Using Virtual Credits to Provide Incentives for Vehicle Communication

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***Abstract*—Participatory sensing has been recently proposed as a replacement for traditional mobile sensing system. In this work, we adopt the concept of participatory sensing for mobile surveillance by involving a human into the loop of data collection. Furthermore, we introduce a virtual credit based mechanism to motivate the participants to collect data and share their bandwidth. We perform an analysis of different parameters which might affect the performance of such a system.**

***Index Terms*—Mobile Surveillance, Participatory Sensing, Incentive, Credit System**

I. Introduction

Participatory sensing [1] is known to be able to leverage the increasing sensing capabilities found in consumer devices, such as smartphones or car video cameras. Data collected from these mobile sensors provides the basis for existing human-centered applications. Participatory sensing places demands on the device owners, which could potentially restrict the pool of willing participants. In this paper we focus on a scenario of distributed vehicle-based mobile surveillance [2]. We are motivated by the observation that video-capable smartphone and in-car video cameras are more and more common these days. Data recorded by these video sensors can be used to reconstruct an accident scene or help police to locate the crime suspect. Here we consider an architecture in which the participants are the drivers or passengers in the cars. The data recorded by the video sensor can be uploaded via the participant's 3G-enabled smartphone to a server and later shared with the other participants. For participants who do not have a 3G connection to the Internet, they can "borrow" their neighboring participants' Internet connectivity. Such bandwidth sharing is achieved by the data generator first forwarding its data to a neighboring 3G-capable participant via WiFi, and then the data is relayed to the server via the Helper's 3G connection. In such an architecture, one critical research issue is how to promote the participants willingness to contribute their sensor data and bandwidth.

In this work, we propose a virtual-credit-based protocol that demands strict fair exchange of sensor data uploads for virtual credit. A user cannot download data directly from the server or indirectly from the other participants without paying credits, nor can they obtain credits for uploads they did not perform. This protocol property provides robust incentives for the participants to contribute their bandwidth and data because the only way a participant can obtain data uploaded by the others or can earn credits is by paying credits or uploading own sensor data (or sharing its Internet connectivity with other participants).

We assume that different data has different levels of utility, and the amount of credits a participant can earn is a function of the utility of the data. For example, a high resolution video clip could be worth more credits than a low-resolution video clip. In addition, we assume that each participant wants to earn as many credits as possible. There are two kinds of node in our system. The "Helper" is either a node that can help the others to upload the data to the server through its 3G connectivity, or a node that can relay the data toward a 3G-capable node. On the other hand, the "Requester" is a node that has some data to be uploaded. In our protocol, considering the possible short encounter time between vehicles, we assume that a Helper can help only one Requester at a time. When a Helper receives multiple requests, it will tend to choose the most-profitable Requester (i.e., the one that could bring the most credits).

Our contribution is twofold. First, we propose an incentive-based framework for vehicle-based mobile surveillance. Second, we use a theoretical model to analyze the effect of different parameters on the performance of our proposed system.

II. Related Work

In participatory sensing, each participant senses different data, and many projects have been launched in this area, some of which are described below.

- Environment: NoiseTube [3] is participatory application monitoring noise pollution using mobile phones. Suelo [4] is an embedded networked sensing system designed for soil monitoring.
- Entertainment: In the Micro-blog [5] project, users generate geo-tagged multimedia called micro-blogs which are then transported over an available wireless network, such as WiFi or cellular systems, to a web-accessible database. BikeNet [6] is a mobile sensing system for mapping the experience of cyclists.
- Transportation: Nericell [7] monitors road conditions using various sensors in a smart phone to detect portholes and bumps, as well as vehicles braking and honking their horns. Green GPS [8] is a service that computes fuel-efficient routes for vehicles between arbitrary end-points

by exploiting the vehicular sensor measurements available through OBD-II.

- Commerce: Bulusu et al. [9] showed that it is feasible to process and deliver product pricing information using the camera in a mobile phone. Livecompare [10] is a system that enables users to find bargains in grocery stores and supermarkets using participatory sensing.

