Using Vehicular Sensor Networks for Mobile Surveillance

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***Abstract*—Mobile surveillance has been recently proposed as a replacement for traditional road-side surveillance system. One important aspect of a mobile surveillance system is to decide what are the events of interest. In this work, we adopt the concept of participatory sensing for mobile surveillance by involving a human into the loop of data collection. We introduce a virtual credit based mechanism to motivate the participants to collect data and share their bandwidth. Finally, we use a large-scale real-world vehicle trace to evaluate the feasibility of our proposed framework.**

I. Introduction

Video surveillance is commonly used by the police and private security officers to determine and investigate crimes and other incidents. For example, when a car accident occurs, the police could use video record to find out who was at fault. However, it has been shown [1] that traditional fixed installations of surveillance systems often only lead to a movement of criminal behaviors to neighboring areas which are not under surveillance, or are being monitored in a less obvious fashion. To improve the capability of traditional systems which need to deploy many cameras in specific locations for wide-area surveillance, mobile surveillance systems [2–7] have been proposed to monitor events using video sensors mounted on mobile devices.

One critical issue in a mobile surveillance system is to decide what are the "interesting" or "unusual" events. Existing mobile surveillance systems are generally designed to record the surrounding area continuously and send the data back to a sink node (e.g. a server). Such an approach not only increases the volume of data that needs to be analyzed, but also wastes significant network bandwidth on unwanted data. One way to resolve this issue is to adopt the concept of "human computation" [8] by involving a human into the loop of data collection, given that a person might have a better insight than a machine about what data is worth collecting. This is also known as participatory sensing [9], and is 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. 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 utilize a large-scale vehicle trace to evaluate the feasibility of deploying such a mobile surveillance system in

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the real world.

II. Related Work

Our work builds on prior work in mobile surveillance, participatory sensing, incentive-based forwarding.

Cucchiara et al. [5] presented an overview of mobile video surveillance systems, focusing in particular on the architectural aspects of state of the art approaches iMouse [4] provides a WSN-based surveillance service combining the advantages of both WSN and video surveillance systems. Greenhill et al. [2] proposed a mobile surveillance system based on observation streams collected from mobile cameras mounted on buses. This approach supports retrieval of raw images based on space time and geometry. However, these works do not consider providing incentives to encourage participants in the network to contribute their data or bandwidth.

In participatory sensing, each participant senses different data, and many projects have been launched in this area, some of which are described below. NoiseTube [10] is participatory application monitoring noise pollution using mobile phones. Suelo [11] is an embedded networked sensing system designed for soil monitoring. BikeNet [12] is a mobile sensing system for mapping the experience of cyclists. Nericell [13] 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 [14] is a service that computes fuel-efficient routes for vehicles between arbitrary end-points by exploiting the vehicular sensor measurements available through OBD-II. Livecompare [15] 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. [16] 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. 'Tit for tat' [17] 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 [15] 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. Unlike our work, all these prior work do not consider the quality of the data and assume every data has the same value. In the Packet Trade Model [18], each intermediate node buys a packet from its previous hop with some credits, and then sells the packet to the next hop for more credits. In Packet Purse [18], the number of packets a node can send or relay to its neighbors is fixed, and the main challenge in this scheme is for the source to predict how many hops are needed. to successfully deliver a message to the destination. Crowcroft et al. [19] proposed that every node can determine the price of providing a forwarding service for other nodes based on its own available bandwidth and battery power. These previous studies assume that the source and the destination are charged for sending and receiving data. However, in this work, we argue that both the source and the sink (i.e. 3G node) should be rewarded for providing and forwarding data.

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 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

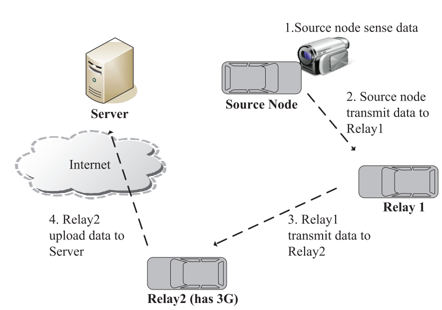

Fig. 1. The scenario examined in this work

community, several metrics have been proposed to estimate the quality of the data such as accuracy, completeness, relevance, timeliness, and reputation [20]. We can broadly divide these metrics into two groups, as shown in Fig. 2. The metrics in the first group tend to change their values over time. The second group of metrics are more static and their values are typically already determined when the data is generated. Some of the above 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.

