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Opportunities in Mobile Crowd Sensing

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Abstract

Mobile crowd sensing is a new paradigm that takes advantage of pervasive mobile devices to efficiently collect data, enabling numerous large-scale applications. Human involvement is one of the most important features, and human mobility offers unprecedented opportunities for both sensing coverage and data transmission. In this article, we investigate the opportunistic characteristics of human mobility from the perspectives of both sensing and transmission, and discuss how to exploit these opportunities to collect data efficiently and effectively. We also outline various open issues brought by human involvement in this emerging research area.

Introduction

With recent advancements in mobile pervasive sensing and transmission technologies, especially the proliferation of smart phones, we are rapidly entering the era of the Internet of Things (IoT), which aims at sensing and interconnecting various physical objects and their surroundings in the realistic world more comprehensively and on a larger scale [1, 2].

If we still use traditional mote-class sensor networks for large-scale and fine-grained sensing, a large number of sensor nodes must be deployed to guarantee the area coverage and communication connectivity, which is economically infeasible or undesirable. Take the CitySee project, for instance: 100 sensor nodes and 1096 relay nodes are deployed for CO_2 monitoring in an urban area of around 1 km^2 [3]. If this system is extended to a larger urban area, for example, within the 5th ring in Beijing (about 900 km^2), we would need to deploy at least 90,000 sensor nodes and around 1,000,000 relay nodes to maintain full area coverage and communication connectivity. Expensive sensor cost together with the deployment and maintenance cost will make it hard to implement.

Fortunately, recent advancements in mobile pervasive sensing and transmission technologies trigger research in leveraging human-carried everyday devices (e.g., smartphones, wearable devices) or vehicle-mounted sensors (e.g., GPS, OBD-II) to monitor large-scale phenomena that cannot easily be measured by a single individual. This sensing paradigm is popularly called mobile crowd sensing (MCS) [4, 5] or *people/human-centric sensing* [6]. Figure 1 illustrates an urban sensing application scenario: a group of mobile users equipped with various sensors, GPS receivers, and wireless communication modules (e.g., Bluetooth, WiFi) move within a monitoring region, opportunistically take samples, and report sensory data to the monitoring center to build a city-scale sensing map of some phenomenon. This novel sensing paradigm has enabled numerous large-scale applications such as urban environment monitoring, traffic monitoring, road surface monitoring, and street parking availability statistics [4].

Human involvement is one of the most important characteristics of MCS. Compared to traditional sensor networks, human mobility offers unprecedented opportunities for both sensing coverage and data transmission. Lane *et al.* [7] discern two classes of sensing paradigms in MCS:

- *Participatory sensing*: It requires the participants to *consciously* opt to meet the application requests by deciding when, where, what, and how to sense.
- *Opportunistic sensing*: It is fully *unconscious*, namely the application may run in the background and opportunistically collect data without active involvement of users (e.g, continuous Wi-Fi signal sensing only needs to keep the Wi-Fi open).

In this article we mainly focus on opportunistic sensing paradigm, which more easily supports large-scale deployments and application diversity [7].

On the other hand, there are two classes of transmission paradigms in MCS:

- *Infrastructure-based transmission*: It considers users reporting and accessing sensory data through the Internet by cellular networks (e.g., 3G/4G mobile networks).
- *Opportunistic transmission*: It enables opportunistic data forwarding among mobile users through intermittent connections with short-range radio communications (e.g., bluetooth, WiFi).

Most existing MCS applications adopt the infrastructure-based transmission paradigm. However, this paradigm cannot be applied in some scenarios where network coverage is poor or network access is expensive. For example, dead spots of network coverage are commonly found in remote areas and even in some parts of major cities. Moreover, the infrastructure is down in disaster recovery scenarios. In this article, we mainly focus on the opportunistic transmission paradigm, which offers another way to collect and share data. It works well without requiring any centralized server or infrastructure for communication and management, and also reduces

