spots are randomly deployed on the simulation map, among which events only happen at K hot-spots. There are C Bluetooth-equipped vehicles in the network. Each vehicle is equipped with sensors to collect the road condition. These vehicles are randomly deployed in the network initially, and can move randomly in the network at a speed S.

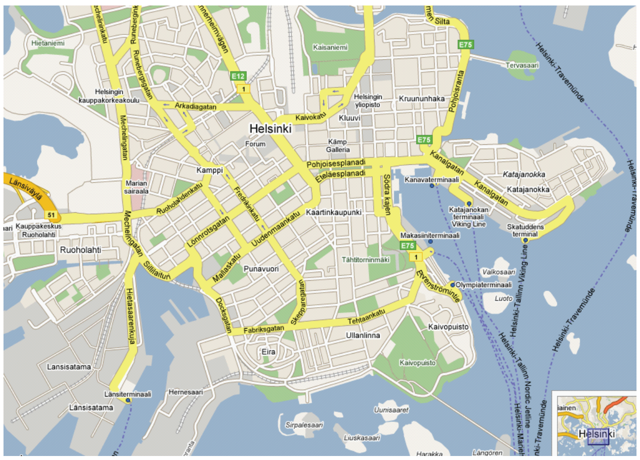


Fig. 6. Simulated map for vehicular DTN

A. The recovery performance under CS-Sharing

In this section, we evaluate the recovery performance under CS-Sharing by varying the sparsity level of the context. In these simulations, we set the number of vehicles to $C = 800$ and the vehicle speed to $S = 90km/h$. We vary the sparsity level K of the context data from 10 to 20. We use the error ratio and the successful recovery ratio as the performance metrics to evaluate the proposed CS-Sharing scheme. These two metrics are defined as follows.

Definition 1. ***Error Ratio:*** *a metric for measuring the reconstruction error of all entries in context vector after the recovery, which can be calculated as*

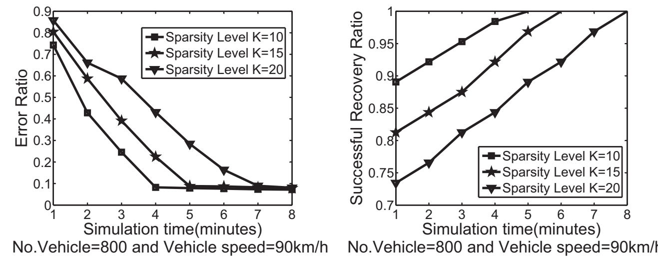
$$\frac{\sqrt{\sum_{i=1}^{N}\left(x_i - \hat{x}_i\right)^2}}{\sqrt{\sum_{i=1}^{N} {x_i}^2}} \tag{14}$$

where N is the number of hot-spots, $\mathbf{x}$ and $\hat{\mathbf{x}}$ are the raw context data and the recovered context data, respectively.

Definition 2. *An element x_i in x is considered to be successfully recovered if the raw data x and the recovered data $\hat{x}$ satisfy that*

$$\frac{|x_i - \hat{x}_i|}{|x_i|} \le \theta \tag{15}$$

where θ is a small threshold for successful reconstruction. In this paper, θ is set to 0.01.



(a) Error Ratio

(b) Successful recovery ratio

Fig. 7. Different sparsity level K

Definition 3. ***Successful Recovery Ratio:*** *a metric measuring the percentage of the context data that are successfully recovered, which can be calculated as:*

$$\frac{\sum_{i=1}^{N}\lambda_i}{N} \text{ where } \lambda_{\mathrm{i}} = \begin{cases} 1 & \frac{|x_i - \hat{x}_i|}{|x_i|} \le \theta \\ 0 & otherwise \end{cases} \tag{16}$$

After obtaining multiple measurements, each vehicle can recover the global context data through the CS recovery algorithm l_1-minimization. In the following simulations, the error ratio and the successful recovery ratio are the average values among all vehicles in the simulation. For a given set of parameters, we repeat the simulations 20 times and take their average.

Fig.7(a) plots the error ratio under different sparsity levels. As the time moves on, there are more vehicles encounters thus more measurements collected by vehicles. Therefore, as shown in Fig. 7(a), for the same sparsity K, the error ratio decreases as the time increases. Moreover, as expected, when K increases, more measurements are needed to recover the global context data to meet the accuracy requirement.

Fig. 7(b) shows the successful recovery ratio under different sparsity level K. According to Eq.(2), the larger the K, the larger the number of measurements needed to successfully recover the global context data. Consequently, with a given number of measurements, the successful recovery ratio reduces as K becomes larger. When time =1 minute, the successful recovery ratios are about 75%, 80%, and 90%, corresponding to $K = 20$, $K = 15$, and $K = 10$, respectively. These demonstrate that our CS-Sharing can correctly recover a large amount of context data within a very short time, which proves that it can be used to efficiently gather context data and share the data among vehicles.

B. Performance comparison with other context sharing schemes

To the best of our knowledge, no existing work applies the compressive sensing to share the information and learn the global context information. To demonstrate the effectiveness of our proposed CS-Sharing scheme, we implement other three schemes (described as follows) which are usually designed for data gathering by sending all data to the sink instead of data sharing for all the vehicles to obtain the global data. Moreover, for performance comparison in a fair way, these three schemes are implemented in the data sharing scenarios similar to this paper.

