Opportunistic Collaboration in Participatory Sensing Environments

Niwat Thepvilojanapong[†], Shin'ichi Konomi[§], Yoshito Tobe[§], Yoshikatsu Ohta[†], Masayuki Iwai[♯], Kaoru Sezaki[♯]

[†]School of Engineering, Mie University, 1577 Kurimamachiya-cho, Tsu city, Mie 514–8507 Japan
{wat, ohta}@net.info.mie-u.ac.jp

[§]Tokyo Denki University, 2–2 Kanda-Nishikicho, Chiyoda-Ku, Tokyo 101–8457 Japan
{konomi, yoshito_tobe}@osoite.jp

[♯]University of Tokyo, 4–6–1 Komaba, Meguro-ku, Tokyo 153–8505 Japan
{masa, sezaki}@iis.u-tokyo.ac.jp

ABSTRACT

The proliferation of networked mobile devices that can capture and communicate various kinds of data provides an opportunity to design novel man-machine sensing environments of which this paper considers participatory sensing. To achieve energy efficiency and reduce data redundancy, we propose Aquiba protocol that exploits opportunistic collaboration of pedestrians. Sensing activity is reduced according to the number of available pedestrians in nearby area. The paper investigates the benefit of opportunistic collaboration in large-scale scenarios through simulation studies. To take microscopic interaction of social crowds into consideration, we adapt the social force model and include it as one of three mobility models applied in our studies. Though the simulation results depend on mobility models, they validate the benefit of opportunistic collaboration employed by Aquiba protocol.

Categories and Subject Descriptors

C.2.1 [**Computer Systems Organization**]: Computer-Communication Networks—*wireless communication*; C.3 [**Special-Purpose and Application-Based Systems**]: Real-time and Embedded Systems

General Terms

Performance, Design, Algorithms

Keywords

Participatory sensing, mobile phones, opportunistic collaboration, energy efficiency, sensing resolution, performance evaluation, simulation, mobility models

1. INTRODUCTION

Proliferation of mobile cellular subscribers as well as advances in MEMS-based sensor technology and low-power RF design has realized the practical usage of mobile sensing devices for the purpose of *participatory sensing* [3, 4, 6] in urban areas. Such ubiquity of cellular phones and embedded sensors allows people to capture and share ambient information as they go about their daily lives—working, playing, and moving (on foot, by car, by bike, or by public transportation). They can provide a dynamic, easy-to-deploy sensing infrastructure in complex urban environments where (dense) deployment of stationary sensing devices is not possible due to various physical and social constraints. Accordingly, urban inhabitants can capture all kinds of detailed data about all physical spaces they can access. Such ambient data can be captured either directly from internal sensors that are integrated with cellular phones or indirectly from external wireless sensors embedded in environments. The captured data can be shared automatically without any human intervention or interactively on the basis of user operations through *Data Commons* [6] that involve a collection of open public-domain data spaces, and evolve over time based on citizen participation.

Recently, participatory sensing has been studied in several aspects including data collection strategies [17], recruiting participants [20], integration with social networks [14], and so on. When focusing on the issue of data collection, a mobile sensing device collects information independently without considering the existence of nearby devices [17, 7, 11]. Real-time collaboration among strangers in participatory sensing environments receives little attention from researchers, though the idea of opportunistic collaboration in our work is inspired by the literature on ad hoc, sensor, and delay-tolerant networks [25, 21, 23, 22, 13]. It is plausible that the use of cellular phones as sensory devices might result in the presence of a large number of densely located mobile sensors in an urban area. As a result, it is quite likely that the ambient information collected by many of the cellular phones would be redundant. To cope with such problem, this paper proposes *Aquiba protocol* which is a general approach to exploit opportunistic collaboration in urban sensing environments. Aquiba considers collaboration without community bonds, i.e., the collaboration could take place automatically among strangers, even without them being aware of it. In particular, sensing tasks of each cellular phone are reduced autonomously according to the availability of nearby mobile sensing devices; thereby energy consumption is also reduced correspondingly.