Users willingness to contribute their data is critical to the success of participatory sensing. Cheng et al. [11] proposed a group-level incentive scheme in which mobile users are grouped and share credits, with credits earned by one user able to be consumed by other group members. Cui et al. [12] introduced the concept of relay union, in which the relays have direct access to WLAN, and earn credits by providing Internet access, while clients pay credits to purchase this. They proposed a revenue and bandwidth model, as well as an optimal pricing and bandwidth allocation strategy. ‘Tit for tat’ [13] is another form of incentive mechanism that is widely used in P2P networks. Every time when a user wants to download something, they first need to contribute their own data. LiveCompare [10] provides incentives through its query protocol. When a user wants to compare the price of a product in a grocery store, they are required to first send a picture of this product’s price tag to the server. In Reverse Auction based Dynamic Price (RADP) [14], the user can sell their sensing data to a service provider with their claimed bid in the auction. Service provider then selects the user who has the lowest bid. Finally, Reddy et al. [15] investigated the use of micro payments as an incentive to monitor the garbage can on a campus. Unlike our work, all these prior work do not consider the quality of the data and assume every data has the same value.

III. System Overview

A. Architecture

In our architecture, we assume that every node is equipped with a wireless network interface (such as WiFi) for local area connectivity, and each piece of data has an utility value. A node that uploads the data to a server can earn some “virtual credits” based on the utility of the data. However, the node that generates the data (e.g., records a video clip using its car video camera) might not have the Internet connectivity (e.g. 3G) needed to upload the data. In such cases, the data source will relay the data directly or indirectly through WiFi to a 3G-capable node. Once the data arrives at the 3G node, this 3G node will help the source node upload the data and, as an incentive for the 3G node, a certain percentage of credits earned for that data will be allocated to this 3G Helper. Given that the source might not able to directly encounter a 3G node, the source could forward the data to a neighboring non-3G node first, with the hope that this node might at some point encounter a 3G one and then relay the data. In any case, every time when data is relayed, some “commission” needs to be paid to the relay node to reward its help. A simple scenario is shown in Fig. 1. In this work, for simplicity, we use a fixed

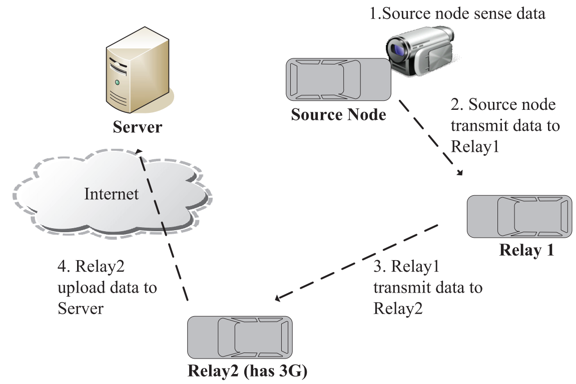


Fig. 1. The scenario examined in this work

commission rate for the relaying service. For example, if we set the commission rate to 7:3, then the source will earn 70% of the total credits for the data it generates; relay 1 will earn 21% (=30%×70%) and relay 2 will earn 9% (=30%×30%) of the total credits. Obviously, the last hop to the server will earn the least credits. Therefore, we define the “minimum utility” for such system, and the relay node will not consider relaying the data if the amount credits that it might earn less than this. Furthermore, we assume that the server will maintain an account for each node. When the data is uploaded to the server, the server will update the account of nodes that participated in the generation and relaying of this data based on the credits they have earned. A node can use the credits in its account to download data from the server when needed.

In this work, we consider that different data can have different utility, which represents the quality of the data. In the database community, several metrics have been proposed to estimate the quality of the data such as accuracy, completeness, relevance, timeliness, and reputation [16]. Some of these metrics are difficult to model (such as accuracy and completeness), while the others require the access to server database (such as uniqueness). In our architecture, given that not every relay node can have direct Internet access to the database on the server, we focus on using the freshness and resolution of the data to estimate its quality. In other words, a relay node will estimate the utility of the recorded video data based on how long it has been generated and its size.

