Collaborative Data Dissemination in Opportunistic Vehicular Networks

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Abstract— Future opportunistic vehicular networks offers viable means for collaborative data dissemination by high-capacity device-to-device communication. This is a highly challenging problem because a) mobile data items are heterogeneous in size and lifetime; b) mobile users have different interests to different data; and c) dissemination participants have limited storages. We study collaborative data dissemination under these realistic opportunistic vehicular network conditions and formulate the optimal data dissemination as a submodular function maximisation problem with multiple linear storage constraints. We then propose a heuristic algorithm to solve this challenging problem, and provide its theoretical performance bound. The effectiveness of our approach is demonstrated through simulation using real vehicular traces.

1. INTRODUCTION

Mobile Internet access is getting increasingly popular for providing various services and applications including video, audio and images. Cisco forecasts that mobile traffic will be growing at an annual rate of 131% in 2011, and will reach over 6.3 exabytes per month in 2015 [1]. Two-thirds of the world's mobile data traffic will be video by 2015. Mobile cellular networks provide the most popular method of mobile access today. With the increase of mobile services and user demands, however, cellular networks will very likely be overloaded and congested in the near future. To cope with this explosive growth in traffic demands, offloading mobile data from the overloaded cellular networks to WiFi networks is currently considered [2,3]. The development of opportunistic vehicular networks offers a viable alternative to mobile data offloading. With an increasing number of vehicles equipped with devices to provide device-to-device communication capacities, large scale vehicular ad hoc networks will soon be available. Many applications in vehicular networks will then appear, including high speed Internet access and multimedia content sharing [4]. Since a vehicular network is highly mobile and sometimes sparse, it is hard to maintain a connected network to distribute the content. However, opportunistic contact between vehicles offers high bandwidth communication capacity for content dissemination, known as opportunistic vehicular content dissemination [5].

Collaborative data dissemination in opportunistic vehicular networks is highly challenging for several reasons: 1) the network contains heterogeneous vehicles, in terms of data preference, 2) the data items are multi-types of different delay sensitivities and sizes, and 3) the data dissemination participants' storages are limited in size. The existing works [6–8] did not consider these realistic conditions. We study collaborative data dissemination in realistic opportunistic vehicular networks, and our contribution is threefold: a) formulate the optimal data dissemination with heterogeneous data items and vehicles of limited storage as a submodular function maximisation with linear constraints; b) propose a heuristic algorithm to solve this NP-hard problem and derive the performance bound of this algorithm; and c) demonstrate the effectiveness of our algorithm in challenging opportunistic vehicular network environments through real trace-driven simulations.

2. PROBLEM FORMULATION

In an opportunistic data dissemination system, the service provider chooses some vehicles that are willing to participate in data dissemination, and transmit data to the chosen vehicles. These vehicles then further propagate the data to other users that subscribe the data by device-to-device opportunistic communication. As illustrated in Figure 1, there are two types of vehicles in the system, data dissemination *participator* and data *subscriber*. A participator may store more than one data item, depending on the buffer and data sizes, and a subscriber may be interested in different data items. In general, there are $N + H$ vehicles in the system, labelled as $i \in \{1, 2, \cdots, N + H\}$, while the traffics of I different data items are labelled as $\mathcal{I}$. For any $k \in \mathcal{I}$, its data length is l_k. As the storage in each vehicle is limited, user s can at most buffer L_s size of data items. We use $\mathcal{H}$

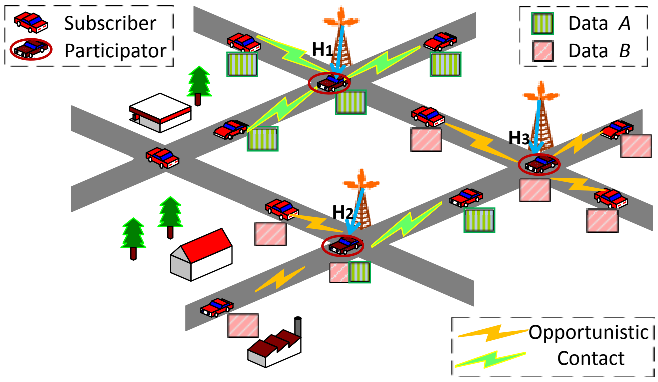


Figure 1: Collaborative data dissemination in the opportunistic vehicular network.