To study Aquiba in large-scale scenarios, computer simulation is a promising tool because of low cost, fast and flexible implementation. Patterns of human movement play a critical role in such a simulation-based study [1]. Therefore we include three mobility models, i.e., random waypoint, Manhattan, and extended social force models, in our study in order to investigate the benefit of opportunistic collaboration under different moving patterns of pedestrians, though the objective is not to compare or evaluate the mobility models. This paper particularly considers the extended social force model because it includes social interactions among pedestrians and also takes streets, sidewalks, walls and other elements that affect pedestrians into consideration. It is important to consider the dynamics of pedestrian crowds according to macroscopic as well as microscopic elements to effectively study opportunistic collaboration in participatory sensing environments.

2. OPPORTUNISTIC COLLABORATION

In this section, the problem formulation is given and followed by the description of Aquiba protocol.

2.1 Problem Formulation

We consider participatory sensing system as follows: (i) a system consists of a server, cellular phones, and sensors; (ii) each cellular phone is equipped with cellular and short-range communication transceivers; (iii) the sensors are embedded in either the cellular phones or environment to capture ambient data; (iv) the server issues a query including desired *temporal sensing resolution* R_i (e.g., once per second) for each kind of sensing data i for each *sensing area* A_i; (v) each cellular phone is able to acquire location information.

2.2 Aquiba Protocol

There are two approaches of Aquiba protocol, i.e., egalitarian and selective distributions, as follows.

2.2.1 Egalitarian Distribution

Upon receiving the query from the server, each mobile sensing device periodically checks whether it is within A_i. If it is within A_i, it starts sensing activity by capturing and uploading data at the rate of R_i, and tries to perform collaborative sensing whenever possible. Aquiba employs a straightforward approach to study the possibility and benefit of opportunistic collaboration, i.e., each pedestrian reduces upload rate to $\frac{R_i}{p_i+1}$, where p_i is the number of detectable pedestrians in A_i. Though the upload rate of each pedestrian is reduced, the collective sensing resolution perceived at the server is still maintained at R_i. Without such collaboration, all p_i+1 pedestrians independently upload data at the fixed rate R_i, which leads to the collective sensing resolution of at least $(p_i+1)R_i$ at the server.

To acquire p_i, each pedestrian in A_i uses short-range radio to broadcast beacon packets periodically. A pedestrian maintains the list of nearby pedestrians from received beacons by setting an expiry time for each pedestrian and deleting the expired ones from the list. Knowing the exact number of pedestrians in A_i leads to the highest benefit, though it is not a requirement of Aquiba. One possible way to achieve more accurate list of pedestrians is to include the current list in the beacon packets.

2.2.2 Selective Distribution

Selective distribution follows the egalitarian except the process of determining the sensing rate of each pedestrian. Not all the pedestrians in A_i, but selected k_i representatives of them ($k_i < p_i + 1$) take the responsibility of uploading data at the rate of $\frac{R_i}{k_i}$ due to some underlying reasons such as different levels of remaining battery, individual preferences and skills, and so on. The most simplistic method to select k_i is to choose them randomly. We can also select them strategically based on the statuses and preferences of pedestrians. An alternative method for selecting representatives is to use clustering, which is a promising solution for certain types of sensing tasks that focus on meaningful subsets of pedestrians in the area. The clustering can be done by either centralized or distributed manners.

Centralized clustering: The centralized approach uses the K-means algorithm [19] to form a cluster of pedestrians in A_i. When entering a sensing area, a pedestrian sends a measurement vector $(x_1, x_2, \ldots, x_n)$ including its location information to the server. Based on the received data, the server performs supervised K-means clustering in order to minimize the total intra-cluster variance of the received data. The server then selects the pedestrian whose measurement vector is the closest to the centroid of the cluster as the cluster representative and informs the representatives of the selection. The selected representatives continue to carry out the sensing task until they leave the sensing area. If some representative leaves the sensing are, the sensing rate needs to be modified in order to maintain the collective sensing resolution perceived at the server. If none of the representatives exist, the selection process will start all over.