In our incentive framework, we assume that each participant node wants to earn as many credits as possible, where the amount of credits a participant can earn is a function of the utility of the data. The initial utility of the data when it is first generated can be defined as $U_{initial} = S$, where S is the size of the data. Once the data is generated, after a period of time T, then the utility of the data becomes, $U = S * e^{-\lambda T}$, the data can be uploaded to the server by the source if the source has a 3G. Otherwise, the data can be forwarded to a 3G node through one or more relays. For the first case, the credits that can be earned by the source are $Credit_S = U \times D$, where D is the number of downloads of this data later by the other nodes that occur later. For the second case, the credits that can

TABLE I

NOTATION USED IN OUR MODEL.

P_{3G}	the ratio of vehicles with 3G capabilities
P_r	the probability that the encountered node will relay the data
ω	the time limit within which the data must be uploaded to the server
ρ	the number of vehicles in the network

be earned by the source are $Credit_{S-R} = Credit_S \times \xi$ where ξ is the enumeration rate. The credits that can be earned by the i_{th} relay is $Credit_{Ri} = Credit_S \times (1-\xi)^i$

B. Profit-based forwarding protocol

The participant nodes in our system can be divided into following two kinds. *Requester*: a node that is currently carrying some data which needs to be forwarded. *Helper*: a node that can help the Requester relay the data to a 3G node.

Both the Requester and the Helper nodes will periodically broadcast a HELLO message to let neighboring nodes know of their existence. Given that the encounter time between two fast-passing vehicles can be very short, in this work we assume that a Helper can help only one Requester at a time. When a Helper hears multiple requests, it only responds to the one with the highest estimated data utility (which will bring it more credits later). Assuming the current utility value of data in the Requester's message is U, the Helper can estimate the possible maximum credits it can earn from relaying this data as

$$U' = U \times e^{-\lambda \times t} \tag{1}$$

where λ is the commission rate, and t is the data transmission time from the Requester to the Helper, which is equal to $\frac{data\ size(S)}{WiFi\ bandwidth(B)}$. The WiFi bandwidth can be estimated as in a prior work [17]. On the other hand, when a Requester receives multiple responses from more than one Helper, it will select the one that will meet a 3G node at the earliest possible time since that the utility of the data decreases over time. When a Helper receives a HELLO message from a Requester, it will first estimate their encounter duration [18] and see if they have enough time for the data transmission. Here we define a encounter as when two nodes are within each other's radio range. This Requester is then added to the candidate list of the Helper if the estimated encounter time is sufficient to complete the data transfer. The Helper will periodically select the Requester from its candidate list that is carrying the data with the highest utility value, which can be estimated using Eq. 1, and send back an ACCEPT. To avoid looping, Helper cannot relay the same data more than once. Similarly, the Requester will also construct a candidate list and select a Helper which can bring it the most profit as the next relay to a 3G node. The idea here is to select the next relay which will encounter a 3G node as early as possible.

In this work, we focus on the percentage of generated data that can be eventually uploaded to the server. Since the utility of data decreases over time and nodes will refuse to provide the relay service if the estimated profit that can be earned from relaying is less than a certain threshold, several factors could affect the performance of such a system, such as the available 3G nodes, node distribution, mobility, and so on. In this section, we use a simple grid topology to analyze the effects of different parameters on the system performance. We model the roads in a urban area as a grid [19] and use Random WayPoint (RWP) to model the node mobility. A node randomly chooses the start point P_s and the end point P_d in the grid. Once the node arrives at P_d, P_d is used as the new starting point and the whole process is repeated again. For simplicity, we assume that nodes move at a constant speed and there are no pauses. We model the decay of data utility over time using a threshold ω. The generated data will be discarded if it cannot be uploaded to the server within ω. The notations used in our model and the following below analysis are given in Table I. Prior works [20][21] have shown that the arrival of contacts is a Poisson random process in the RWP model. Assuming the sequence of the passed waypoints in the time interval $[0, \omega]$ is $s_1, ..., s_i$ and δ_i is the duration of the interval between waypoint s_i to the next waypoint s_{i+1}. The inter-contact time δ_i, where $1 \leq i \leq n-1$ then follows the exponential distribution with parameter λ_c, where λ_c is the contact arrival rate. Here we assume all nodes have the same contact arrival rate. The sum ω_n= δ_1+δ_2+...+δ_{n-1} is a random variable and has a gamma distribution with parameters λ_c and *n*. We assume that the probability that a Helper will relay the data for the Requester is P_r. Since the inter-contact time between waypoints follows an exponential distribution with the parameter λ_c, the inter-distance of the waypoints also follows an exponential distribution with the parameter $\lambda_d = \lambda_c / V$ [22]. A prior work [20] proved that the inter-contact rate λ_c can be approximated by $\lambda_c = 2 \cdot R \cdot E[V^*] \cdot \int_0^L \int_0^L f^2(x,y)dxdy$, where $E[V^*]$ is the average relative speed between two nodes, $f(x, y)$ is the p.d.f of the spatial node distribution, and L is the length of the grid area. Thus, if we assume that nodes are uniformly distributed (i.e. $f(x,y) = 1/L^2$), the inter-contact rate can then be rewritten as