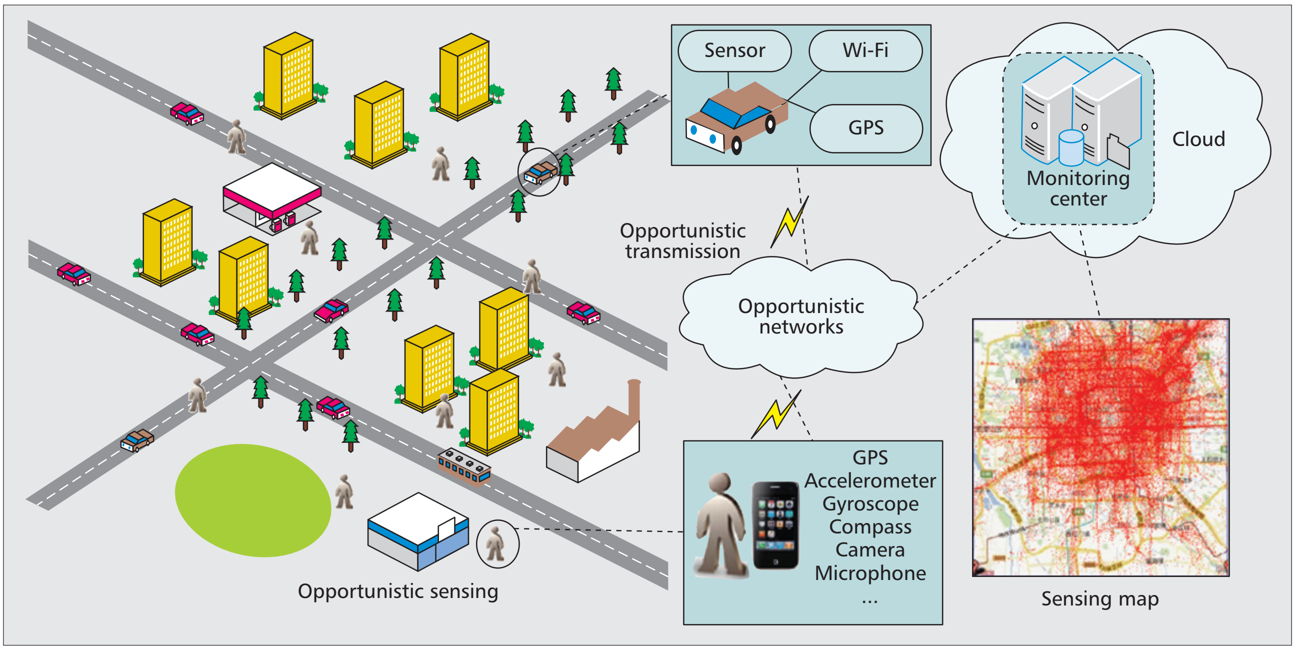

Figure 1. An illustration of opportunistic urban sensing.

the workload of cellular networks in dense areas. Moreover, it is more energy-efficient and less expensive, which is very important because most users hope to save battery energy and data usage on their mobile devices.

In the following, we discuss the opportunities and challenges that human involvement brings to the MCS. We investigate the opportunistic characteristics of human mobility from the perspectives of both sensing and transmission. We discuss how to exploit the opportunities that human mobility offers for sensing and transmitting efficiently and effectively. Finally, we summarize our conclusions and various open issues.

Human Involvement: A Double-Edged Sword

In traditional mote-class sensor networks, humans are only the end consumers of the sensory data collected from unattended and autonomous systems. In contrast, one of the most important characteristics of MCS is deeper involvement of humans in the whole loop of the data-to-decision process, including sensing, transmission, analysis of big sensory data, and decision making. This characteristic is a double-edged sword. From a positive perspective, it brings unprecedented opportunities.

- It is easier to deploy the network at lower cost, because millions of mobile devices or vehicles already exist in many cities around the world. Moreover, human mobility can be exploited to improve sensing coverage and data transmission. On one hand, mobile nodes can sense the surroundings wherever their holders arrive opportunistically, which enables building large-scale sensing applications. On the other hand, opportunistic contacts among mobile users can be exploited to deliver sensory data in networks with intermittent connections based on the store-carry-and-forward paradigm [8].
- It is easier to maintain the network, because mobile nodes often have more power supply, stronger computation, and larger storage, and communication capacity. Moreover, mobile nodes are always managed and maintained in good condition by their holders. For example, people could charge their mobile phones as needed every day.
- It is more extensible and flexible, because we only need to recruit more users to adapt to the expansion of the system scale.

From a negative perspective, human involvement also brings many new challenges.