Distributed clustering: The distributed approach utilizes short-range radio for carrying out clustering, and adopts the idea of the low-energy adaptive clustering hierarchy protocol [8]. Each pedestrian elects itself to be the cluster representative with some defined probability ($\mathcal{P}$) that is proportional to k_i. The probability can be inversely proportional to (i) the number of nearby pedestrians, i.e., $\mathcal{P} = \frac{k_i}{p_i}$, or (ii) the size of the sensing area, i.e., $\mathcal{P} = a\frac{k_i}{A_i}$, where a is a constant. Once the pedestrians have elected themselves to be cluster representatives, they announce this role to other pedestrians using short-range radio. Other factors such as remaining battery can also be included when determining the probability of being cluster representatives.

3. EVALUATION METHODOLOGY

The characteristics of mobility models are discussed in this section, followed by the details of simulation setup and two performance metrics for evaluation.

3.1 Mobility Models

Each mobility model has different characteristics including spatial dependence, geographic restrictions, spatial node distribution, and several properties related to connectivity graph [1, 16]. Since the performance of protocol varies drastically across mobility models, we include three mobility models in our study. We briefly discuss each mobility model as follows (the details can be found in the references).

3.1.1 Random Waypoint Model

The random waypoint (RWP) model [2] is widely used because of its simplicity and wide availability. The spatial node distribution is non-uniform, i.e., the node density is highest at the center, whereas the node density is almost zero around the boundary of area. Since each node moves independently of others, the spatial dependence of RWP model is low.

In our simulation, the pause time and maximum speed were set to 60 s and 2 m/s, respectively. The simulation area is a 200m-by-200m square space and three sensing areas are circular regions centered at (30, 30), (60, 60), and (100, 100) with a radius of 10 m.

3.1.2 Manhattan Model

Bai et al. [1] introduced the Manhattan (MHT) model to emulate the movement of nodes on streets defined by maps. It is useful in modeling movement in an urban area where a pervasive computing service between mobile devices is provided.

The map is composed of a number of horizontal and vertical streets. Each street has two lanes for each direction. The node is allowed to move along the grid of horizontal and vertical streets on the map. At an intersection, the node turns left, right, or goes straight with the probability of 0.25, 0.25, and 0.5, respectively. The velocity $\vec{v_i}(t+1)$ of a node i at a time slot $t+1$ depends on its velocity $\vec{v_i}(t)$ and acceleration $\vec{a_i}(t)$ at the previous time slot t. Also, the velocity $\vec{v_i}$ of a node i is restricted by the velocity $\vec{v_j}$ and position of the node j preceding it on the same lane of the street.

Due to the use of lanes in opposite directions in the map, the positive degree of spatial dependence of a node with nodes in the same direction cancels the negative degree of spatial dependence of the node with nodes traveling in the opposite direction. If we consider the spatial dependence of the nodes moving in the same direction, the spatial dependence is high. The spatial node distribution is not uniform, i.e., the node density is higher at intersections in comparison with lanes.

Fig. 1 illustrates the 200m-by-200m map including three

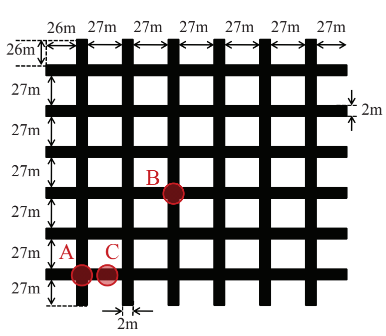


Figure 1: A map for MHT model.

circular sensing areas (A, B, and C) with a radius of 10 m for evaluation purpose. The maximum velocity, maximum acceleration, pause time, and safety distance were set to 2 m/s, 1 m/s^2, 60 s, and 0.5 m, respectively.