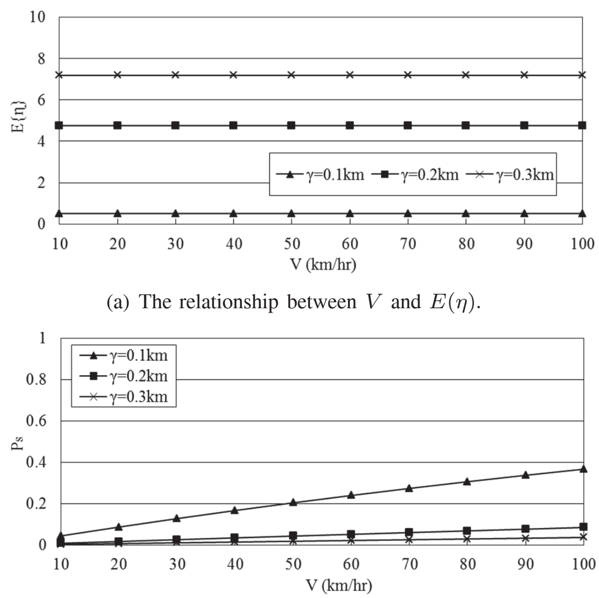
$$\lambda_c = \frac{2 \cdot R \cdot E[V^*] \cdot \vartheta}{((\kappa - 1) \cdot \gamma)^2} \tag{2}$$

where ϑ represents the number of combinations of picking two arbitrary nodes from ρ nodes, i.e., $\vartheta = C(\rho, 2) = \rho(\rho-1)/2$. There are $\kappa \times \kappa$ intersections in the grid topology, and we assume that there are ρ nodes, where $\rho \leq \kappa^2$. Note that $R << (\kappa - 1) \times \gamma$, where γ is the grid length. The relative speed $E[V^*]$ can be approximated as $\frac{4V}{\pi}$, where V is the speed of the node [23].

Accordingly, the probability of contact distance being smaller than the radio range is $P_d = P(d \leq R) = 1 - e^{-\lambda_d R}$, where d is the contact distance between the contact nodes. Given the relaying probability P_r, the probability that the Requester can find a relay node within the radio range is

$$P_d = P(d/P_r \leq R) = P(d \leq P_r * R) = 1 - e^{-\lambda_d P_r R}. \tag{3}$$

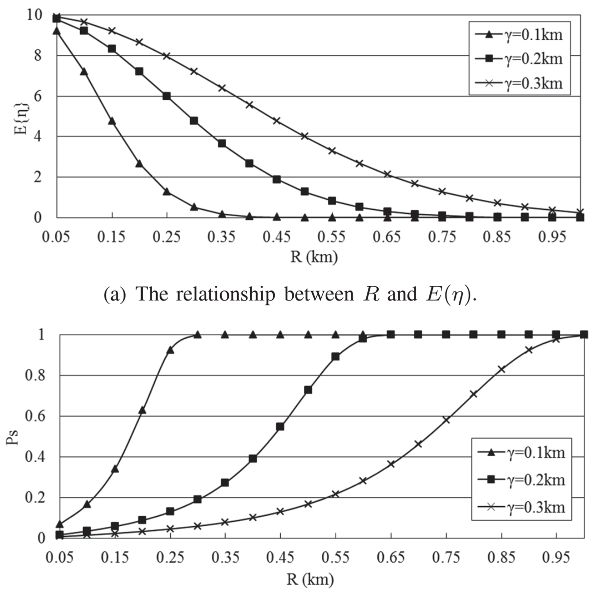
We define a successful transmission as when the data is transmitted from the data generator to the 3G interface within



(a) The relationship between V and $E(\eta)$.

