Self-Optimizing Citizen-centric Mobile Urban Sensing Systems

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Abstract

In this paper, we develop a novel networking scheme that supports both real-time and delay-tolerant urban sensing applications. This maintains optimality through self-adapting its communications strategy using either inexpensive short-range opportunistic transmissions or reliable long-range cellular radios. Core to this scheme is the trading of mobile sensor data in a virtual market where we demonstrate that our scheme can incentivize phone users to participate. We show that the scheme can optimise network throughput while minimising total phone costs, in terms of 3G and battery costs.

1 Introduction

The integration of sensing, computing and communication capabilities in mobile devices has turned them to a powerful computing and sensing platform. The ubiquity of these sensor-rich smart-phones is beginning to play an increasingly important role in the evolution of cyber-physical systems (CPS) in urban scenarios.

Sensing is a crucial component for CPS, which process and react to the data gathered from the physical environment autonomously. The sheer numbers of mobile phone users combined with the relatively powerful computing and communication capabilities of modern phones, make mobile sensing a much more flexible and cost-effective paradigm than traditional CPS such as Wireless sensor Networks. Furthermore, the inherent phone owner mobility enables increased sensing coverage both spatially and over time; providing opportunities to collect data at a higher granularity and with broader coverage. Mobile sensing can exploit the social structures of the physical world to improve the performance of cyber world and in doing so provides better services to the users in the physical world by optimising the organization of the available resources in cyber world. This paves the way towards large-scale citizen-centric urban sensing applications for smart cities [12].

Figure 1 illustrates a typical Mobile Urban Sensing System (MUSS). According to the demands of specific sensing applications, mobile phones can produce sensing data such as available parking places, traffic congestion, noise levels, air pollution, and smart meter readings. The sensor data can be sent to the MUSS server through cellular communication or be multi-hopped via short-range radios such as WiFi direct, Bluetooth, and LTE direct.

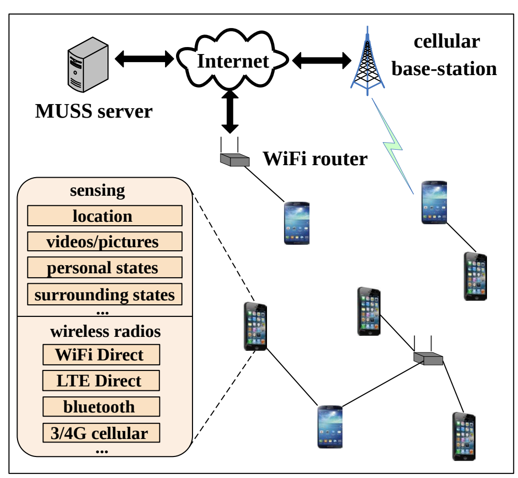

Figure 1: Conceptual illustration of the mobile urban sensing system.

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A MUSS has the following distinguishing characteristics:

1. **Large Sensing Coverage and huge volume of data:** MUSS has the potential to monitor every interesting element in a city, and then relay sensed data to the Internet. As a result, it is predicted to be one of the major sources of big data.
2. **Self-organization/Self-healing:** In MUSS, mobile phone users can join and leave the network very frequently. Similarly disasters and the dynamic nature of urban environments can cause network failure. Therefore, MUSS should adapt autonomously to current network states such as channel conditions and evolving logical network topologies.
3. **Heterogeneous data types:** Due to the diversity of MUSS applications and their potential to require large sensing coverage, sensor data formats will vary considerably; from simple physical readings such as ambient light to video frames. In turn this data would differ in lifetime, monetary value, and privacy level, etc.
4. **Social/Economic Concerns of Self-Interest Phone Users** Mobile phone users may not be willing to fulfil a MUSS task, due to privacy concerns and the potential costs that would be incurred impacting battery usage and the amount of money they pay for communications 3/4G. Therefore, taking account of the social and economic behaviours of phone users is vital to the success of MUSS.