3.1.3 Extended Social Force Model

Participatory sensing not only considers macroscopic data (e.g., the average temperature of a city) but also microscopic data (e.g., the temperature or number of people in a train station). We therefore need a realistic mobility model that takes into consideration microscopic as well as macroscopic patterns of pedestrian mobility. The social force model [10, 9] has been proposed to emulate the motion of pedestrians as if they were subjected to *social forces*. The speed $\vec{v}$ of pedestrian is governed by the four force terms: (i) the acceleration towards the next destination considering a desired speed, (ii) the repulsive force due to borders, (iii) the similar repulsive force due to other pedestrians, and (iv) the attractive force due to people/objects/events. The model also takes into consideration fluctuations due to accidental or deliberate deviations from the optimal behavior.

We introduce the extended social force (ESF) model by integrating the social force model with a simple probabilistic route-choice behavior. At an intersection, a pedestrian who walks on the left sidewalk of a street turns left or goes straight with the same probability of 0.5. Similarly, we determined the probabilities of pedestrians walking on the right sidewalk of a street. Since the ESF model takes into consideration spatial structures and interactions among pedestrians, it realistically demonstrates the development of collective behavior. Similar to the MHT model, the spatial node distribution of ESF model is higher at intersections in comparison with streets. The spatial dependence is the highest among three mobility models.

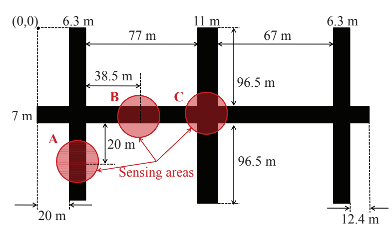


Figure 2: A map for ESF model.

A map illustrated in Fig. 2 is drawn on the basis of real streets. Three circular sensing areas (A, B, and C) with a radius of 10 m for evaluation purpose are also shown in the figure. The sensing areas A, B, and C were selected as representatives of a vertical street, a horizontal street, and an intersection, respectively. In the simulation, the desired speed is approximately Gaussian distributed with a mean value of 1.3 m/s and a standard deviation of 0.3 m/s [9].

3.2 Simulation Setup

We use a discrete event simulator, *ns*–2 [18], to study the egalitarian distribution of Aquiba. The properties and parameters of short-range transceiver follow the specifications of CC2420, which is a single-chip 2.4-GHz IEEE 802.15.4 complaint and ZigBee-ready RF transceiver [24]. The transmit power drain at 0 dBm is 31.32 mW and the receive power drain is 35.46 mW [26]. The maximum data rate of IEEE

802.15.4 is 250 kbps. The radio range of IEEE 802.15.4 in simulated networks was set to 10 m. When considering the circular sensing areas with a radius of 10 m, it is not necessarily that all pedestrians can transmit their beacon packets to all others in the same sensing area. We deliberately determine such simulation environment in order to study the performance of Aquiba when short-range radio cannot cover the entire sensing area. It is intuitive that the performance of Aquiba should be better if short-range radio is able to cover the entire sensing area, i.e., our simulation setup is conservative.

The simulated cellular network is assumed to be a 3G mobile telecommunications network, where the maximum forward and reverse link speeds were set to 3.1 and 1.8 Mbps, respectively. To determine the values of power consumption for simulated networks, we developed a prototype of mobile sensing device by using the Casio G'zOne W62CA cellular phone [5] and conducted preliminary experiments. Based on the experiments, the transmit power drain of the prototype was 567.03 mW and acquiring location information using GPS chip embedded in the phone required 509.1 mW of power drain[1]. In the simulations, cellular phones acquire location information whenever a sensing task is conducted in order to include location as contextual information of sensor data.

We varied population density by injecting 50, 100, 200, 300, and 400 pedestrians in the maps in order to analyze the performance in the cases of crowded and uncrowded areas. Each simulation lasted for 30 minutes and we trimmed the first five minutes of each scenario in order to eliminate the warm-up effect of mobility models. The desired sensing rate R_i was set to once per second for all sensing areas.

3.3 Performance Metrics

We define two metrics for evaluation purpose as follows.