(b) The relationship between V and P_s.

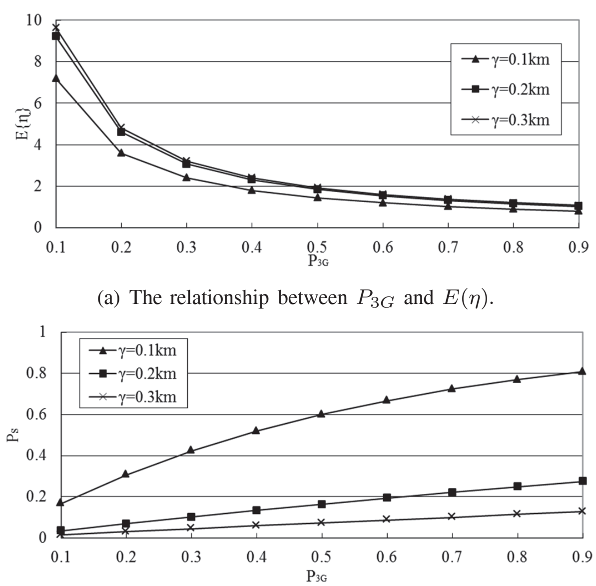
Fig. 2. P_{3G}=0.1, P_r=0.1, ω=0.001 hr, ρ=15, R=0.1km



(a) The relationship between R and $E(\eta)$.

(b) The relationship between R and P_s.

Fig. 3. P_{3G}=0.1, P_r=0.1, ω=0.001 hr, ρ=15, V=40 km/h



(a) The relationship between P_{3G} and $E(\eta)$.

(b) The relationship between P_{3G} and P_s.

Fig. 4. P_r=0.1, ω=0.001 hr, ρ=15, V=40 km/h, R=0.1 km

the time limit ω. Note that we ignore the transmission time from the 3G interface to the server and also the transmission loss. When the data is transmitted from the Requester to the 3G transmitter, the average number of passing nodes is $1/p_{3G}$ including the source node and the 3G transmitter. We can derive the average number of hops as

$$E\{\eta\} = (1 - P_d)\left(\frac{q}{P_d P_r} + \phi\right) \tag{4}$$

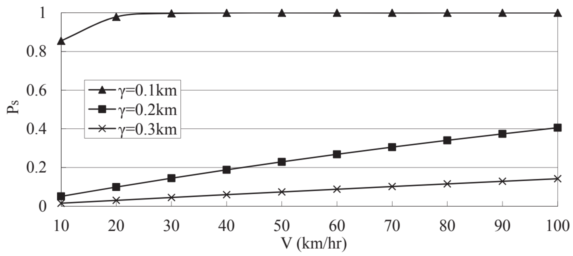
where q and ϕ are the quotient and remainder of $\frac{1/P_{3G}}{1/(P_d P_r)}$. Thus, P_s can be deduced as

$$P_s = P(E\{\eta\} * \delta_i \leq \omega) = P(\delta_i \leq \frac{\omega}{E\{\eta\}}) = 1 - (e^{-\lambda_c \omega / E\{\eta\}}) \tag{5}$$

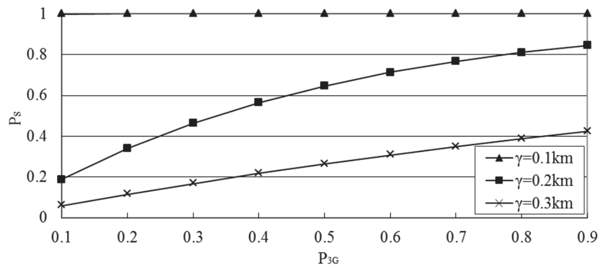
As suggested by Eq. 5, the success rate is a function of the inter-contact rate (i.e. λ_c) and the average number of hops required to reach a 3G node (i.e. $E(\eta)$). In order to understand which of these parameters has a more significant effect on P_s, we performed a set of simulation with a 10×10 grid topology and the grid unit was 100 meters. Initially the nodes are uniformly distributed at the intersections of the topology. The time limit ω is set at 0.001 hour and the speed of vehicles is 40 km/hr. The radio range R is 100 meters.