- The number of mobile users, the availability of sensors, and the data quality always change over time due to the randomness of human mobility and the dynamics of human contexts such as the residual battery energy of mobile nodes and people's preferences. All these factors make it more difficult to guarantee reliable sensing quality in terms of coverage, latency, and confidence.
- Human involvement naturally brings privacy concerns. Mobile users may not want to share their sensory data, which may contain or reveal their private and sensitive information (e.g., their current location).
- While participating in MCS, mobile users consume their own resources (e.g., battery and computing power) and have potential privacy threats. Thus, incentive mechanisms are necessary to provide participants with enough rewards for their participation costs. From the sensing perspective, proper incentives must be offered to users for completing specific sensing tasks [9]. From the transmission perspective, users need to be rewarded for forwarding data for each other [10].

OPPORTUNISTIC CHARACTERISTICS OF HUMAN MOBILITY

In traditional sensor networks, nodes are often static, or have random or controlled mobility. In contrast, in MCS human mobility has some unique characteristics such as spatio-temporal correlation, hotspots' effects, and sociality. Identifying these characteristics is beneficial to estimate sensing quality, perform network planning, design efficient sensing and transmission protocols, and develop accurate mobility models.

OPPORTUNITIES IN OPPORTUNISTIC SENSING

At present, little work focuses on the *sensing opportunities* provided by human mobility, which have important impacts on the sensing quality of many MCS applications (e.g., urban environment monitoring applications). Here we consider the application scenario in Fig. 1, assuming that it aims to build a sensing map of some phenomenon (e.g., CO_2 concentration) in a large monitoring region (e.g., within the 5th ring in Beijing) during a time span T (e.g., 6:00–24:00 every day). In fact, there are two basic problems unsolved:

- How can the sensing opportunities and sensing quality be measured?
- How many mobile users can provide enough sensing opportunities to achieve the required sensing quality?

In traditional stationary sensor networks, the coverage is used to measure the sensing quality, which cannot change over time. In contrast, the coverage in MCS is time-variant due to human mobility. Therefore, we propose a new metric called *inter-cover time* to characterize the opportunity with which a subregion is covered [11]. Especially in the time domain, we divide T into multiple sampling periods of T_s, as illustrated in Fig. 2a. In the space domain, we divide the monitoring region into a set of grid cells, as illustrated in Fig. 2b. A grid cell is said to be covered by a mobile user only when a new sampling period arrives and the location of the mobile user is just within the area of the grid cell.The inter-cover time is defined as the time elapsed between two consecutive periods of coverage of the same grid cell. Obviously, shorter inter-cover time results in better sensing quality for a grid cell. In order to explore the pattern of inter-cover times occurring in realistic scenarios, we perform empirical measurement studies on real mobility traces of thousands of taxis collected in Beijing and Shanghai, two of the largest cities in China. According to our analysis results, we find that the distribution of the aggregated inter-cover times follows a *truncated power-law* distribution (it has a power-law tendency at the head part and decays exponentially at the tail) regardless of the size of grid cells and the number of mobile users.

In order to solve the second basic problem, we first use a metric called the *opportunistic coverage ratio* to characterize the relationship between the sensing quality and the number of users. The opportunistic coverage ratio is defined as the expected ratio of grid cells that can be opportunistically covered during a specific time interval. It can be derived as a function of the distribution of the aggregated inter-cover times,

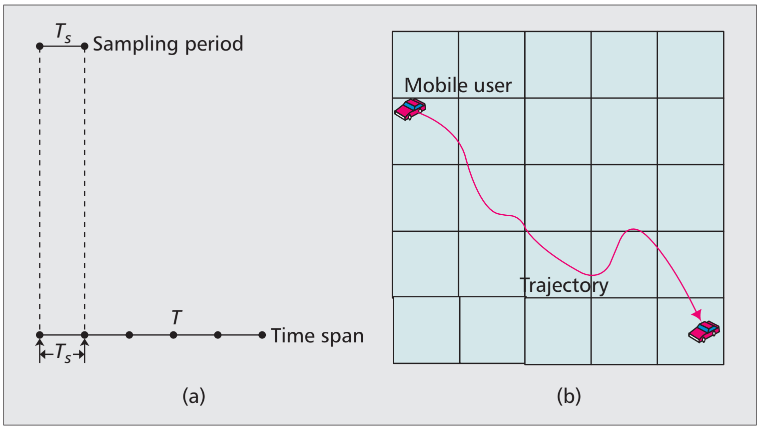

Figure 2. An illustration of discretizing the time-space domain: a) time domain; b) space domain.

which increases monotonically with the number of users and the time interval. Then we formulate this problem as follows: What is the minimum number of mobile users that need to be deployed so that the opportunistic coverage ratio is not less than a threshold during a specific time interval? For example, according to our analysis on the real datasets, we need to deploy at least 5800 and 6300 taxis in Beijing and Shanghai, respectively, so that the opportunistic coverage ratios in a region of 900 km^2 are not less than 90 percent during the time interval of one hour.