3.3.1 Sensing Resolution

For a given sensing area A_i, if the total number of packets arrives at the server within a short period T is S, the ratio of sensing resolution perceived by the server to R_i can then be expressed by Eq. (1).

$$\mathcal{R} = \frac{\min\left(\frac{S}{T}, R_i\right)}{R_i}. \tag{1}$$

It is apparent from the equation that $\mathcal{R}$ ranges from zero (the lowest level) to one (the highest level). If users are interested in P consecutive periods of T, $\mathcal{R}$ is an average of P periods as expressed by Eq. (2).

$$\mathcal{R} = \frac{\sum_{j=1}^{P} \mathcal{R}_j}{P}, \text{ where } P = 1, 2, 3, \ldots \tag{2}$$

The definition of $\mathcal{R}$ can be extended to M arbitrary sensing areas, i.e., Eqs. (1) and (2) become Eqs. (3) and (4), respectively, when finding average $\mathcal{R}$ of M areas.

$$\mathcal{R} = \frac{\sum_{m=1}^{M} \mathcal{R}_m}{M}. \tag{3}$$

$$\mathcal{R} = \frac{\sum_{m=1}^{M} \left[\left(\sum_{j=1}^{P} \mathcal{R}_{m,j}\right)/P\right]}{M}. \tag{4}$$

[1]The result obtained from our experiments is nearly the same as that reported in previous work [15].

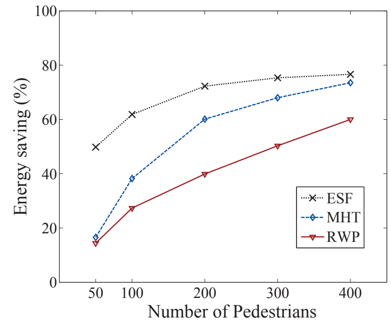


Figure 3: Percentage of energy saving.

3.3.2 Energy Saving

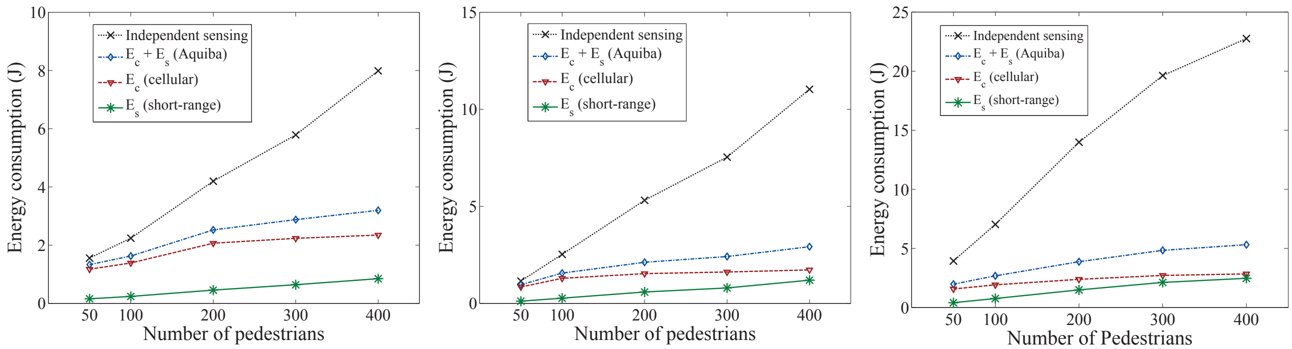
The performance of Aquiba is compared with the independent sensing approach in which the opportunistic collaboration among pedestrians is not carried out. Let E and E_{co} be the total energy consumed by independent and collaborative sensing approaches, respectively. The percentage of energy saved by Aquiba is $\frac{(E-E_{co})}{E} \times 100\%$. Note that the energy consumed by Aquiba are from both cellular (E_c) and short-range (E_s) radios, i.e., $E_{co} = E_c + E_s$.