As shown in Fig. 2(a), the variations of V do not have significant effects on the expected number of expected hop $E(\eta)$. This result can be inferred directly from Eq. 4. When the contact distance (d) between nodes is large (i.e. a sparse network), P_d will be small for a given R. As a result, q will be equal to 0 and ϕ will be equal to $1/P_{3G}$. Therefore, $E(\eta)$ = $(1-P_d) \times \frac{1}{P_{3G}}$. However, since inter-contact rate λ_c is affected by V, P_s is changed when we vary V, as shown in Fig. 2(b). In addition, P_s is increasing when we reduce the grid length from 0.3km to 0.1km. This is because a smaller grid length will lead to a smaller inter-node distance and a higher inter-contact rate λ_c. On the other hand, as shown in Fig. 3(a) and 3(b), the change of R can affect both $E(\eta)$ and P_s, according to Eq. 4 and Eq. 5. Finally, although $1/P_{3G}$ does not affect the inter-contact rate λ_c, it will have a direct impact on $E(\eta)$ which in turn affects P_s, as shown in Fig 4.

On the other hand, for a dense network, P_d will be bigger which results in a smaller $E(\eta)$, a higher inter-contact rate λ_c. As a result, P_s will be higher. As shown in Fig. 5, when we increase the radio range R from 100m to 300m, P_s is increased as compared to Fig. 2(b) and Fig. 4(b).



(a) The relationship between V and P_s.



(b) The relationship between P_{3G} and P_s.

Fig. 5. P_r=0.1, ω=0.001 hr, ρ=15, V=40 km/h, R=0.3 km

IV. Conclusion and future work

In this work, we propose an incentive scheme for a vehicle-based mobile surveillance system by adopting the concept of participatory sensing. We show that car inter-contact rate can be as equally important as 3G penetration ratio to the success of such a system via an analytical analysis. Our future plan is to build a real-world testbed by implementing our incentive framework on the Android and iOS platforms.

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References

[1] J. Burke, D. Estrin, M. Hansen, A. Parker, N. Ramanathan, S. Reddy, and M. B. Srivastava, "Participatory sensing," in *In: Workshop on World-Sensor-Web (WSW06): Mobile Device Centric Sensor Networks and Applications*, 2006, pp. 117–134.

[2] R. Cucchiara and G. Gualdi, "Mobile video surveillance systems: An architectural overview," in *Mobile Multimedia Processing*, 2010, vol. 5960, pp. 89–109.

[3] N. Maisonneuve, M. Stevens, M. E. Niessen, and L. Steels, "Noisetube: Measuring and mapping noise pollution with mobile phones," in *Information Technologies in Environmental Engineering*, ser. Environmental Science and Engineering. Springer Berlin Heidelberg, 2009, pp. 215–228.

[4] N. Ramanathan, T. Schoellhammer, E. Kohler, K. Whitehouse, T. Harmon, and D. Estrin, "Suelo: human-assisted sensing for exploratory soil monitoring studies," in *Proceedings of the 7th ACM Conference on Embedded Networked Sensor Systems*, 2009, pp. 197–210.

[5] S. Gaonkar, J. Li, R. R. Choudhury, L. Cox, and A. Schmidt, "Micro-blog: sharing and querying content through mobile phones and social participation," in *Proceeding of the 6th international conference on Mobile systems, applications, and services*, 2008, pp. 174–186.