to denote the set of vehicles that are willing to participate the data dissemination, and $\mathcal{N}$ for the other subscriber vehicles, where $|\mathcal{H}| = H$ and $|\mathcal{N}| = N$. Any subscriber in $\mathcal{N}$ may be interested in a data item, and obtains it through device-to-device communication from the participators. Thus, we associate subscriber i is with a vector $\mathbf{w}_i = [w_{i,1}\ w_{i,2} \cdots w_{i,I}]^{\mathrm{T}}$, where $w_{i,k}$ defines the user's interest in data item k and $w_{i,k} = 0$ means that user i is completely not interested in data k. Without loss of generality, $\sum_{k=0}^{I} w_{i,k} = 1$ for $\forall i$. Vehicles can communicate with each other only when they move to within the transmission range, which is called a communication contact. The communication contact between vehicles i and j is assumed to obey the Poisson process with a contact rate $\gamma_{i,j}$. Poisson distributed contact rate has been validated to fit well to real vehicular traces and is widely used to model opportunistic vehicular systems [9–11].

Let $\mathbf{X} = (x_{s,k})$, $s \in \mathcal{H}$, $k \in \mathcal{I}$, be the storage allocation policy, in which $x_{s,k} \in \{0, 1\}$ and $x_{s,k} = 1$ indicates that participator s stores item k in its buffer. A lifetime T_k is assigned to each item k, and all the users will discard this data at deadline T_k. If subscribers do not receive a required item from dissemination participators after the lifetime is expired, they will try to get it directly from the service provider. Therefore, we should maximise the expectation of the disseminated data size in all the subscribers, and this objective function can be expressed as $U(\mathbf{X}) = \sum_{k\in\mathcal{I}} l_k \sum_{i\in\mathcal{N}} d_{i,k}$, where $d_{i,k}$ is the probability that user i receives data k before deadline T_k. As more than one participator may store item k, we define the *dissemination opportunity* metric for $s \in \mathcal{H}$, $i \in \mathcal{N}$ and $k \in \mathcal{I}$, as $t_{s,i,k}$, which is the probability that user i obtains content k from participator s. Because the contact rate between s and i follows the Poisson distribution with rate $\gamma_{s,i}$ and the contact event is independent of user interests, we model the dissemination opportunity as the Poisson process with rate $\gamma_{s,i} w_{i,k}$. Hence, $t_{s,i,k} = 1 - e^{-x_{s,k}\gamma_{s,i} w_{i,k} T_k}$ and $d_{i,k} = 1 - \prod_{s\in\mathcal{H}}(1 - t_{s,i,k})$. The expectation of the total disseminated data size can then be written as:

$$U(\mathbf{X}) = \sum\nolimits_{k\in\mathcal{I}} l_k \sum_{i\in\mathcal{N}} \Big(1 - e^{-w_{i,k} T_k \sum_{s\in\mathcal{H}} x_{s,k}\gamma_{s,i}}\Big). \tag{1}$$

For the subset of $\mathcal{H} \times \mathcal{I}$, $\mathbf{A} \subseteq \mathcal{H} \times \mathcal{I}$, we define the storage allocation policy $\mathbf{X}$ as

$$\mathbf{X} = F(\mathbf{A}), \text{ s.t. } x_{s,k} = 1 \text{ if } (s,k) \in \mathbf{A} \text{ and } x_{s,k} = 0 \text{ if } (s,k) \notin \mathbf{A}.$$

Since $F(\mathbf{A})$ is a bijection, the utility function $U(\mathbf{X})$ over the subset $\mathbf{A} \subseteq \mathcal{H} \times \mathcal{I}$ is

$$\widehat{U}(\mathbf{A}) = U(F(\mathbf{A})) = \sum\nolimits_{k\in\mathcal{I}} l_k \sum\nolimits_{i\in\mathcal{N}} \Big(1 - e^{-w_{i,k} T_k \sum_{s:(s,k)\in\mathbf{A}} \gamma_{s,i}}\Big). \tag{2}$$

Thus, maximising the system's expected disseminated data size for all the items and over all the subscribers can be specified as the following optimisation problem

$$\max U(\mathbf{X}) \text{ or } \max \widehat{U}(\mathbf{A}), \text{s.t. } x_{s,k} \in \{0,1\}, \forall s \in \mathcal{H}, k \in \mathcal{I}, \text{ and } \sum\nolimits_{k\in\mathcal{I}} l_k x_{s,k} \le L_s, \forall s \in \mathcal{H}, \tag{3}$$

where $\sum_{k\in\mathcal{I}} x_{s,k} l_k \le L_s$ is the buffer size constraint of dissemination participator s.