4. SIMULATION RESULTS

Regardless of mobility models and the number of pedestrians, the ratios of perceived sensing resolutions $\mathcal{R}$ achieved by Aquiba are nearly perfect, i.e., $\mathcal{R}$ approaches one which is the highest level[2]. It means that Aquiba is able to report sensing data judiciously according to R_i and A_i determined by the server.

The results of energy saving are presented in Fig. 3. Each mark in the figure is averaged over the three sensing areas. The percentages of energy saving achieved by Aquiba range from 14% to as high as 77%. Energy consumption is reduced the most in ESF model, followed by MHT and RWP models. Energy saving of RWP is the lowest because the population density at any given point and time is the lowest due to high degree of freedom to move. Thereby a pedestrian seldom meets others and the opportunity of collaboration is the lowest in comparison with the other mobility models. Based on the same principle, higher population density of ESF model leads to the highest energy saving due to the effectiveness of collaborative sensing. Energy saving of MHT, which lies between RWP and ESF, presents an interesting result. When there are 50 pedestrians (i.e., low population density), 17% energy saving of MHT is comparable to that of RWP (14%). As the number of pedestrians increases to 400 (i.e., high population density), energy saving of MHT rapidly increases to 74% which is as high as that of ESF (77%). Because of movement characteristics defined by MHT and geographical restrictions determined by the map, pedestrian crowds quickly develop when increasing the number of pedestrians in the simulated map. Although the characteristics of mobility model affect simulation results, we can conclude that controlling sensing tasks by applying Aquiba protocol does not harm sensing resolution perceived at the server while helping in minimizing energy consumption. The results also validate the efficacy of Aquiba when

[2]The graphs of $\mathcal{R}$ are omitted due to lack of space.



(a) RWP traces.   (b) MHT traces.   (c) ESF traces.

Figure 4: Energy consumption.

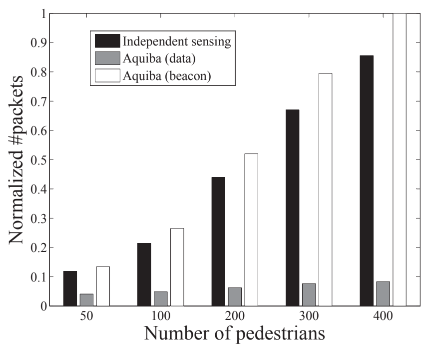


Figure 5: Number of packets in area C of ESF trace.

short-range radio cannot cover the entire sensing areas determined in the simulations.

Since Aquiba uses two kinds of radios for communication purposes, Fig. 4 details the energy consumed by short-range (E_s) and cellular (E_c) transceivers separately, and also includes the total energy consumed by both Aquiba and independent sensing approach for comparison purposes. When considering E_s separately, it is apparent from the figures that ESF consumes the highest energy. The underlying reason is the same as described above, i.e., pedestrians in ESF have the highest opportunity of collaborative sensing due to the highest spatial dependence and geographic restrictions, thereby short-range radio is used the most frequent in order to determine the number of nearby pedestrians.

Energy consumed (or current drawn) by transceivers are slightly different depending on manufacturers. To avoid such inconsistency of energy consumption when conducting simulations, Fig. 5 shows the normalized number of data and beacon packets transmitted in sensing area C when applying ESF traces. The results show that the number of data packets generated by Aquiba is 2 to 14 times less than that of independent sensing approach. We conclude that it is not harmful to use low-power short-range radio in order to reduce the usages of high-power cellular radio. Also the additional benefit of Aquiba is to reduce redundant data packets received at the server.