- **Straight.** As discussed in the introduction, a straight-forward approach to achieve context sharing is to exchange the raw data upon a vehicles encounter.
- **Custom CS.** Following data gathering algorithms in [6], [23], we implement a compressive sensing based data sharing scheme, denoted as Custom CS. In the scheme, for a given sparsity level, a pre-defined $M \times N$ Gaussian matrix is utilized as the measurement matrix according to the sparsity level, and M messages are transmitted in each data exchanging procedure when vehicles encounter.
- **Network coding.** Following algorithms in [38], [39], we implement a network coding based data sharing scheme, in which each vehicle mixes all the messages via algebraic operations to generate the aggregate message to transmit, and vehicles recover the global context information by solving a linear problem defined by messages stored after the vehicles gathered N messages.

We apply the following three metrics to evaluate the performance.

- Successful delivery ratio: the ratio of the successful delivery messages to the total number of messages that need to be transmitted.
- The number of accumulated messages: the number of accumulated messages needed to transmit among all the vehicles in the system.
- Time needed to obtain the global context: the time duration needed for all the vehicles in the system to obtain the global context.

Fig. 8 plots the successful delivery ratio under different data sharing schemes. Our CS-Sharing and Network Coding have the same and the highest successful delivery ratio (i.e., 100%), as both algorithms transmit a fixed-length aggregate message during each vehicle encounter. With the straight-forward raw data exchanges, as the simulation time moves on, vehicles can acquire a large number of messages which makes the transmissions difficult during a short vehicle encounter. This results in the big message loss, and thus quick decrease of the successful delivery ratio, lower than 50% after running 4 minutes. With a fix number of M messages to transmit in each data exchange process, the curve of Custom CS is nearly parallel to the x-axis.

Fig.9 compares the number of accumulated messages to transmit. As expected, our CS-Sharing and Network Coding have the lowest message cost with only one aggregate message transmitted in each vehicle encounter. Custom CS always transmits a fix number of M messages, while every vehicle in Straight needs to transmit all its stored messages which increases with the simulation time. Therefore, the number of accumulated messages in Straight is smaller than that in Custom CS initially, but quickly picks up after the simulation time is beyond 7 minutes.

Fig.10 plots the time needed for all the vehicles to obtain the global context data. Among all the implemented four schemes, our CS-Sharing achieves the lowest time needed. Network coding faces "All or Nothing" problem. That is, if N messages are combined using the network coding, the receiver has to collect at least N messages to recover the N original messages. Thus each vehicle needs to obtain at least N messages to obtain the global context with N hot-spots, which would take a long time to complete. In contrast, CS-sharing can conquer the "All or Nothing" problem faced by the network coding to greatly speed up the information collection. Although the Custom CS adopts compressive sensing technique, as it needs to transmit M messages upon a vehicle encounter, a message loss may lead to the failure of recovering the global context data. Therefore, Custom CS presents the worst performance.

These simulation results demonstrate that, compared with other three data sharing schemes, our CS-Sharing can achieve significantly higher performance, with the lowest message cost and the highest information collect speed.

VIII. Conclusion

In vehicular networks, data can be shared among vehicles through exchanges upon their encounters. To more efficiently leverage the short encountering duration for better opportunistic sharing of the context data, we propose a novel CS-Sharing scheme to enable decentralized context sharing in vehicular DTNs. To reduce the communication cost, rather than transmitting the raw context information, each vehicle opportunistically forwards to other vehicles it encounters an aggregate message summarized from its sensory data stored. In addition, CS-Sharing exploits the sparsity of events to further reduce the total number of message exchanges needed. We propose a novel data structure and an aggregation method that can take advantage of the random and opportunistic vehicle encounters to naturally form the measurement matrix required for CS. Our results demonstrate that in our simulation setting, CS-Sharing allows vehicles in a large network to obtain the full context information within only 1 minute with the successful recovery ratio larger than 90% and a low communication cost.

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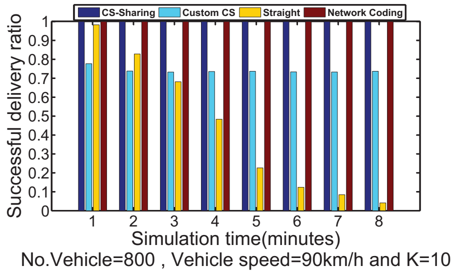

Fig. 8. Success delivery ratio

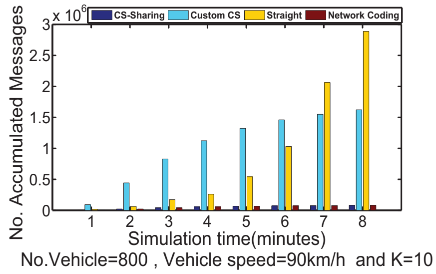

Fig. 9. The number of accumulated messages

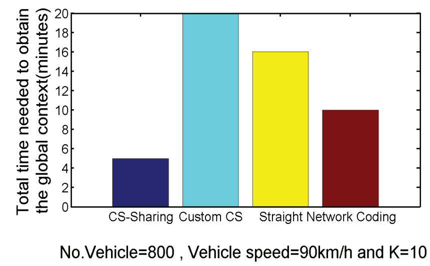

Fig. 10. Time needed to obtain the global context

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