3. DATA DISSEMINATION ALGORITHM

Submodularity is found in various problems [12–14]. A function f defined on subsets of the universe $\mathbf{C}$ is called *submodular*, if and only if $f(\mathbf{A} \cup x) - f(\mathbf{A}) \ge f(\mathbf{B} \cup x) - f(\mathbf{B})$ holds for $\forall \mathbf{A} \subseteq \mathbf{B} \subseteq \mathbf{C}$ and $\forall x \in \mathbf{C} \backslash \mathbf{B}$. Due to space limitation, we offer the following theorem without proof.

Theorem 1. The system utility function $\widehat{U}(\mathbf{A})$ is a submodular function on $2^{\mathcal{H}\times\mathcal{I}}$, and the problem (3) is NP-complete.

Thus, the problem (3) is an NP-hard submodular function maximisation with multiple linear constraints (MLCs). The computer science community has studied this type of optimisation [12,15]. In [12], an algorithm is proposed to solve this problem by an approximation, but it has a very high complexity. Taking the system with 5 participators and 10 data items as an example, the computation time for the first step of Rounding Procedure in [12] is more than 10^{15}. We propose a greedy based heuristic algorithm to solve this problem by allocating storage one by one.

When one more copy of an item is stored in a participator, which meets the constraints, the objective function is enhanced. The gain in the objective function is generally different for different choices of item and participator. As our first greedy strategy, we select the items and participators that maximise the gain on the objective function at each stage, that is, select (s_0, k_0) as

$$(s_0, k_0) = \arg \max_{(s,k)\in\mathbf{P}} \Big(\widehat{U}(\mathbf{A}\cup(s,k)) - \widehat{U}(\mathbf{A})\Big), \tag{4}$$

where $\mathbf{A}$ is the set of chosen data items and participators, and $\mathbf{P}$ is the set of possible solutions that satisfy the storage constraint. The length of each data is also important because, although an item may offer a large gain, it may also have a huge length such that other items cannot be stored. Our second greedy strategy is to calculate the gain per unit data length for each choice of item and participator, and select the pair that maximises this per-unit-length gain, that is, select

$$(s_0, k_0) = \arg \max_{(s,k)\in\mathbf{P}} \frac{\widehat{U}(\mathbf{A}\cup(s,k)) - \widehat{U}(\mathbf{A})}{l_k}. \tag{5}$$

Our heuristic algorithm, listed in Algorithm 1, performs both these two greedy strategies and chooses the better result from the two solutions. Algorithm 1 is a pseudo-polynomial-time algorithm with the complexity $O(H^3I^2N)$, which is acceptable in practice. We analyse the performance bound of this algorithm in the following theorem. Space limitation precludes the proof.

Theorem 2. Denote the optimal solution of the problem (3) by $\mathbf{OPT} = \arg\max_{\mathbf{A}\in\mathbf{Q}} \widehat{U}(\mathbf{A})$, where $\mathbf{Q} \subseteq 2^{\mathcal{H}\times\mathcal{I}}$ is the feasible solution set. The solution obtained by Algorithm 1, $\mathbf{OPT}^*$, satisfies

$$\widehat{U}(\mathbf{OPT}^*) \geq \frac{1}{2}\Big(1 - e^{-\frac{L-\mu}{L}}\Big)\widehat{U}(\mathbf{OPT}), \text{ where } L = \sum\nolimits_{s\in\mathcal{H}} L_s \text{ and } \mu = (H-1)\cdot \max_{k\in\mathcal{I}} l_k.$$