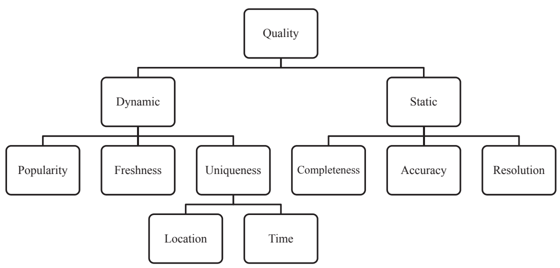

Fig. 2. Taxonomy of criteria for data quality

B. Compute the credits

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 $U = S * e^{-\lambda \times T}$, where λ is the commission rate and T is the time that has elapsed since the data was generated. 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 be earned by the source is $Credit_{S-R} = Credit_S \times \xi$, where ξ is the enumeration rate. If the relay is not the last hop, and it is the i_{th} relay, the credits that it could earn is $Credit_{Ri} = Credit_S \times \xi \times (1-\xi)^{i-1}$. If the relay is the last hop, which is the i_{th} relay node, the credits it could earn is $Credit_{Ri} = Credit_S \times (1-\xi)^{i}$.

C. 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 to a 3G-node, such as the source.
- Helper: a node that can help the Requester relay the data to a 3G node.

TABLE I
INFORMATION IN HELLO MESSAGE

N	node type: 1: Requester 2: Helper
S	size of the data
V	speed and direction of the node
C	whether the node has 3G capabilities or not
T	the time elapsed since the data was generated by the source (Requester only)
H	how many times the data has been relayed (Requester only)
U	current utility of the data (Requester only)
h	the node's current minimum hop count to a 3G node
τ	the most recent time when a 3G node was seen by the previous relays

Both the Requester and the Helper nodes will periodically broadcast a HELLO message to let neighboring nodes know of their existence. The information carried in the HELLO message is shown in Table I. 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 $U' = U \times e^{-\lambda \times t}$, 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 [21]. 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 [22] and see if they have enough time for the data transmission. Here we define an 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 (i.e., the highest U'). 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 study, we consider the use of three different metrics for choosing the next relay. The first is Hop number (h), which is the number of times the data has been relayed since a 3G node was last seen. The second metric $\hat{D}$ is the possible maximum distance between the candidate Helper and a 3G node, i.e., $\hat{D} = E \times V + R \times h$. Here R is radio range, E is the time that has elapsed since a 3G node was last seen by one of the previous relay nodes, and this is equal to $(current\ time - \tau)$. Both h and τ are embedded in the HELLO message, as shown in Table I. Every node stores these information in its internal memory and update h and τ every time when it overhears a HELLO message as follows: when node N_i encounters node N_j, assuming the values of their h and τ are (h_i, τ_i) and (h_j, τ_j) respectively. These two nodes will compare their h and τ. If, say, $h_i < h_j$, then N_j will update its internal table with $h_j = h_i$ and $\tau_j = \tau_i$. V is the Helper's average speed, and R is the radio range. The last metric $\hat{T}$ is an estimated time for the candidate Helper to encounter a 3G node, and this is $\hat{T} = \hat{D}/V$. The Requester will select the Helper with the smallest h (or $\hat{D}$ or $\hat{T}$) from its candidate list as the next forwarder. The distance-based metric (i.e. $\hat{D}$) was also used previously in the Terminodes Project [23] to select the next relay. In section VI, we will evaluate the performance of these three metrics using real-world vehicle traces.

IV. Simulation

In this section, we first use a detailed packet-level vehicular simulator MOVE [24] to evaluate the performance of using different Helper selection strategies. We then discuss the feasibility of deploying our proposed architecture in the real world using a trace-driven simulation. We enable CSMA/CA in our simulations and use the TwoRayGround model to simulate the radio propagation. Each car periodically (every one second) broadcasts HELLO messages to neighboring nodes. We employ 802.11 MAC as the underlying MAC protocol, and 3G nodes and source nodes are randomly assigned in the simulation. Each simulation runs for 2,000 seconds, and the maximum radio transmission range is 250m. The enumeration rate is 0.3.

In the first experiment, we use a 10×10 grid map for the road network T, and the length of each grid is 400m. The roads have four lanes and are bi-directional. As described in Section IV, in this work we consider the use of three different metrics (i.e. number of hops, distance and time) for the Helper selection strategy. In our experiment, we compare these three metrics with first-come-first-serve (FCFS) (which means that the Requester will pick the first Helper that responds to its request). In order to motivate the participant to upload the data to the server as soon as possible, we define the success rate (which is $\frac{the\ amount\ of\ data\ uploaded\ to\ the\ server}{the\ amount\ of\ data\ generated}$) as a function of the number of relays (i.e. i) and how long the data has been in the network since it was generated (i.e. T). As shown in III-B and III-C, when ξ is small, i will become the dominant factor that determines if the data can be eventually uploaded to the server. As a result, we find that using the estimated number of hops to a 3G node performs better than the other approaches, as shown in Fig. 3, since it tries to minimize i. On the other hand, FCFS has the worst performance, because it does not consider the geographical relationship between the Helper and the 3G node. Finally, time-based and distance-based approaches have similar performance, since the average speed for most of the cars is not significantly different, as it is restricted by the speed limits, in operation on the roads being used.

