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A Study of Cooperative Human Probes in Urban Sensing Environments

Niwat THEPVILOJANAPONG[†,††*a)], Shin'ichi KONOMI[†,††], *and* Yoshito TOBE[†,††], *Members*

SUMMARY Portable sensory devices such as sensors equipped mobile phones enable convenient sensing and monitoring of urban areas. Such devices, which are always carried by humans, are referred to as *Human Probes*. Instead of carrying out sensing activities independently, cooperation of Human Probes helps in realizing efficient urban sensing environments. In this paper, we propose an *Architecture of Qualitative Urban Information Blending and Acquisition (Aquiba)*, in which the sensing activities are adjusted autonomously according to cooperation of Human Probes. Aquiba introduces a cooperative sensing approach which aims to maintain desired sensing resolution efficiently while minimizing overall energy consumption. To study the performance of Aquiba, we have conducted comprehensive simulations ranging from small- to large-scale scenarios along with applying three different movement patterns of human. The simulation results demonstrate that Aquiba is capable of providing high sensing resolution and reducing overall energy consumption.

key words: *urban sensing, cooperative sensing, energy efficiency, sensing resolution, performance evaluation, simulation, Aquiba*

1. Introduction

The number of mobile phone users has rapidly increased since the turn of the millennium [1]. Such ubiquity of mobile devices that can capture, communicate, and visualize various kinds of information provides an exciting opportunity to design a novel *humans-in-the-loop* sensing environment. A massive number of such mundane, personal devices are flowing in our everyday spaces, creating an opportunity to obtain, share, and use sensor data in the ways that are intricately enmeshed with human flows and activities.

Recently, with the use of networked sensing outside the controlled environment of laboratories, i.e., in open, urban areas, the concept of participatory or people-centric sensing has been introduced [2], [3]. In addition, ordinary people carrying sensors in urban areas are likely to participate and interested in data collection [4], [5]. Such participatory sensing is termed by us as *citizen-based urban sensing* or *Human-Probe sensing*. It is asserted that the main purpose of networked sensing is to "make the invisible visible" and support meaningful urban life [4]. Recent mobile phones such as the Apple iPhone and Nokia N95 are equipped with various sensors, including microphones, GPS, and so on. The use of such mobile phones eliminates the hindrance of deploying myriad static sensors across a wide area, and leads to a fully distributed citizen-based urban sensing.

Although Human-Probe sensing is a promising alternative to the deployment of static sensors, the research on this topic is still in its infancy and faces many challenges. For example, while a large number of Human Probes might densely locate in a nearby area, each one collects information independently without considering the existence of others. As a result, it is quite likely that the information collected by multiple Human Probes would be redundant or nearly identical. Therefore, it is important to understand and minimize redundancy of Human-Probe sensing because redundancy directly relates to communication costs and energy consumption. Nevertheless, controlling the sensing activities of Human Probes is generally nontrivial, since the mobility of citizens is often completely uncontrolled and a priori unknown.

In this paper, we propose an *Architecture of Qualitative Urban Information Blending and Acquisition (Aquiba)* for efficient collection of environmental data in urban sensing environments. To achieve such purpose, Aquiba simultaneously considers sensing resolution and energy consumption when controlling the sensing activities of Human Probes. Intuitively, sensing resolution is proportional to the number of received sensor readings. Therefore, we might increase the sensing rate of each Human Probe in order to achieve higher sensing resolution. On the other hand, frequent sensing rate leads to high energy consumption which is undesirable. In order to minimize total energy consumption while still achieving high sensing resolution, Aquiba autonomously adjusts the sensing rate of each Human Probe based on the availability of nearby Human Probes which always changes along the time.

The rest of the paper is organized as follows. Section 2 classifies the characterization of Human Probes. Section 3 proposes Aquiba protocol. Section 4 describes evaluation methodology. Simulation results and discussion are given in Sect. 5. Section 6 discusses related work. We conclude our paper in Sect. 7.

2. A Background and Classification of Human Probes

The use of Human Probes for networked sensing leverages the ubiquity of mobile phones and allows mobile users to capture sensing information as they go about their daily lives. Though Human-Probe sensing can be exploited to

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[†]The authors are with the School of Science and Technology for Future Life, Tokyo Denki University, Tokyo, 101-8457 Japan.
[††]The authors are with CREST, Japan Science and Technology Agency (JST), Tokyo, 102-0075 Japan.
[*]Presently, with the School of Engineering, Mie University.
a) E-mail: wat@osoite.jp

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capture and share various types of data in the urban life context, only *personal-independent sensors* are promising for this approach. The personal-independent sensors are defined as the sensors that the measured data are independent of personal or individual differences. In particular, such sensors are designed to measure ambient or surrounding information of Human Probes such as weather, air quality, and environmental-related information. The examples of personal-independent sensors include temperature, humidity, illumination, carbon monoxide, carbon dioxide, nitrogen oxide sensors, and so on. The sensed data can be captured either *directly* from internal sensors that are integrated with mobile phones or *indirectly* from external sensors. The data can either be collected *automatically* without any human intervention, or *interactively* on the basis of user inputs.