5. CONCLUSION

Systems that integrate sensing tasks into our daily lives, such as participatory sensing, are a benefit of the development in man-machine symbiosis that involves very close coupling between human and electronic devices [12]. In this paper, we have introduced Aquiba protocol that exploits opportunistic collaboration of man-machine systems to realize energy-efficient participatory sensing. To investigate Aquiba in large-scale environments, we have conducted simulation studies by taking three mobility models into consideration because each model has quite different characteristics including spatial dependence, geographic restrictions, spatial node distribution, and so on. Unlike conventional ad hoc and sensor networks, participatory sensing needs a realistic mobility model that takes into consideration microscopic as well as macroscopic factors of pedestrian movements. Thus the social force model, which satisfies the above requirements, is one of mobility models applied in our simulation studies. The simulation results demonstrate that Aquiba can reduce energy consumption 14% to as high as 77% depending on mobility models and population densities. Though several issues are still open for further discussion, this preliminary study is a first step towards providing an efficient participatory sensing in urban environments through collaborative mechanisms. An issue which is worth mentioning here is a motivation to join participatory sensing. The existing paid service launched by the Weathernews Inc. already removed this concern from us [27]. Although users must pay a monthly fee to publish environmental data through the Weathernews' server, a large amount of users still join the service because of their enthusiasm. Nevertheless, participatory sensing can be a free service, and we can provide participants with an incentive. For example, we may implement a points-based system that awards points that can be redeemed coupons, gifts, services, etc.

6. REFERENCES

[1] F. Bai, N. Sadagopan, and A. Helmy. The IMPORTANT framework for analyzing the Impact of Mobility on Performance Of RouTing protocols for Adhoc NeTworks. *Ad Hoc Networks*, 1(4):383–403, Nov. 2003.

[2] J. Broch, D. A. Maltz, D. B. Johnson, Y.-C. Hu, and J. Jetcheva. A performance comparison of multi-hop

wireless ad hoc network routing protocols. In *Proceedings of the 4th ACM International Conference on Mobile Computing and Networking (MobiCom 1998)*, pages 85–97, Dallas, Texas, USA, Oct. 1998.

[3] J. Burke, D. Estrin, M. Hansen, A. Parker, N. Ramanathan, S. Reddy, and M. B. Srivastava. Participatory sensing. In *Proceedings of the Workshop on World-Sensor-Web (WSW 2006)*, pages 6–10, Boulder, Colorado, USA, Nov. 2006.

[4] A. T. Campbell, N. D. Lane, E. Miluzzo, R. A. Peterson, H. Lu, X. Zheng, M. Musolesi, K. Fodor, S. B. Eisenman, and G.-S. Ahn. The rise of people-centric sensing. *IEEE Internet Computing*, 12(4):12–21, July/August 2008.

[5] Casio Computer Co.,Ltd. G'zOne W62CA. `http://k-tai.casio.jp/products/w62ca/`, accessed July 2010.

[6] D. Cuff, M. Hansen, and J. Kang. Urban sensing: out of the woods. *Communications of the ACM*, 51(3):24–33, Mar. 2008.

[7] 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 (SenSys 2007)*, pages 87–101, Sydney, Australia, Nov. 2007.

[8] W. R. Heinzelman, A. Chandrakasan, and H. Balakrishnan. An application-specific protocol architecture for wireless microsensor networks. *IEEE Transactions on Wireless Communications*, 1(4):660–670, Oct. 2002.

[9] D. Helbing, L. Buzna, A. Johansson, and T. Werner. Self-organized pedestrian crowd dynamics: Experiments, simulations, and design solutions. *Transportation Science*, 39(1):1–24, Feb. 2005.

[10] D. Helbing and P. Molnár. Social force model for pedestrian dynamics. *Physical Review E (Statistical Physics, Plasmas, Fluids, and Related Interdisciplinary Topics)*, 51(5):4282–4286, May 1995.

[11] B. Hull, V. Bychkovsky, Y. Zhang, K. Chen, M. Goraczko, A. Miu, E. Shih, H. Balakrishnan, and S. Madden. CarTel: A distributed mobile sensor computing system. In *Proceedings of the 4th International Conference on Embedded Networked Sensor Systems (SenSys 2006)*, pages 125–138, Boulder, Colorado, USA, Nov. 2006.

[12] J. C. R. Licklider. Man-computer symbiosis. *IRE Transactions on Human Factors in Electronics*, HFE-1:4–11, Mar. 1960.