OPPORTUNITIES IN OPPORTUNISTIC TRANSMISSION

The transmission opportunities of human mobility and their impacts on the data delivery performance have been intensively studied and relatively well understood in opportunistic networks or delay-tolerant networks (DTNs). The *inter-contact time* is one key metric to characterize the transmission opportunities of the same couple of mobile users. Since the inter-contact time reflects the frequency of opportunities for forwarding messages from one user to another, it directly affects the data delivery performance. Obviously, longer inter-contact time results in longer delivery delay and lower delivery ratio. Now, several empirical results based on human mobility traces have reached a common conclusion that the distribution of the aggregated inter-contact times follows a *truncate power-law* [8].

On the other hand, human sociality has a key impact on human mobility, since it decides the spatial properties of human mobility (i.e., where people move). Thus, human sociality has been considered an important factor affecting the performance of opportunistic forwarding protocols. Recently, several works have mainly focused on social-based forwarding protocols to improve opportunistic transmission performance by leveraging the ample social information encoded in human mobility. The reason behind these protocols is that the underlying social attribute is more stable than the time-variant network topology, and hence can be used for better relay selections. Table 1 classifies these protocols based on the social metrics they exploit.

OPPORTUNISTIC SENSING

Due to human dynamics, it is an important and complex problem to identify the right set of mobile users that can produce the desired data with proper parameters (e.g., sampling rate) to achieve the required sensing quality in energy-efficient ways. Reddy *et al.* considered the participatory sensing paradigm and developed a recruitment framework to enable organizers to identify well-suited participants for data collections based on geographic and temporal availability as well as participation habits [12]. A commonly used method for opportunistic sensing is to make every mobile user sense periodically. However, this method is very inefficient because many redundant data samples may be produced by a large number of mobile users. In order to reduce data redundancy and improve energy efficiency, it is necessary to design a cooperative sensing method to control sensing activities of mobile users such that they produce just enough data samples for the application.

First, we notice that the sensing coverage is spatio-temporal correlative. Let us still consider the discrete time-space model in Fig. 2. We further divide the time span T into multiple coverage periods, where each coverage period contains multiple sampling periods. It is reasonable to assume that a grid cell needs to be covered once or several times within a coverage period, instead of each point in the grid cell being covered at any time. Moreover, frequent samplings make it more likely that a grid cell will be covered at a higher cost. Therefore, it is necessary to design a scheduling mechanism for each mobile user to decide when and where to perform sampling tasks.

Social metrics	Meanings	Typical protocols
Centrality	The social position of a user	SimBet, PeopleRank, BUBBLE
Similarity	The social distance between two users	SimBet, MobiSpace
Social relationship	Acquaintance, friend, or stranger	SMART
Social structure	Virtual community or physical hotspots	BUBBLE, Hotent

Table 1. A summary of existing social-based opportunistic forwarding protocols.