The Human-Probes approach not only considers sensing but also other relevant processes such as aggregation, communication, and usage of data. In these processes, mobile devices may send the captured information to a *server* or *other devices*; and users may have *full*, *partial*, or *no control* over the transmission of the information. They may share the information as soon as they capture it (*immediate sharing*) or store it for a while before sharing it (*delayed sharing*). The shared information *may or may not be aggregated* before it is used. The information can be shared through *Data Commons* [4] that involve a collection of open public-domain data spaces, and evolve over time based on citizen participation.

Participatory sensing [2] similarly considers various processes for communities to gather, analyze, and share local knowledge. Opportunistic sensing [3] focuses on a different mode of data capture in which sensing is not the primary activity of people, i.e., they have other primary activities and therefore sensing is opportunistically embedded in these activities. In this case, there is no point of control over human mobility patterns and actions that facilitate sensing coverage. Human Probes consider not only participatory and opportunistic modes of data capture but also *cooperation without community bonds*. Such cooperation could take place automatically among strangers, even without them being aware of it. It is important to consider the dynamics of pedestrian crowds and their self-organizing patterns to effectively support such cooperation.

In this context, two critical, interrelated factors should be considered in Human Probes environments — data quality and redundancy. Improving or guaranteeing the quality of data captured by using mobile phones [4] is a challenging task. In order to respond to this challenge, system designers may lean towards redundant data capture. However, while widespread redundancy may not always provide significant improvement of the data quality, it always results in higher energy consumption. For example, people in proximity to each other might capture similar or duplicate sensing data. Consequently, considering groups of people in crowded as well as uncrowded urban areas is necessary when investigating the use of Human Probes. There are a number of reasons behind many people being in the same place at a certain time. It could be either because they are friends or have similar interests or because they "happened to be there" as a part of a dynamic pattern that emerges from complex interactions between behavioral forces affecting individuals. We can therefore design a cooperative mechanism for Human Probes without relying on the ubiquity of closely knit pedestrian groups; indeed our approach allows for the design and analysis of Human Probes by using dynamic, emergent, and ephemeral pedestrian 'groups.'

3. Aquiba: Cooperative Human Probes

This section provides assumptions followed by the details of Aquiba protocol.

3.1 Assumptions

The following assumptions are made on the basis of the various factors relating to Human-Probe sensing.

(A1) We consider a system that consists of a server, mobile phones, and sensors.
(A2) The mobile phones are equipped with two kinds of wireless interfaces — cellular and short-range communication interfaces.
(A3) The sensors are either embedded in the mobile phones or positioned at various locations in the environment.
(A4) The server issues a query including the desired *sensing rate* R_i for each data type for each *sensing area* A_i.
(A5) The mobile phones are able to acquire their current location information.

In addition, Aquiba focuses on exploiting personal-independent sensors to capture ambient information as mentioned in the previous section.

3.2 Aquiba Protocol

Upon receiving a request from the server, each Human Probe periodically checks whether it is within the specified sensing area. If it is within the sensing area, it performs the cooperative sensing with the aims to achieving the desired sensing rate R_i for each sensing area A_i in an efficient manner. In contrast with uncooperative Human Probes that always transmit the measured data at the requested rate, cooperative Human Probes use a lower rate of $\frac{R_i}{k_i}$, where k_i is the number of Human Probes in the sensing area A_i. Figure 1 illustrates the concept of cooperative sensing employed by Aquiba protocol. The sensing activity of cooperative Human Probes (the black circles in the figure) is lower than that of the uncooperative.

Aquiba protocol attempts to distribute the work load of sensing tasks evenly amongst Human Probes. To achieve this, each Human Probe is required to maintain information of other Human Probes in the same sensing area. We apply a naive strategy in which the mobile phones in the sensing area use short-range radio to broadcast beacon packets periodically. Each of the beacon packets comprises the source node's ID. Upon receiving the beacon packets, a Human Probe can determine the current number of neighboring Human Probes and adjust its sensing rate accordingly. Each Human Probe needs to set an expiry time for each neighboring probe and delete the expired neighbors from its neighbor table periodically. A more complex technique, such as including the IDs and the corresponding expiry times of all current neighbors in the beacon packet, can also be used as well. Note that we apply the naive strategy in our evaluation (Sects. 4 and 5).

Due to limited communication range of short-range radio, it is not necessarily that all Human Probes can transmit their beacon packets to all others in the same sensing area. Though, it is possible to increase transmit power so as to extend communication range, it may sacrifice the entire system because additional energy consumption of short-range radio may lead to a negative result, i.e., the total energy consumption is higher than that of uncooperative approach. To avoid the negative effect, having perfect information of other Human Probes in the same sensing area is not a requirement of Aquiba, and we do not increase transmit power of short-range radio in order to transmit beacon packets to all far-away Human Probes.