4. SIMULATION RESULTS

The performance of our **Heuristic Algorithm** is compared with the following schemes: 1) **Random Algorithm**, in which each participator chooses the data items randomly to fill its buffer until no more item can be stored; 2) **Homogeneous Algorithm** [8], where the system allocates the buffer based on the assumption that all participators have the same storage size and the lengths of all data items are identical; and 3) **SFM Algorithm** [12], which uses some approximation algorithms to maximise a submodular set function subject to MLCs. Our evaluation was conducted on two realistic vehicular mobility traces, *Shanghai* trace [16] and *Beijing* trace, which record the positions of vehicles carrying GPS devices. In *Beijing* trace, we utilised the GPS devices to collect the taxi locations and timestamps of 2700 participating taxis, and used GPRS modules to report the records every one minute for moving taxis. In the simulation, a node updated its contact rates with other nodes in real-time, based on the up-to-date contact counts since the network started, and we used halftime of the trace to obtain the contact rates of each node pairs. We randomly chose 10% of the vehicles as the participators and used the rest as the subscribers. We set the number of data items as 35 in *Shanghai* trace and 50 in *Beijing* trace. The sizes of data items were generated randomly and uniformly in the range of $[50\,\mathrm{kB},\ 150\,\mathrm{kB}]$, while the data lifetimes followed the uniform distribution in $[0,\ 2T_a\,\mathrm{s}]$, where T_a is the average data lifetime. The participator buffer sizes were randomly and uniformly generated in $[0,\ 2l_a\,\mathrm{kB}]$, where l_a is the average buffer size. User interests to different data items followed the exponential distribution with an expectation of 20.

The results for *Shanghai* trace are shown in Figure 2, where the dashed curve indicates the theoretical disseminated data size calculated by each algorithm and the solid curve is obtained

Algorithm 1 Heuristic algorithm for data dissemination.

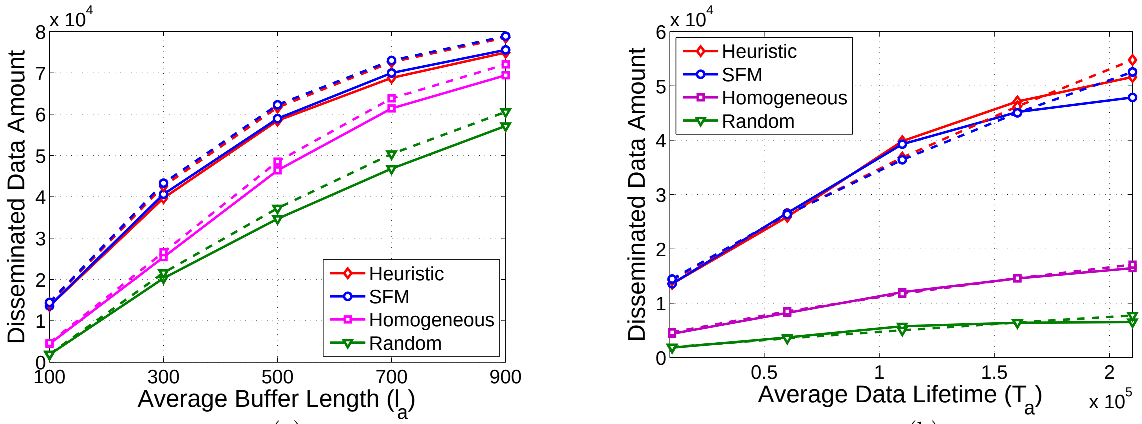
Initialise $m = 0$ and $\mathbf{A}_0 = \emptyset$;
while $m = 0$ or $\widehat{U}(\mathbf{A}_m) - \widehat{U}(\mathbf{A}_{m-1}) > 0$ **do**
  $m = m + 1$; $(s_m, k_m) = \arg\max_{(s,k)\in\mathbf{P}} \left(\widehat{U}(\mathbf{A}_{m-1} \cup \{(s,k)\}) - \widehat{U}(\mathbf{A}_{m-1})\right)$; $\mathbf{A}_m = \mathbf{A}_{m-1} \cup \{(s_m, k_m)\}$;
end while
Initialise $j = 0$ and $\mathbf{B}_0 = \emptyset$;
while $j = 0$ or $\widehat{U}(\mathbf{B}_j) - \widehat{U}(\mathbf{B}_{j-1}) > 0$ **do**
  $j = j + 1$; $(s_j, k_j) = \arg\max_{(s,k)\in\mathbf{P}} \frac{\widehat{U}(\mathbf{B}_{j-1} \cup \{(s,k)\}) - \widehat{U}(\mathbf{B}_{j-1})}{l_k}$; $\mathbf{B}_j = \mathbf{B}_{j-1} \cup \{(s_j, k_j)\}$;
end while
if $\widehat{U}(\mathbf{A}_m) > \widehat{U}(\mathbf{B}_j)$ **then**
  $\mathbf{OPT}^* = \mathbf{A}_m$;
else
  $\mathbf{OPT}^* = \mathbf{B}_j$;
end if
Return $\mathbf{OPT}^*$ and $\widehat{U}(\mathbf{OPT}^*)$;