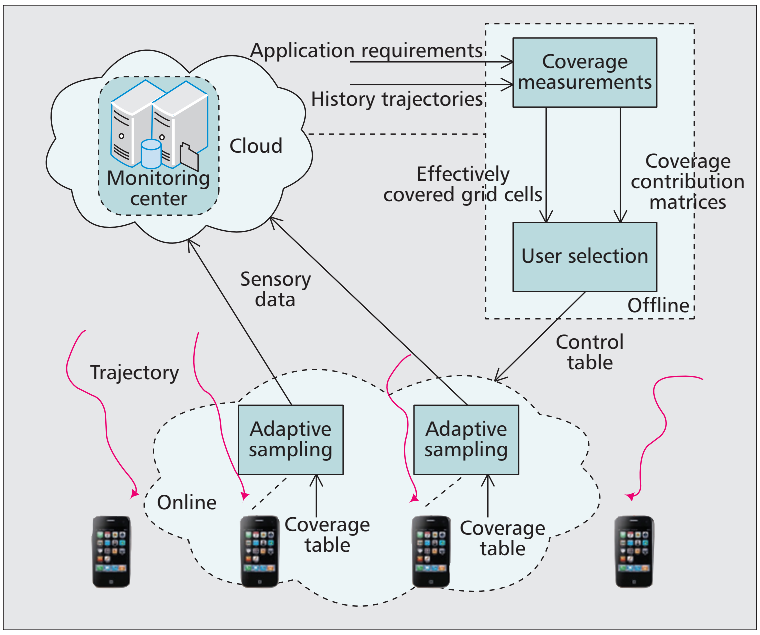

Figure 3. An overview of the cooperative opportunistic sensing framework.

Second, since different mobile users always have heterogeneous mobility regions with some randomness, they could make different contributions to the coverage. It is important to design a user selection mechanism to eliminate user redundancy and hence reduce data redundancy.

Based on the above analysis, we design a cooperative opportunistic sensing framework [13], as illustrated in Fig. 3. First, the time-space domain of the monitoring region is discretized according to the application requirements. Then we obtain a set of effectively covered grid cells (the number of times these grid cells can be covered within each coverage period are not less than a specified threshold) and coverage contribution matrices (representing the times that one mobile user covers different grid cells within different coverage periods) for each mobile user, according to the history trajectories of all mobile users. We design two mechanisms to reduce user redundancy and data redundancy:

- The offline *user selection* mechanism. It can select the minimum number of users to achieve the coverage requirements for those effectively covered grid cells based on the coverage contribution matrices of mobile users.
- The online *adaptive sampling* mechanism. It can control the sampling rates of the selected users adaptively. In particular, it sets two tables, a control table and a coverage table, locally stored at each user. The control table is used to decide whether each user needs to participate in sampling tasks within each coverage period according to the results of a user selection mechanism. The coverage table records the number of times that each grid cell has been covered during some coverage period, and then each user decides whether to take samplings according to the current coverage table.

OPPORTUNISTIC TRANSMISSION

In the past few years, many opportunistic forwarding protocols have been proposed in opportunistic networks. Among these protocols, epidemic routing was the first and most generic one without knowing anything about the mobility of users. It tried to grasp each forwarding opportunity, thus resulting in the minimum delivery delay under ideal conditions (unlimited resources such as bandwidth and buffer space) at high cost. In order to reduce the cost, many variants of epidemic routing have been proposed (k-hop schemes, probabilistic forwarding, spray-and-wait, etc.). Some protocols attempted to identify the best relay node to achieve better trade-off between delivery delay and transmis-