Beacon interval is an important parameter of Aquiba protocol. Using a short beacon interval when the desired sensing rate is low may affect the performance of Aquiba due to high energy consumption of beacon packets. An adaptive beaconing approach is a possible solution in which the beacon interval is set to be inversely proportional to the desired sensing rate (R_i). Thereby the frequency of broadcasting beacon packets as well as energy consumption decreases when the sensing rate is low. However, a long beacon interval deteriorates the freshness of neighbor information (i.e., the number of other Human Probes in the same sensing area). As a result, the sensing resolution may drop from the desired level. To maintain the sensing resolution at the highest level when applying the adaptive beaconing approach, we may allow Human Probes to upload data at the rate of $\frac{R_i}{k_i-\alpha}$, where α is an arbitrary integer. Table 1 summarizes energy consumption when applying the adaptive beaconing approach. Long beacon interval due to low R_i explicitly leads to low energy consumption of short-range radio. The upload rate is lower than R_i due to cooperative sensing, and the total energy consumption should be lower than that of uncooperative approach. On the other hand, it is explicit that short beacon interval leads to high energy consumption of short-range radio. However, the upload rate is much lower than R_i because the effectiveness of Aquiba is apparent when the sensing rate is high. Therefore the energy consumed by cellular transceiver is also much lower than that of uncooperative approach. In this case, high energy consumed by short-range radio is amortized by low usages of cellular radio, i.e., the total energy consumption should be reduced when comparing to that of uncooperative approach.

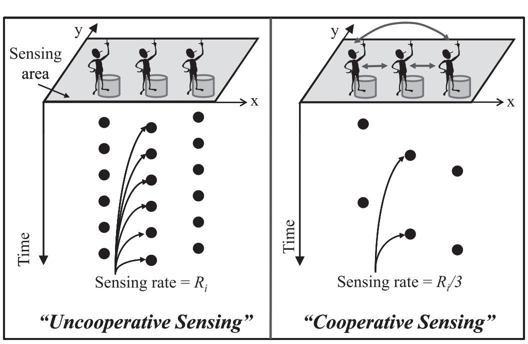


Fig. 1 An illustration of cooperative sensing employed by Aquiba protocol.

4. Evaluation Methodology

This sections defines performance metrics, followed by mobility models, and simulation setup.

4.1 Performance Metrics

We define two metrics for evaluation purpose as follows.

4.1.1 Sensing Resolution

Sensing resolution (ρ) indicates how closely Human Probes satisfy the desired sensing rates in a given sensing area. The value ranges from zero (the lowest level) to one (the highest level). For a given sensing area, if the total number of packets arrives at the server from time t to $t + \Delta T$ is S, the sensing resolution in this short period is defined by Eq. (1).

$$\rho_{t,t+\Delta T} = \frac{\min\left(\frac{S}{\Delta T}, R_i\right)}{R_i} \tag{1}$$

There are several derivatives of Eq. (1) when considering longer period or multiple sensing areas as follows. If the users are interested in a longer period, i.e., $P \cdot \Delta T$, the long-term sensing resolution is an average of all short-term resolutions as expressed in Eq. (2).

$$\rho_{t,t+P\cdot\Delta T} = \frac{\sum_{j=0}^{P-1} \rho_{t+j\cdot\Delta T, t+(j+1)\Delta T}}{P} \tag{2}$$

The users may consider measured data from multiple sensing areas. We can also find averages of both short-term

Table 1 Energy consumption when applying adaptive beaconing approach. The last two columns are mentioned in comparison with those of uncooperative Human Probes.

Sensing rate (R_i)	Beacon interval	Short-range radio's energy	Upload rate	Cellular radio's energy	Total energy
Low	Long	Low	$< R_i$	Lower	Lower
High	Short	High	$\ll R_i$	Much lower	Lower

and long-term sensing resolutions of m sensing areas as expressed in Equations (3) and (4), respectively.

$$\rho^{m}_{t,t+\Delta T} = \frac{\sum_{i=1}^{m} \rho^{i}_{t,t+\Delta T}}{m} \tag{3}$$

$$\rho^{m}_{t,t+P\cdot\Delta T} = \frac{\sum_{i=1}^{m} \rho^{i}_{t,t+P\cdot\Delta T}}{m} \tag{4}$$

4.1.2 Energy Saving

Let E and E_{Aquiba} be the total energy consumed by uncooperative and cooperative approaches, respectively. The percentage of energy saving (ξ) or energy reduced by a cooperative approach when comparing with uncooperative approach can be calculated by Eq. (5).

$$\xi = \frac{(E - E_{Aquiba})}{E} \times 100\% \tag{5}$$

Note that the energy consumed by Aquiba are from both cellular (E_c) and short-range (E_s) radios, while uncooperative Human Probes use only cellular radio. Thus $E = E_c$ and $E_{Aquiba} = E_c + E_s$.