In this paper, we show how to provide autonomic and cost-effective networking services for MUSS considering all the features discussed above. We firstly present a brief review of mobile phone sensing research, and examine the main communication techniques designed to support MUSS. We develop a joint pricing and data routing scheme aiming to support both real-time and delay-tolerant MUSS applications by seamlessly combining cellular communication [9] and opportunistic networking [2]. Off-loading communication to low cost(free), short range communications releases the burden on traditional communications technologies which will reach upper physical bounds if all future city CPS systems use them.

2 Background

In this section, we present a brief review of current mobile sensing research and communication support for mobile phone sensing. For recent comprehensive surveys, we refer the reader to [8, 7, 4].

2.1 Mobile Phone Sensing

According to different sensing scales, mobile phone sensing applications can be categorized into personal sensing, community sensing, and public sensing; HyperFit [6], CenceMe [10],CarTel [5] are examples of personal, community and public sensing deployments respectively. Community and public sensing can play significant role in the development of CPS in smart cities where one wishes to better understand large-scale phenomena through citizens collaboration.

Defined by awareness of phone users, mobile phone sensing can be classified into two different sensing paradigms: *Participatory Sensing* requires active participation from the phone users in terms of collecting and sampling the data. e.g., manual entry of lowest prices or deals for goods or taking a picture.*Opportunistic Sensing* shifts the burden of MUSS tasks from the phone users to the background sensing system, which makes it more suitable for community/public sensing.

Currently, the majority of mobile sensing applications send sensing data directly to the server through single-hop 3/4G *cellular radio communications*. However, due to limitations such as 3/4G costs to the phone users [9] and cellular system's capacity bounds [3], using cellular communication solely would not be a feasible solution for the potential huge volume of urban sensing data.

With the increase in the short-range communication capabilities of smart phones, such as in WiFi Direct for Android OS 4.0+, efficient neighbour discovery [1], and the development of smart Device-to-Device (D2D) communications [3]; it becomes more and more promising to use *opportunistic networking* [2] for delay-tolerant MUSS applications [1, 13, 14]. By leveraging inherent human mobility and low-cost short-range communication, sensor data can be sent to base-stations (e.g. WiFi routers) in a carry-and-forward fashion by relaying the data in short hops via different mobile phones.

This opportunistic networking can significantly reduce energy and telephony costs for phone users and at the same time mitigate sensor data traffic load over cellular communication channels.

3 A Citizen-centric Networking Scheme for MUSS

In this section, we present our lightweight and fully distributed networking scheme to support both real-time and delay-tolerant MUSS applications in a cost-effective way, through the combination of cellular communication and WiFi direct. Specifically, we consider a MUSS network that consists of three types of nodes: smart phones, static WiFi routers, and a cellular base-station as shown in Figure 2 Each phone can report sensed data to the mobile sensing server through 3G cellular radio directly, or through a WiFi router nearby. In addition, two nearby phones have the opportunity to communicate directly to each other through WiFi Direct during their contact duration, such as phones B and C shown in Figure 2. In our model, each data packet produced by a smart phone has a monetary value (e.g. which can be represented in terms of a national currency or tokens to be traded in other ways such as to purchase mobile phone apps). Further, each packet is has a lifetime *e.g.*, 10 minutes, and its duration is tightly coupled to the worth specific applications attribute to the packet. The MUSS operates in discrete time with a unit time slot t =1, 2, ... Every phone x maintains a data buffer that stores the sensor data packets generated by its own sensors, and the data received from other phones.

3.1 Algorithm Description

At every time slot t =1, 2, ..., our scheme operates as follows:

Sensor Data Sampling

1. According to the requirements of the MUSS application (e.g. the demands of external MUSS users), each phone x generates sensor data packet(s), and then assigns its monetary value and initial Time-To-Live (TTL) value to each packet. Then, x inserts the sensor data packets into its phone data buffer.

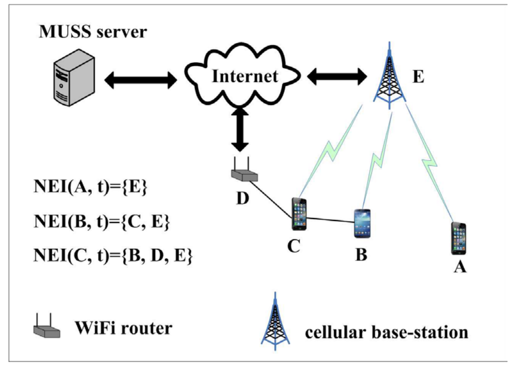


Figure 2: Example of MUSS network to describe the proposed scheme.