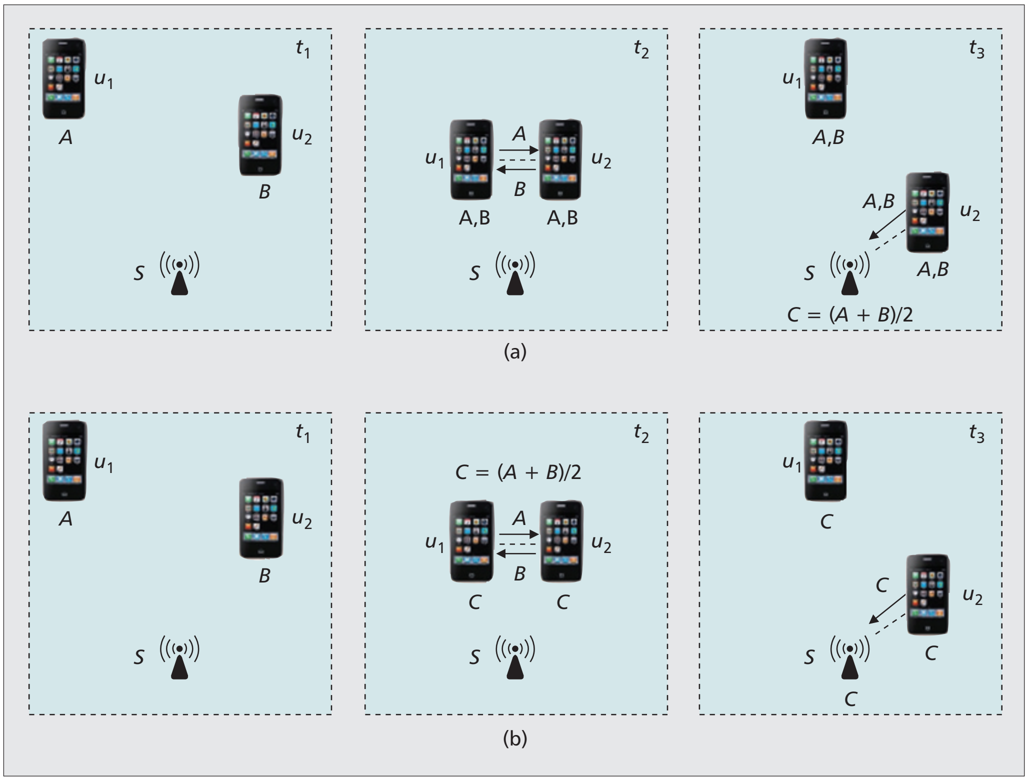

Figure 4. An illustration of data forwarding with or without fusion: a) forwarding sensory data without fusion; b) forwarding sensory data with fusion.

Due to human dynamics, it is an important and complex problem to identify the right set of mobile users that can produce the desired data with proper parameters (e.g., sampling rate) to achieve the required sensing quality in energy-efficient ways.

sion overhead by exploiting the context information (e.g., the mobility of a node and its current energy level). More recently, several works have exploited human sociality for improving opportunistic transmission performance.

However, most existing opportunistic forwarding protocols have focused on the sharing or dissemination of data interesting to individual mobile users instead of the sensory data collection in MCS, and thus failed to consider the spatial-temporal correlation among sensory data and its impact on the network performance. It would be beneficial to combine opportunistic forwarding and in-network processing based on a store-carry-process-and-forward paradigm. On the other hand, most existing social-based opportunistic forwarding protocols use traditional approaches in social networks or ego networks to evaluate social metrics. We argue that these approaches have high spatio-temporal complexity due to transient user contacts and intermittently connected environment, and hence cannot be applied in large-scale opportunistic scenarios. It is necessary to develop a lightweight approach to exploiting human sociality for improving opportunistic transmission performance.

THE IMPACT OF DATA FUSION

Considering the spatial-temporal correlation among sensory data, it is beneficial to integrate opportunistic forwarding protocols with *data fusion* (or *data aggregation*) for two reasons:

- Users may be interested only in the aggregated results of sensory data (e.g., the average temperature or noise level).
- Sensory data collected in close proximity or time periods may be highly correlated, and data fusion can effectively eliminate redundancy and hence reduce network overhead.

Although many routing protocols supporting data fusion have been proposed in traditional sensor networks, to the best of our knowledge, few works have investigated opportunistic forwarding protocols supporting data fusion in MCS.

We use Fig. 4 to illustrate the importance of coupling between opportunistic forwarding and data fusion. Assume that two users u_1 and u_2 carry two correlated packets (e.g., two samples produced in the same grid cell within the same time period) at time t_1, and opportunistically forward the packets to a sink node S. Finally, S obtains the average of two samples. Figure 4a illustrates the forwarding process without data fusion: when u_1 meets u_2 at time t_2, they forward data to each other; then at time t_3, u_2 meets the sink node S, and delivers both two packets A and B to S; S takes the average of two samples after it has received both of the original packets. Thus, the transmission overhead (i.e., the total number of transmissions) is 4. Next, let us see the forwarding process with data fusion as illustrated in Fig. 4b: when u_1 meets u_2, they forward data to each other, and store the fused result, a new packet $C = (A + B)/2$, instead of two original packets; then at time

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t_3, u_2 meets S, and delivers packet C to S. Thus, the transmission overhead is 3, lower than that of the forwarding process without data fusion.

Although the idea of integrating opportunistic forwarding with data fusion seems simple and straightforward, we still face some new challenges for both performance modeling and protocol design in practice. Previous work on performance modeling of opportunistic forwarding protocols assumed that all packets were propagated individually. However, the packets are spatial-temporally correlated in the forwarding process with data fusion, which causes a more complex propagation process. In our work [14], an ordinary differential equation was derived for modeling the dissemination law of correlated packets, which could serve as fundamental guidelines on integrating opportunistic forwarding with data fusion for achieving tradeoff among various performance metrics.