4.2 Mobility Models

Since mobility models affect the performance of Human Probes, we briefly describe the characteristic of each mobility model in this section.

4.2.1 Random Waypoint Model

The random waypoint (RWP) model [6] is widely used because of its simplicity and wide availability. Each node begins by remaining stationary for a period of "pause time." It then selects a random destination and moves to the destination at a constant speed chosen uniformly and randomly between zero and the maximum speed v_{max}. Upon reaching the destination, the node stops again for the pause time, selects another destination, and proceeds there as previously described, repeating this behavior for the duration of simulation. In our simulation, the pause time and v_{max} were set to 60 s and 2 m/s, respectively. The simulation area is a 200 m-by-200 m square space and three sensing areas are circular regions centered at (30, 30), (60, 60), and (100, 100) with a radius of 10 m.

4.2.2 Manhattan Model

Bai et al. [7] 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.

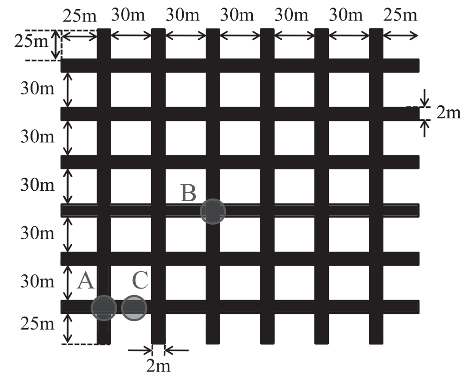


Fig. 2 A map including three sensing areas (A, B, and C) for MHT traces.

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 as expressed in Eq. (6).

$$|\vec{v}_i(t+1)| = |\vec{v}_i(t)| + random \times \left| \int \vec{a}_i(t)dt \right| \tag{6}$$

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 as expressed in Eq. (7).

$$\forall i, \forall j, \forall t: \ |\vec{v}_i(t)| \le |\vec{v}_j(t)| \text{ and } D_{i,j}(t) \le SD \tag{7}$$

$D_{i,j}$ is the distance between nodes i and j, and SD is the safety distance between any two nodes. Thus the MHT model has high spatial and temporal dependencies.

Figure 2 illustrates the 212 m-by-212 m map including three 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.

4.2.3 Extended Social Force Model

Helbing and Molnár [8] proposed the social force model (SFM) to emulate the motion of pedestrians as if they were subjected to "social forces." In this model, the position of a pedestrian i can be represented by a point $\vec{r}_i$ in space and his/her velocity $\vec{v}_i$ is governed by the four force terms as expressed in the following equation [9].

$$\frac{d\vec{v}_i}{dt} = \vec{f}_i + \vec{f}_{iB} + \sum_{j \ne i} \vec{f}_{ij} + \sum_{k} \vec{f}_{ik} + fluctuations \tag{8}$$

Each force is calculated as follows [9].

- Each pedestrian wants to walk with an individual desired speed v_i^0 into the direction $\vec{e}_i$ of his/her next destination. Deviation of the actual velocity $\vec{v}_i$ from the desired velocity $\vec{v}_i^0 = v_i^0 \vec{e}_i$ due to disturbances (by obstacles or avoidance maneuvers) are correct within the so-called relaxation time $\tau_i \approx 1$ s:

$$\vec{f_i} = \frac{1}{\tau_i}\left(v_i^0\vec{e_i} - \vec{v_i}\right). \tag{9}$$

In normal situations, the desired speed v_i^0 is approximately Gaussian distributed with a mean value of 1.3 m/s and a standard deviation of 0.3 m/s.

- Pedestrian keep some distance from borders to avoid the risk of getting hurt. This effect can be described by a repulsive force $\vec{f_{iB}}$, which decreases monotonically with the distance $\| \vec{r_i} - \vec{r}_B^i \|$ between the place $\vec{r_i}$ of pedestrian i and the nearest point $\vec{r}_B^i$ of the border. In the simplest case, this force can be expressed in terms of a repulsive potential V_B [8]:

$$\begin{aligned}\vec{f_{iB}}(\vec{r_i}) &= -\nabla_{\vec{r_i}} V_B(\| \vec{r_i} - \vec{r}_B^i \|) \\ &= 50e^{-5\|\vec{r_i}-\vec{r}_B^i\|}.\end{aligned} \tag{10}$$

- Similar repulsive force term $\vec{f_{ij}}$ can describe that each pedestrian i keeps a situation-dependent distance to the other pedestrians j. The repulsive interaction force has been specified according to the formula

$$\begin{aligned}\vec{f_{ij}} = {} & A_i^1 \exp\left[\left(r_{ij} - d_{ij}\right)/B_i^1\right]\vec{n}_{ij} \\ & \cdot\left(\lambda_i + (1-\lambda_i)\frac{1+\cos\left(\varphi_{ij}\right)}{2}\right) \\ & A_i^2 \exp\left[\left(r_{ij} - d_{ij}\right)/B_i^2\right]\vec{n}_{ij}.\end{aligned} \tag{11}$$