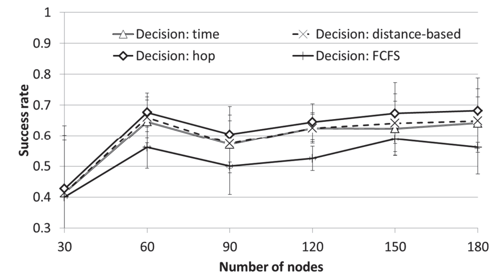

Fig. 3. Comparison of different Helper selection strategies

Next, given that it is difficult to evaluate our proposed architecture in the real world, we employ trace-driven simulations using a detailed GPS trace of taxis in Shanghai [25]. Because the trace consists of several months of data and it is impossible to use the entire trace for our trace-driven simulations, we only use a portion in our simulation. We simulate the vehicle movement in a 5km $\times$ 5km downtown area. The node density is around 40 cars per square kilometer. We use the trace to evaluate the effects of the 3G penetration rates and radio ranges on the success rate.

As shown in Fig. 4, with a 3G penetration rate of 20%, the success rate is around 80%. However, as shown in Fig. 5, the communication range supported by WiFi (100m to 300m) can only enable less than 50% of the generated data to eventually be uploaded to the server. The recently standardized 802.11p [26] (with a theoretical range of 1000m) will be more suitable for our proposed framework.

Finally, given a 20% 3G penetration ratio, around 60% of the cars can find a 3G node within 6 hops and in less than 500 seconds, as shown in Fig. 6 and Fig. 7.

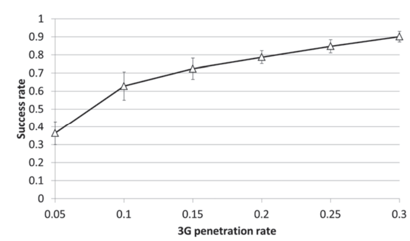

Fig. 4. The effect of 3G penetration ratio on the success rate in Shanghai city

V. 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 first 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. We then use a large-scale real-world taxi trace to evaluate the performance of our proposed architecture and show that a wireless technology that has a long radio range (such as

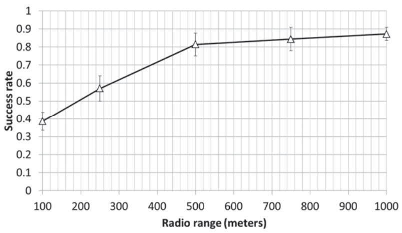

Fig. 5. The effect of radio range on the success rate in Shanghai city (3G penetration rate: 0.1)

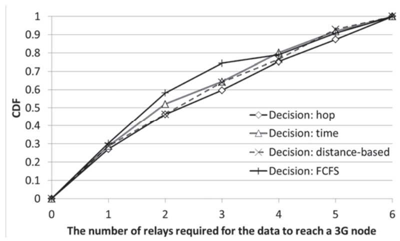

Fig. 6. The number of relays required for the data to reach a 3G node

DSRC) might be required for the inter-vehicle communication in our proposed framework. We are currently building a real-world testbed by implementing our incentive framework on the Android and IOS platforms.

VI. Acknowledgment

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References

[1] H. M. Dee and S. A. Velastin, "How close are we to solving the problem of automated visual surveillance?: A review of real-world surveillance, scientific progress and evaluative mechanisms," *Mach. Vision Appl.*, vol. 19, pp. 329–343, September 2008. [Online]. Available: http://dl.acm.org/citation.cfm?id=1416799.1416802

[2] S. Greenhill and S. Venkatesh, "Virtual observers in a mobile surveillance system," in *Proceedings of the 14th annual ACM international conference on Multimedia*, ser. MULTIMEDIA '06. New York, NY, USA: ACM, 2006, pp. 579–588. [Online]. Available: http://doi.acm.org/10.1145/1180639.1180759

[3] G. Pingali, Y.-L. Tian, S. Ebadollahi, J. Pelecanos, M. Podlaseck, and H. Stavropoulos, "An end-to-end echronicling system for mobile human surveillance," in *Computer Vision and Pattern Recognition, 2007. CVPR '07. IEEE Conference on*, june 2007, pp. 1 –2.