Instantaneous Neighbour Discovery

2. Each node x builds a one-hop neighbour table $NEI(x, t)$, consisting of the cellular base-station, and all phones and WiFi routers that can connect to x through WiFi radios at current slot t. Neighbour discovery schemes such as [1] can be used. Take Figure 2 for instance, the instantaneous one-hop neighbour table of phone C, $NEI(C, t)$, consists of three nodes: B, D, and E.

Transmission Quality Estimation

3. Each node x estimates its transmission capacity, $rate_{x,y}(t)$, between itself and each of its instantaneous neighbours y in $NEI(x, t)$, i.e. the maximum number of packets that x can transmit to y, based on the data rates of their wireless radios and WiFi duty-cycle settings of x and y [1].

4. Each node x estimates the monetary costs of sending and receiving a packet, denoted as $scost_x(t)$ and $rcost_x(t)$ respectively, based on its remaining energy, system resource usage, and 3G bills costs. It worth noting that if x is a WiFi router or the cellular base-station, its receiving cost, $rcost_x(t)$, is equal to zero.

Pricing

5. Each phone x sets its current data selling price, $sell_x(t)$, as the total monetary value of the data packets in its data buffer multiplied by a positive system parameter α, set by the server. For instance, if α = 0.1 and x's data packets are worth 10 cents,

therefore $sell_x(t) = 1$ cent per packet. Then phone x communicates the selling price $sell_x(t)$ to all nodes in $NEI(x,t)$. Recall, the selling prices of any cellular base-station and WiFi router are set as zero for every slot.

Profits computing

6. Each phone x computes the potential individual profits, $profits_{x,y}(t)$, it could obtain by selling data to each of its neighbours y in $NEI(x,t)$. $profits_{x,y}(t)$ is computed as a function of the cost (that would be incurred in this potential data trading) and selling price differences between x and y

$$\begin{aligned} & profits_{x,y}(t) \\ & = (sell_x(t) - sell_y(t) - scost_x(t) \\ & \quad -rcost_y(t))rate_{x,y}(t) \end{aligned} \tag{1}$$

Data Trading

7. Denote y^* as the neighbour that can currently give phone x maximum profits if it sells on its data. If $profits^*_{x,y}(t) > 0$, then x sells $rate^*_{x,y}$ (t) number of packets to y. Note that the number of packets are a function of the communications rate so as to not overload that link. A data packet with a smaller TTL will be forwarded with a higher priority. Packets which have reached a 0 TTL value will be dropped as they are deemed no longer useful to the application.

8. Upon receiving data packets from the seller x, the buyer y^* pays $(sell_x(t) - sell_y(t) - rcost_y(t))rate_{x,y}(t)$ total amount of money to x, which means that the cost incurred in this trade is paid by the seller x.

In this scheme, devices can seamlessly switch between short range and long-range communication. At a moment in time each seller node selects the neighbour node with the minimal price and minimal transmission cost as the potential buyer (The node to recieve the data). It encourages system to transmit data to other neighbours using short-range communication due to high cost of long-range communication (3G).

The above scheme is very lightweight, as it implements simple arithmetic calculations and does not require any historic information to be maintained. Also it does not require future knowledge of mobile phones and their trajectory to be speculated.

3.2 Throughput Optamality and Self- *

Since the total value of the data carried by each phone in its buffer is proportional to its queue backlog, it can be verified that the proposed scheme implicitly solves a stochastic optimization problem (i.e. we minimize the total transmit and receive costs for all phones) in a fully distributed way, by using the Lyapunov "drift-plus-penalty" method [11]. According to Lyapunov optimization theory, optimal throughput and long-term minimization of global system costs can be achieved, by controlling the weight between queue backlogs and communications costs [11]. In our scheme, this weight is controlled by the price scaling parameter α. Based on the Lyapunov "drift-plus-penalty" method, it is not difficult to verify that as α decreases, the global system costs (total cost of all phone users) also decrease, but the average queue backlogs increase resulting an increase in end-to-end transmission delays. Therefore, by controlling the pricing parameter α it is not difficult to prove that the proposed scheme can not only achieve throughput optimality, which is highly desirable when transmitting large volumes urban sensing data; but it can also minimize the total cost incurred by the phone users [14, 11].