We have chosen $A_i^1 = 0, A_i^2 = 3\,\mathrm{m/s}^2$, and $B_i^2 = 0.2\,\mathrm{m}$. $d_{ij} = \| \vec{x_i} - \vec{x_j} \|$ is the distance between the centers of mass of pedestrians i and j, $r_{ij} = (r_i + r_j) \approx 0.6\,\mathrm{m}$ the sum of their radii r_i and r_j, and $\vec{n}_{ij} = (\vec{x_i} - \vec{x_j})/d_{ij}$ the normalized vector pointing from pedestrian j to i. Finally, $\lambda_i \approx 0.75$ and $\cos\left(\varphi_{ij}\right) = -\vec{n}_{ij}\cdot\vec{e_i}$.
- Pedestrians are sometimes attracted by window displays, sights, special performances (street artists), or unusual events at places $\vec{r_i}$. The situation can be modelled by attractive force $\vec{f_{ik}}$ similarly to repulsive effects, but with an opposite sign and a longer rance of interaction. In our simulation, we follows the simplification that can be made in computer simulations [8] by not taking $\vec{f_{ik}}$ into consideration.

Equation (8) also takes into consideration fluctuations due to accidental or deliberate deviations from the optimal behavior.

We have extended the SFM by integrating it 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. A 200 m-by-87 m map illustrated in Fig. 3 is drawn on the basis of real streets in downtown Tokyo (Shibuya area). 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.

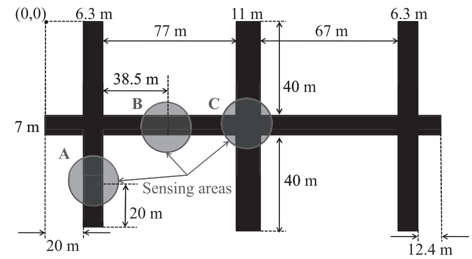


Fig. 3 A map including three sensing areas (A, B, and C) for SFM traces.

We note here that the purpose of employing three mobility models is not to compare the three mobility models directly. Instead, we would like to study the effectiveness and applicability of Aquiba in various situations, i.e., when different movement patterns of human are applied on different maps.

4.3 Simulation Setup

We use a discrete event simulator, *ns*–2 [10], to study the performance 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 [11]. It draws the current 19.7 mA and 17.4 mA in receive and transmit modes, respectively. The transmit power drain at 0 dBm is 31.32 mW and the receive power drain is 35.46 mW [12]. 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 Human Probes 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 simulations are 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-phone-based Human Probe by using Casio G'zOne W62CA [13] cellular phone 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†. In the simulations, Human Probes acquire location information whenever a sensing task is conducted in order to include location as contextual information of sensed data.

The desired sensing rate R_i was set to once per second

†We note that the result obtained from our experiments is nearly the same as that reported in previous work [14].

for all sensing areas. This value is merely one of possible scenarios for studying the performance of Aquiba. Lower sampling rate is enough to capture ambient temperature, while higher rate is required to detect changes of ambient information for warning systems including monitoring of volcano, flood, poisonous gas, and radioactive level [15], [16]. Currently, some active volcanos open for public sightseeing, but sometimes they are closed due to high level of poisonous gas. To react and deal with abruptly changing situations in time, a sensing rate of one Hz or as high as 100 Hz is required for specific warning systems [15], [16].

As indicated in previous section, the sensing areas are circular regions with a radius of 10 m. The size of sensing area would be sufficient for most of personal-independent sensors including temperature, humidity, carbon monoxide, carbon dioxide, nitrogen oxide sensors, and so on. We varied the density of Human Probes by injecting 50, 100, 200, 300, and 400 Human Probes 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.

5. Simulation Results

The results of sensing resolution (ρ) and energy saving (ξ) when 50 to 400 Human Probes walk according to three mobility models are shown in Figs. 4 and 5, respectively. Each mark in the figures is averaged over three sensing areas A, B, and C defined in Sect. 4.2. Note that we use different widths and heights of maps for RWP, MHT, and SFM, i.e., 200 m-by-200 m, 212 m-by-212 m, and 200 m-by-87 m, respectively. As a result, the population density of each map is also different.

Regardless of mobility models and the number of Human Probes, sensing resolutions provided by the Aquiba protocol (Fig. 4) are nearly perfect, i.e., achieving or approaching one which is the highest level. It means that Aquiba is able to report sensing data judiciously according to the sensing rate and regions determined by users. Note that the values of 95% confidence interval of sensing resolution are quite small, i.e., the largest one is 0.01; thus we omit the confidence intervals from Fig. 4.