[4] Y.-C. Tseng, Y.-C. Wang, K.-Y. Cheng, and Y.-Y. Hsieh, "imouse: An integrated mobile surveillance and wireless sensor system," *Computer*, vol. 40, no. 6, pp. 60 –66, June 2007.

[5] R. Cucchiara and G. Gualdi, "Mobile video surveillance systems: An architectural overview," in *Mobile Multimedia Processing*, ser. Lecture Notes in Computer Science, X. Jiang, M. Ma, and C. Chen, Eds. Springer Berlin / Heidelberg, 2010, vol. 5960, pp. 89–109, 10.1007/978-3-642-12349-8-6.

[6] G. Gualdi, A. Albarelli, A. Prati, A. Torsello, M. Pelillo, and R. Cucchiara, "Using Dominant Sets for Object Tracking with Freely Moving Camera," in *The Eighth International Workshop on Visual Surveillance - VS2008*. Marseille, France: Graeme Jones and Tieniu Tan and Steve Maybank and Dimitrios Makris, 2008. [Online]. Available: http://hal.inria.fr/inria-00325634/en/

[7] B.-F. Wu, H.-Y. Peng, C.-J. Chen, and Y.-H. Chan, "An encrypted mobile embedded surveillance system," in *Intelligent Vehicles Symposium, 2005. Proceedings. IEEE*, June 2005, pp. 502 – 507.

[8] L. von Ahn, "Human computation," in *Design Automation Conference, 2009. DAC '09. 46th ACM/IEEE*, july 2009, pp. 418 –419.

[9] 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.

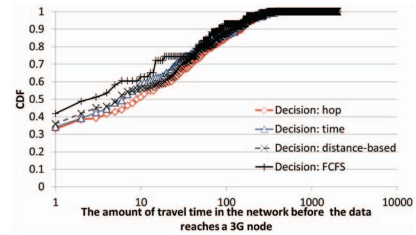

Fig. 7. The amount of travel time in the network before the data reaches a 3G node

[10] 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, 10.1007/978-3-540-88351-7-16.

[11] 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*, ser. SenSys '09. New York, NY, USA: ACM, 2009, pp. 197–210. [Online]. Available: http://doi.acm.org/10.1145/1644038.1644058

[12] 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*, ser. SenSys '07. New York, NY, USA: ACM, 2007, pp. 87–101. [Online]. Available: http://doi.acm.org/10.1145/1322263.1322273

[13] 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*, ser. SenSys '08. New York, NY, USA: ACM, 2008, pp. 323–336. [Online]. Available: http://doi.acm.org/10.1145/1460412.1460444

[14] 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*, ser. MobiSys '10. New York, NY, USA: ACM, 2010, pp. 151–164. [Online]. Available: http://doi.acm.org/10.1145/1814433.1814450

[15] 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*, ser. HotMobile '09. New York, NY, USA: ACM, 2009, pp. 4:1–4:6. [Online]. Available: http://doi.acm.org/10.1145/1514411.1514415

[16] 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.

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

[18] L. Buttyan and J.-P. Hubaux, "Enforcing service availability in mobile ad-hoc wans," in *Proceedings of the 1st ACM international symposium on Mobile ad hoc networking & computing*, ser. MobiHoc '00. Piscataway, NJ, USA: IEEE Press, 2000, pp. 87–96. [Online]. Available: http://dl.acm.org/citation.cfm?id=514151.514164

[19] J. Crowcroft, R. Gibbens, F. Kelly, and S. Östring, "Modelling incentives for collaboration in mobile ad hoc networks," *Perform. Eval.*, vol. 57, pp. 427–439, August 2004. [Online]. Available: http://dl.acm.org/citation.cfm?id=1032151.1032153

[20] 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*, ser. DASFAA'11. Berlin, Heidelberg: Springer-Verlag, 2011, pp. 478–489. [Online]. Available: http://dl.acm.org/citation.cfm?id=1996686.1996749

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

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

[23] J.-P. Hubaux, J.-Y. Le Boudec, S. Giordano, M. Hamdi, L. Blazevic, L. Buttyan, and M. Vojnovic, "Towards mobile ad-hoc wans: terminodes," in *Wireless Communications and Networking Confernce, 2000. WCNC. 2000 IEEE*, vol. 3, 2000, pp. 1052 –1059 vol.3.

[24] "Move (mobility model generator for vehicular networks)," 2011, [Online; accessed 1-November-2011]. [Online]. Available: http://lens.csie.ncku.edu.tw/MOVE

[25] "Suvnet-trace data." [Online]. Available: http://wirelesslab.sjtu.edu.cn

[26] B. Cohen, "Incentives build robustness in bittorrent," June 2003.