We designed two novel protocols by leveraging data fusion: Epidemic Routing with Fusion (ERF) and Binary Spray-and-Wait with Fusion (BSWF), and proved that both protocols outperformed those without data fusion (i.e., epidemic routing and spray-and-wait).

Evaluation and Exploitation of Human Sociality

By analyzing GPS traces of pedestrians from the real world, we find three phenomena:

- People always move around a set of popular locations, called *public hotspots*, instead of purely random movements.
- Each individual shows preference for some particular locations, called *personal hotspots*.
- Both types of hotspots have two key features enabling a lightweight opportunistic forwarding protocol: *burstiness*, implying that there are only a small number of hotspots required to exchange among users, and *stability*, implying that only infrequent updating of hotspots is required.

Motivated by the above observations, we exploit hotspots to design a new routing metric, called Hotent (for HOTspot ENTropy) [15]. To reduce the high spatio-temporal complexity of traditional social network analysis technologies, Hotent converts the problem of evaluating social metrics to a similarity matching problem according to the following three steps:

- Using the *inverse symmetric entropy* of personal hotspots of two users to evaluate the *similarity* between them
- Using the *relative entropy* between public hotspots and personal hotspots to evaluate the *centrality* of users
- Using the *law of universal gravitation* to integrate centrality and similarity into the Hotent metric, based on the metaphor of mass for user centrality and distance for the similarity between two users

We have verified that Hotent largely outperformed other state-of-the-art work, especially in terms of packet delivery ratio and average number of hops per packet.

Conclusions and Open Research Issues

This article discusses the opportunities and challenges in mobile crowd sensing brought on by human involvement. In particular, we have investigated the opportunistic characteristics of human mobility. From the sensing perspective, we use a new metric called *inter-cover-time* to characterize the sensing opportunities, and use another metric called *opportunistic coverage ratio* to evaluate the sensing quality of MCS applications. From the transmission perspective, we review some main results: the distribution of inter-contact-times and human sociality have important impacts on opportunistic transmission performance. We also present some approaches to exploiting the opportunities that human mobility offers for sensing and transmission efficiency and effectiveness.

There are many open issues in this emerging research area, including the following.

Evaluation of sensing quality: This is a complex problem affected by many factors. First, the space distribution of human mobility has important impacts. We can consider an MCS system as an "urban camera," and a large number of mobile devices form the charge-coupled device (CCD) sensor of this camera. An urban camera is able to record urban phenomena in the form of sensing images by measurements from mobile devices. However, different from the commonly used definition of resolution for digital images and cameras, the resolution of an urban camera is not simply the pixel count of a mobile phone camera. This is because the pixels of a digital camera form a fine grid, but the pixels of an urban camera have scattered and dynamic distribution. Thus, it is necessary to redefine the resolution of MCS systems, and investigate the relationship between the resolution and the number of mobile users. Second, mobile users have heterogeneous data quality. It is important to evaluate users' data quality, and get rid of malicious and low-quality data.

Integration of MCS and static sensing: Although traditional sensor networks have higher cost and poorer scalability, they often have more reliable sensing quality, which can be used to compensate for inadequate sensing opportunities provided solely by an MCS system. Since sensing opportunities are imbalanced among different regions, it is important to study where to deploy how many specialized sensor nodes, and how to collaborate with mobile nodes to achieve the required sensing quality.

Integration of opportunistic forwarding and in-network processing: As a starting point, we investigated the integration of some simple data fusion functions (e.g., averaging, summation, voting, and max/min) and two basic opportunistic forwarding protocols. In the future, we need to further explore whether more complex in-network processing approaches can be combined with other opportunistic forwarding protocols (e.g., context-aware and social-based forwarding) and how much performance can be improved.

Adaptive opportunistic forwarding protocols: Although extensive opportunistic forwarding protocols have been proposed, almost all of them only applied to some specific scenarios rather than every scenario. Since transmission opportunities are imbalanced among different physical regions and virtual communities, it is still an important and challenging problem to study when and where to use which protocols (strong-connectivity-oriented or weak-connectivity-oriented), and how to switch them adaptively.

Context-aware incentive mechanisms: Since the preferences of mobile users always change dynamically with their contexts, we should offer personalized incentives to users for optimizing the system utility by identifying users' contexts, mobility, and social properties.

Balance among sensing quality, incentive, and privacy: We need to consider various factors synthetically and systematically.

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