Although uncooperative Human Probes, which report sensing data with higher frequency in comparison with Aquiba, are able to provide as high sensing resolution as Aquiba, it is intuitive that energy consumption is different. In what follows, we consider how much energy Aquiba is able to reduce in comparison with that of uncooperative Human Probes by using Eq. (5). Figure 5 shows that the percentages of energy saving achieved by Aquiba range from 14% to 77%. Energy consumption is reduced the most in SFM, followed by MHT and RWP. Energy saving of RWP is the lowest because the population density is the lowest and each Human Probe has high degree of freedom to move, thereby a pedestrian seldom meets others and the possibility of cooperative sensing is lower in comparison

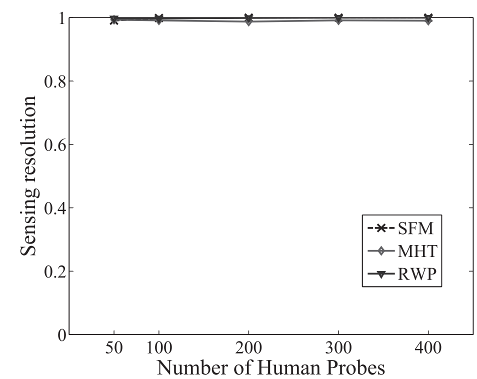


Fig. 4 Sensing resolution (ρ).

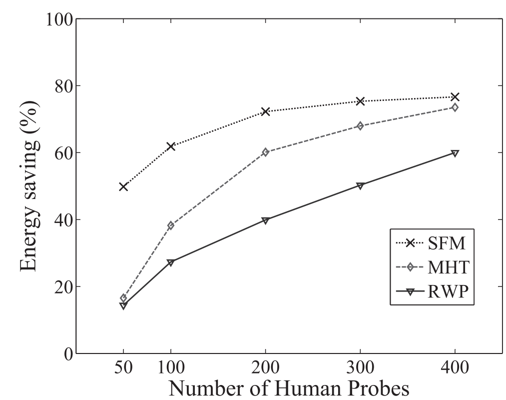
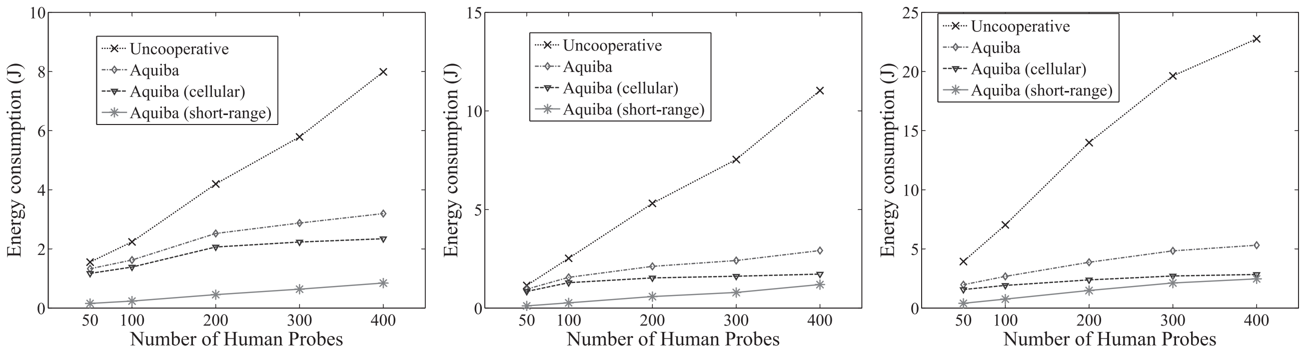


Fig. 5 Percentage of energy saving (ξ).

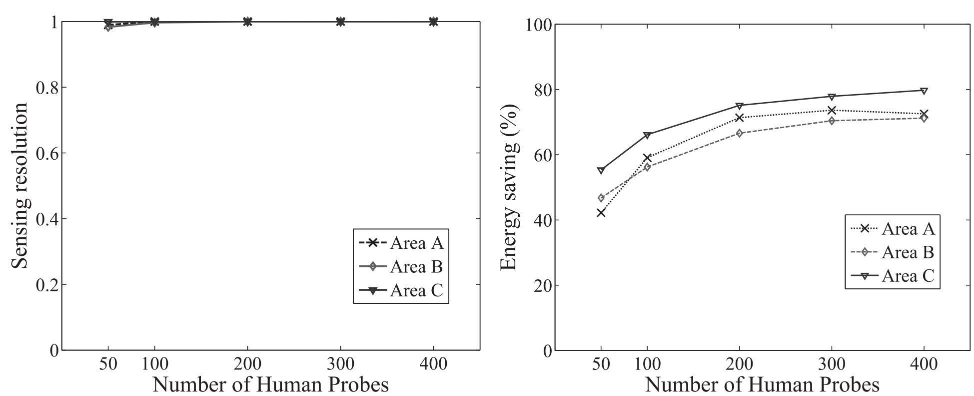
with the other models. With the same principle, the higher density of Human Probes in SFM much crowd the streets which leads to the highest energy saving due to the effectiveness of cooperative sensing. Energy saving of MHT, which lies between RWP and SFM, presents an interesting result. When there are 50 Human Probe (i.e., sparse Human Probes), 17% energy saving of MHT is comparable to that of RWP (14%). As the number of Human Probes increases from 50 to 400 (i.e., dense Human Probes), energy saving of MHT rapidly increases to 74% which is as high as that of SFM (77%). Because of the movement characteristics defined by MHT and the restriction of movable area determined by the map, pedestrian crowds quickly develop when increasing the number of Human Probes in the simulated map. Although the characteristics of mobility model affect simulation results, we can conclude that controlling sensing rate which is proposed by Aquiba protocol does not harm sensing resolution while helping in minimizing energy consumption.