Besides achieving throughput optimality, our scheme exhibits the following autonomic behaviours.

1. *Self-optimization* Since the neighbour table on each phone can include a cellular base-station, and all WiFi routers and other phones nearby, the phones can optimize their profit by automatically switching data transmission between WiFi radio and cellular radio, according to selling prices and transmission costs.

2. *Self-organization* This scheme is fully distributed, because it requires only the local information of each mobile phone and its current one-hop neighbours. This enables MUSS to self-organize based on current network state and topology. Moreover it is flexible enough to cope with partial failure of communication infrastructure *e.g.*, by natural disasters and can scale across urban space.

4 Evaluation

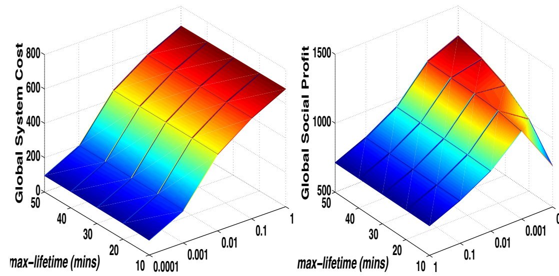
4.1 Simulation Settings

To evaluate the performance of our scheme, we constructed extensive simulations using the realistic simulator Castalia (http://castalia.npc.nicta.com.au/). We randomly deployed a 151-node MUSS in a $800m \times 800m$ geographic area, consisting of 10 WiFi routers, 140 mobile phones, and one cellular base-station. We set the duration of a slot to 1 second and each simulation lasts for 10^6 seconds (around 12 days). The transmission ranges of the WiFi direct radio was set to 50 meters i.e. the typical WiFi direct transmission range in practice (http://www.wi-fi.org). The time-varying transmission capacities of all cellular and WiFi radios were randomly set between 1 and 50 packets per second. We used a realistic human mobility model, Heterogeneous Human Walk (HHW) [15], to simulate the mobility of smart phones. The movement speed of each phone was randomly distributed between 1 and 10m/s (i.e. representing walking speeds and typical urban vehicular speeds).

Each sensor and mobile phone produces sensor packets with a random monetary value of 10 credits at a rate of one packet per second. For every mobile phone, the receiving and transmitting costs of WiFi radios were randomly set between 0.1 and 1 credits per packet, while that of the cellular communications were set between 1 and 10 credits per packet.

4.2 Impact of Packet Lifetime and Pricing Parameter α

In this set of simulations, we study the impact of different packet lifetimes and the pricing parameter α on the global system cost and global social profits. The lifetime (i.e. the initial TTL value) of each generated packet was randomly set between 5 seconds and the $max-lifetime$ minute, this latter parameter is a simulation variable ranging from 10 to 50 minutes. The randomness of the packet lifetime assignment can reflect the heterogeneity of mobile sensing data. The simulation results are shown in Figure 3a and Figure 3b. In all simulations, around 10%-65% of the sensor data traffic is sent through cellular radios, and the rest is sent over WiFi direct radios.

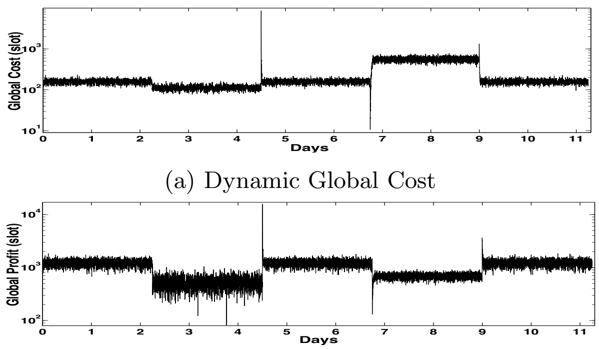


(a) Global Cost (b) Global Profits

Figure 3: Impact of sensor data lifetime and parameter α on System Cost and Global Profits.