[13] L. Luo, C. Huang, T. Abdelzaher, and J. Stankovic. EnviroStore: A cooperative storage system for disconnected operation in sensor networks. In *Proceedings of the 26th Annual Joint Conference of the IEEE Computer and Communications Societies (INFOCOM 2007)*, pages 1802–1810, Anchorage, Alaska, USA, May 2007.

[14] E. Miluzzo, N. D. Lane, K. Fodor, R. Peterson, H. Lu, M. Musolesi, S. B. Eisenman, X. Zheng, and A. T. Campbell. Sensing meets mobile social networks: the design, implementation and evaluation of the CenceMe application. In *Proceedings of the 6th International Conference on Embedded Networked Sensor Systems (SenSys 2008)*, pages 337–350, Raleigh, North Carolina, USA, Nov. 2008.

[15] P. Mohan, V. N. Padmanabhan, and R. Ramjee. Nericell: rich monitoring of road and traffic conditions using mobile smartphones. In *Proceedings of the 6th International Conference on Embedded Networked Sensor Systems (SenSys 2008)*, pages 323–336, Raleigh, North Carolina, USA, Nov. 2008.

[16] S. M. Mousavi, H. R. Rabiee, M. Moshref, and A. Dabirmoghaddam. MobiSim: A framework for simulation of mobility models in mobile ad-hoc networks. In *Proceedings of the 3rd IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob 2007)*, page 82, New York, USA, Oct. 2007.

[17] M. Musolesi, M. Piraccini, K. Fodor, A. Corradi, and A. T. Campbell. Supporting energy-efficient uploading strategies for continuous sensing applications on mobile phones. In *Proceedings of the 8th International Conference on Pervasive Computing (Pervasive 2010)*, pages 355–372, Helsinki, Finland, May 2010.

[18] Network simulator – ns–2. `http://www.isi.edu/nsnam/ns/`, accessed July 2010.

[19] L. Rabiner and B.-H. Juang. *Fundamentals of Speech Recognition*. Prentice Hall Signal Processing Series. Prentice Hall PTR, Apr. 1993.

[20] S. Reddy, D. Estrin, and M. Srivastava. Recruitment framework for participatory sensing data collections. In *Proceedings of the 8th International Conference on Pervasive Computing (Pervasive 2010)*, pages 138–155, Helsinki, Finland, May 2010.

[21] R. C. Shah, S. Roy, S. Jain, and W. Brunette. Data mules: Modeling a three-tier architecture for sparse sensor networks. In *Proceedings of the 1st IEEE International Workshop on Sensor Network Protocols and Applications (SNPA 2003)*, pages 30–41, Anchorage, Alaska, USA, May 2003.

[22] T. Small and Z. J. Haas. Resource and performance tradeoffs in delay-tolerant wireless networks. In *Proceedings of the ACM Workshop on Delay Tolerant Networking (WDTN 2005)*, pages 260–267, Philadelphia, Pennsylvania, USA, Aug. 2005.

[23] T. Spyropoulos, K. Psounis, and C. S. Raghavendra. Spray and wait: An efficient routing scheme for intermittently connected mobile networks. In *Proceedings of the ACM Workshop on Delay Tolerant Networking (WDTN 2005)*, pages 252–259, Philadelphia, Pennsylvania, USA, Aug. 2005.

[24] Texax Instruments. CC2420: single-chip 2.4-GHz IEEE 802.15.4 complaint and ZigBee-ready RF transceiver. `http://focus.ti.com/docs/prod/folders/print/cc2420.html`.

[25] A. Vahdat and D. Becker. Epidemic routing for partially-connected ad hoc networks. Technical Report CS-2000-06, Duke University, July 2000.

[26] C.-Y. Wan, S. B. Eisenman, A. T. Campbell, and J. Crowcroft. Overload traffic management for sensor networks. *ACM Transactions on Sensor Networks*, 3(4):18, Oct. 2007.

[27] Weathernews Inc. Weathernews. `http://weathernews.com/`, accessed July 2010.