Aquiba determines the frequency of uploads from the number of other Human Probes in the same sensing area. According to the current simulation setup, Human Probes do not have perfect information of all other Human Probes in the same sensing area. In particular, the number of Human Probes detected by using beacon packets is lower than the actual value. As a result, the frequency of uploads as well as energy consumption will be higher than the ideal case of



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

Fig. 6 Energy consumption.



(a) Sensing resolution (ρ). (b) Percentage of energy saving (ξ).

Fig. 7 Performance of Aquiba protocol when applying the extended SFM traces.

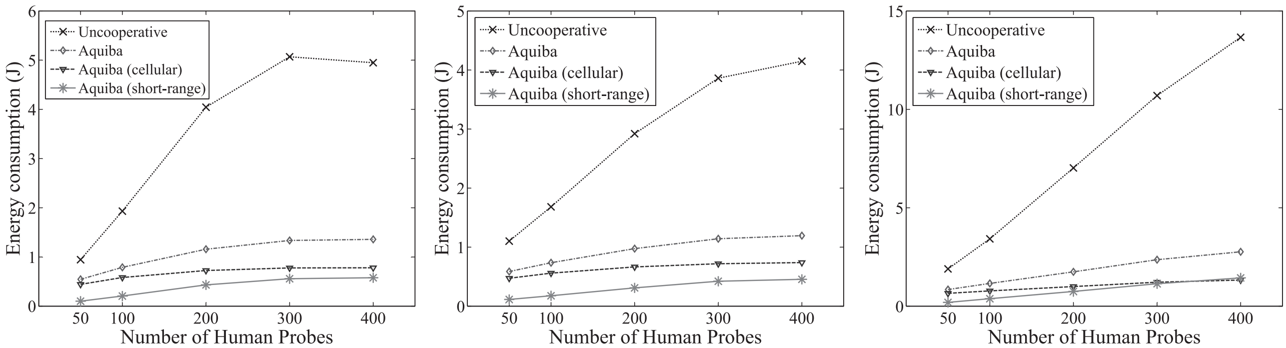
Aquiba. However, this situation does not affect Aquiba to fulfill the requirements of sensing tasks. The above simulation results show that Aquiba can still achieve nearly the highest level of sensing resolution while being able to reduce considerable amount of energy consumption. As a conclusion, our simulations validate the applicability of Aquiba when short-range radio cannot cover the entire sensing area.

Since Aquiba uses two kinds of radios for communication purposes, Fig. 6 shows energy consumed by short-range (E_s) and cellular (E_c) transceivers separately, and also includes the total energy consumed by both Aquiba (E_{Aquiba}) and uncooperative Human Probes (E) for comparison purposes. The results of total energy consumption are consistent with those of energy saving (ξ) reported above, i.e., the total energy consumptions of uncooperative Human Probes increases faster than those of Aquiba when increasing the number of Human Probes. Thereby, the effectiveness of energy saving by Aquiba is better if there are higher number of Human Probes in the sensing areas. When considering E_s separately, it is apparent from the figures that SFM consumes the highest energy followed by MHT and RWP. The underlying reason is the same as described above, i.e., Human Probes in SFM have the highest probability of cooperative sensing due to the smallest map, thus short-range radio is used the most frequent so as to determine the number of neighboring Human Probes.

We further investigate the detailed performance of Aquiba by focusing on the extended SFM which is the only mobility model that includes several social forces of human into consideration. Figures 7(a)† and 7(b) show the simulation results of each sensing area separately when varying the number of Human Probes in the map. The long-term sensing resolution in Fig. 7(a) is mostly stable at one, which is the preferred resolution, for all sensing areas. Although the resolution of 50- and 100-Human-Probe scenarios cannot achieve one, the values are quite high, i.e., the worst case is 0.98 in sensing area B when there are 50 Human Probes. The reason of the slight drop in resolution is stale neighbor information. By applying the beaconing approach, it takes time to capture the presence or absence of neighboring Human Probes in a sensing area. In particular, if a Human Probe leaves the area, the other Human Probes in the area should increase their sensing rates immediately. However, the other Human Probes still recognize the obsolete Human Probe as a neighbor for a while until the information of obsolete neighbor has been deleted from the neighbor table.