We use time-average global system costs and global social profits (both in credits per second) to measure the performance of our scheme. Here the global system cost is measured as the sum of both the transmission and reception costs of all phones, and global social profits is computed as the total value of all the successfully received packets (by the MUSS server) minus the total system cost.

As illustrated in Figure 3a, the total system cost shows a monotonically decreasing trend as the pricing parameter α decreases; this verifies our optimal throughput discussion in Subsection 3.2. By setting a sufficiently small α, the global system cost can be arbitrarily close to the minimal, according to Lyapunov optimization theory. However, the end-to-end delay becomes large as α decreases, resulting a higher risk of a packet being dropped, taking TTL into account. This is reflected in Figure 3b, where the global social profit shows a concave curve as α decrease when the packet life time is large. This is caused by the joint effects of decreased system cost and increased in dropped packets. When max-lifetime is sufficiently large, global social profits exhibit a monotonically increasing function of α. This is because the impact of packet loss caused by expired TTL on the global social profits can be ignored. It is worth noting that every phone obtained positive profit in all simulations. This means that our scheme manages to incentivize phone users to participate in the MUSS because they receive a fair reward.



(a) Dynamic Global Cost

(b) Dynamic Global Profits

Figure 4: Impact of Dynamic environment on System Cost and Global Profits.

4.3 Self-Configuration in Dynamic Environment

To study the ability of our proposed scheme to adapt to changing scenarios, we constructed experiments by dividing the total simulation time into five periods of equal duration of 2×10^5 secs. In first period, MUSS operates normally with operational cellular and Wifi communication. In the second period, we disabled the cellular communication of all nodes so that data packets can only be transmitted and received directly through Wifi direct radios (simulating cellular failure similar to what has occured in disaster situations). MUSS returns back to normal (mixed) state in the third period. In fourth period we disabled Wifi direct communication between all the nodes in the network, so that nodes can only transmit data packets through cellular communication. Finally, network returns again to normal state in the fifth period.

Here we used global system costs and global social profits in every slot (both in credits) to measure the effect of changing topology over time. Here the global system cost is measured as the sum of both the transmission and reception costs of all phones in a slot. Global social profits is computed as the total value of all the successfully received packets (by the MUSS server) minus the total system cost in a slot.

In Figure 4, we can see that in the second period, the global system cost decreases when we cellular communication is disabled. This is due to all the transmissions being relayed through Wifi direct only, which is cheaper than cellular communication. However, global phone user profits also decrease in spite of the decrease in cost. This is due to the large delay in multi-hop transmission which results in increased number of dropped packets with smaller TTL. In the fourth period, system costs increase significantly when Wifi direct communication is disabled due to the high cost of cellular communication. This is also reflected by the decrease in global profits of the MUSS. We can also see that the network self-adjusts very quickly to the changing conditions of the network. When the network returns to normal operation in third and fifth period, the data buffer of the phones contain large numbers of data packets that are sent instantly after availably of alternate option. This is the reason behind sudden spikes in system cost and global profits at the start of these periods. Once the backlog reduces, the system becomes stable.

5 Conclusion

In this paper, we study how to provide a cost-effective networking service for real-time and delay tolerant applications in Mobile Urban Sensing System (MUSS). We first highlight the challenges of MUSSs and review current mobile sensing research. Then we propose a joint pricing and routing scheme to support both real-time and delay-tolerant MUSS applications through seamless integration of cellular and short-range communications of mobile phones. The proposed scheme is not only lightweight and fully distributed, but can also achieve optimal throughput, which is highly suitable to deliver large amount of mobile sensing data. Through simulations, we demonstrate that our scheme can minimize global system costs, as well as effectively incentivize phone users to participate in the MUSS. We also show that our scheme self adapts to dynamic network conditions. To support future complex MUSSs, many open research challenges remain including faithful sensor data market design for discouraging phone users to subvert the market through misinformation, networking schemes with social privacy awareness, as well as joint sensor data analysis, filtering and networking.

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