[6] S. B. Eisenman, E. Miluzzo, N. D. Lane, R. A. Peterson, G.-S. Ahn, and A. T. Campbell, "The bikenet mobile sensing system for cyclist experience mapping," in *Proceedings of the 5th international conference on Embedded networked sensor systems*, 2007, pp. 87–101.

[7] P. Mohan, V. N. Padmanabhan, and R. Ramjee, "Nericell: rich monitoring of road and traffic conditions using mobile smartphones," in *Proceedings of the 6th ACM conference on Embedded network sensor systems*, 2008, pp. 323–336.

[8] R. K. Ganti, N. Pham, H. Ahmadi, S. Nangia, and T. F. Abdelzaher, "Greengps: a participatory sensing fuel-efficient maps application," in *Proceedings of the 8th international conference on Mobile systems, applications, and services*, 2010, pp. 151–164.

[9] N. Bulusu, C. T. Chou, S. Kanhere, Y. Dong, S. Sehgal, and D. Sullivan, "Participatory sensing in commerce : Using mobile camera phones to track market price dispersion," *Fuel*, pp. 6–10, 2008.

[10] L. Deng and L. P. Cox, "Livecompare: grocery bargain hunting through participatory sensing," in *Proceedings of the 10th workshop on Mobile Computing Systems and Applications*, 2009, pp. 4:1–4:6.

[11] L. Cheng, C. Chen, J. Ma, and Y. Chen, "A group-level incentive scheme for data collection in wireless sensor networks," in *Consumer Communications and Networking Conference, 2009. CCNC 2009. 6th IEEE*, jan. 2009, pp. 1 –5.

[12] Y. Cui, T. Ma, and X. Cheng, "Multi-hop access pricing in public area wlans," in *Proceedings of IEEE INFOCOM*, april 2011, pp. 2678–2686.

[13] B. Cohen, "IEEE 1609 - family of standards for wireless access in vehicular environments (wave)," January 2006.

[14] J.-S. Lee and B. Hoh, "Sell your experiences: a market mechanism based incentive for participatory sensing," in *Pervasive Computing and Communications (PerCom), 2010 IEEE International Conference on*, 29 2010-april 2 2010, pp. 60 –68.

[15] S. Reddy, D. Estrin, M. Hansen, and M. Srivastava, "Examining micro-payments for participatory sensing data collections," in *Proceedings of the 12th ACM international conference on Ubiquitous computing*, 2010, pp. 33–36.

[16] N. K. Yeganeh and M. A. Sharaf, "A framework for data quality aware query systems," in *Proceedings of the 16th international conference on Database systems for advanced applications*, Berlin, Heidelberg, 2011, pp. 478–489.

[17] C. Sarr, C. Chaudet, G. Chelius, and I. Lassous, "Bandwidth estimation for IEEE 802.11-based ad hoc networks," *IEEE Transactions on Mobile Computing*, vol. 7, no. 10, pp. 1228 –1241, October 2008.

[18] V. Namboodiri and L. Gao, "Prediction-based routing for vehicular ad hoc networks," *IEEE Transactions on Vehicular Technology*, vol. 56, no. 4, pp. 2332–2345, July 2007.

[19] W. Viriyasitavat, F. Bai, and O. Tonguz, "Dynamics of network connectivity in urban vehicular networks," *IEEE Journal on Selected Areas in Communications*, vol. 29, no. 3, pp. 515–533, March 2011.

[20] R. Groenevelt, P. Nain, and G. Koole, "Message delay in manet," in *Proceedings of the 2005 ACM SIGMETRICS international conference on Measurement and modeling of computer systems*, 2005, pp. 412–413.

[21] Y. Liao, Z. Zhang, and L. Gao, "Modeling redundance-based routing in delay tolerant networks," in *in Proc. CCNC*, 2007.

[22] S. Yousefi, E. Altman, R. El-Azouzi, and M. Fathy, "Analytical model for connectivity in vehicular ad hoc networks," *IEEE Transactions on Vehicular Technology*, vol. 57, no. 6, pp. 3341–3356, November 2008.

[23] M. Abdulla and R. Simon, "A simulation study of common mobility models for opportunistic networks," in *Proceedings of the 41st Annual Simulation Symposium*, 2008, pp. 43–50.