by simulating the system with the buffer allocation strategy of each algorithm. The accuracy of our formulated problem is validated by the fact that the theoretical and simulation results are very close. Figure 2 (a) shows that, with a fixed average data lifetime and different average buffer sizes, our Heuristic algorithm achieves almost the same performance of the SFM algorithm, and it outperforms the Random and Homogeneous algorithms considerably. The results under a fixed average buffer size and different average data lifetimes are shown in Figure 2 (b). It can be seen that, for the average lifetime larger than 10000 s, our Heuristic algorithm even achieves about 2% to 9% higher data amount than the SFM algorithm. Moreover, our Heuristic algorithm dramatically outperforms the Random and Homogeneous algorithms. The results using *Beijing* trace are shown in Figure 3. Again, the simulation results agree with the theoretical results, and similar observations to those for *Shanghai* trace can be drawn. For *Beijing* trace, our Heuristic algorithm achieves a slightly better performance than the SFM algorithm.

The above results confirm that our Heuristic algorithm performs much better than the Homogeneous algorithm, which does not consider the heterogeneous features of data length and buffer size, and the Random algorithm. Most significantly, our Heuristic algorithm achieves almost the same or slightly better performance in comparison with the SFM algorithm, which is not very piratical due to its very high computational complexity. This demonstrates the effectiveness of our approach.

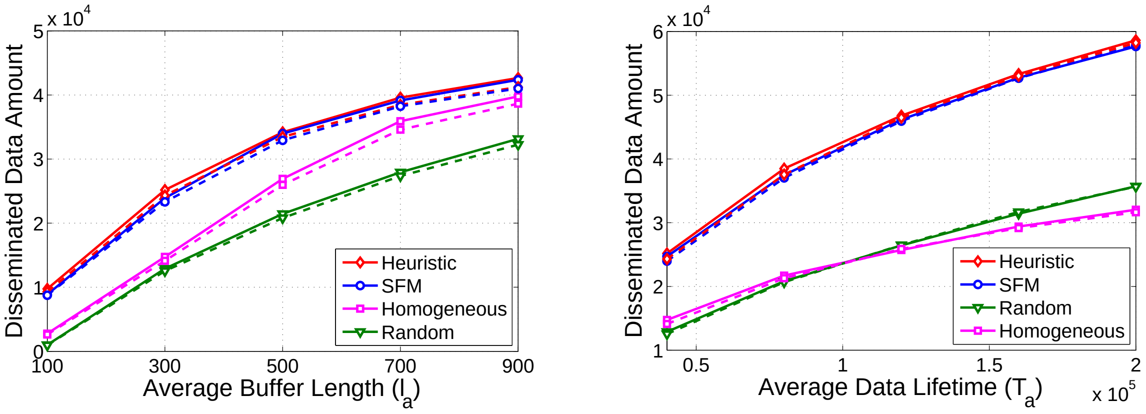
5. CONCLUSIONS

We have studied the collaborative mobile data dissemination in a realistic opportunistic vehicular network environment, where the network is heterogeneous, in terms of the disseminated data being



(a) (b)

Figure 2: Results of different algorithms for *Shanghai* trace with (a) the fixed average data lifetime of 10000 s and variable average buffer size, and (b) the fixed buffer size of 100 kB and variable average data lifetime, where dashed curves are theoretical results and solid curves are simulation results.



(a) (b)

Figure 3: Results of different algorithms for *Beijing* trace with (a) the fixed average data lifetime of 40000 s and variable average buffer size, and (b) the fixed average buffer size of 300 kB and variable average data lifetime, where dashed curves are theoretical results and solid curves are simulation results.

multi types with different delay sensitivities and lengths as well as the participators' storages being limited with difference sizes. By formulating this challenging problem as a submodular function maximisation, we have designed an efficient heuristic algorithm to allocate the buffer. Simulation results have demonstrated that our algorithm achieves almost the same performance as the very high-complexity SFM algorithm, traditionally used to solve this type of challenging problems.

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