Figure 7(b) shows that it is worth to use short-range communication in order to reduce overall energy consump-

†We also omit 95% confidence interval of sensing resolution from the figure because the values are quite small.



(a) Sensing area A. (b) Sensing area B. (c) Sensing area C.

Fig. 8 Energy consumption of each sensing area when applying the extended SFM traces.

tion. The energy is reduced at least 42% (50 Human Probes in area A) and as high as 80% (400 Human Probes in area C) in comparison with those of uncooperative approach. As one would expect, energy consumption is effectively reduced when the number of Human Probes increases. However, the percentages of energy saving slightly improve when the number of Human Probes is higher than 200 because the map is crowded enough with Human Probes. Energy saving is the best in sensing area C (the middle intersection in Fig. 3) because the average density of Human Probes is higher than those of areas A (a vertical street) and B (a horizontal street). It is obvious that pedestrians who pass through the rightmost and middle intersections in Fig. 3 consecutively will exactly enter area C, but only some of them who do not turn right or left into vertical streets at the middle intersection will pass through area B.

Figure 8 presents the breakdown of energy consumption (E_s and E_c) of Fig. 7(b). The energy consumed by short-range and cellular transceivers of areas A, B, and C are shown in Figs. 8(a), 8(b), and 8(c), respectively. Human Probes in area C utilize short-range radios the most due to the highest cooperation at the central intersection of the map. When the number of Human Probes reaches 400, the energy consumed by short-range transceivers in area C (Fig. 8(c)) exceeds that of cellular transceivers. However, the total energy consumption is much lower than that of uncooperative Human Probes. Therefore, it is plausible to utilize short-range radios in order to minimize total energy consumption.

Energy consumed (or current drawn) by transceivers are slightly different depending on manufacturers. To avoid inconsistent current drawn when conducting simulations, Fig. 9 shows the normalized number of data and beacon packets transmitted by Human Probes in sensing area C when applying SFM traces. For each number of Human Probes indicated in the horizontal axis, the left bars indicate uncooperative Human Probes which generate only data packets, while data (cellular communication) and beacon (short-range communication) packets transmitted by Aquiba are shown in the middle and right bars, respectively. The results show that the number of data packets generated by Aquiba is 2 to 14 times less than that of uncooperative Human Probes. 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. The additional benefit of Aquiba is to reduce redundant data packets received at the server.

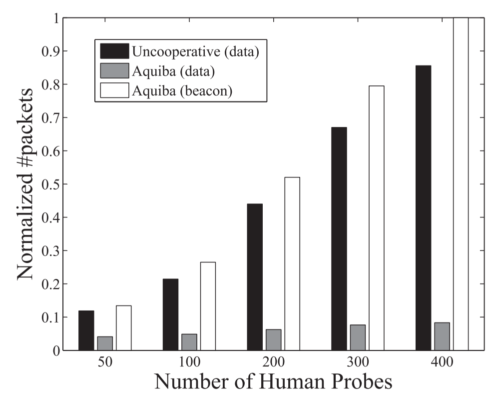


Fig. 9 Number of packets in sensing area C.

6. Related Work

Wireless sensor networks have been received attention from researchers for a decade [17]. The research topics range from physical to application layers in which energy saving is an important issue because energy is a very scarce resource of sensor nodes [18]. To collect data efficiently in terms of energy consumption, various MAC, routing, and transport protocols have been introduced in the literature [19]–[21]. However, such research including large-scale deployments of sensor nodes in the real world [22], [23] considers static sensor networks which are different from Human-Probe sensing.

There also exist prior works that take node mobility into consideration [24]–[26]. Though ensuring eventual message delivery is the goal of such research, energy saving is also a concern [26]. Nevertheless, such approaches exploit only one kind of wireless communications, i.e., short-range radio, while Human-Probe sensing utilizes both short-range and cellular radios. Since energy consumption and radio characteristics of short-range and cellular transceivers are quite different, a new protocol for the purpose of urban sensing is required.

Recently, participatory sensing, which is an alternative to the deployment of numerous static sensors, has attracted considerable attention from researchers. The mule three-tier architecture [27], which is comprised of sensors, data mules, and access points, has contributed to the development of the concept of participatory sensing. As the mobile data mules traverse along a path, they opportunistically collect sensing data from encountered sensors and upload them to a server through nearby access points.

In order to promote citizen-based urban sensing, Ishida et al. [28] introduced the concept of *implicit sensing*; they used footwear containing pressure sensors. The pressure sensors use the IEEE 802.15.4 radio to send the sensor readings to a client module, which in turn forwards the data to a server via a cellular network. However, they did not take energy saving into consideration. CenceMe [29] integrates sensing presence and social networks by capturing a user's current activity status and sharing such information in social network. By developing and evaluating a prototype on a Nokia N95 mobile phone, the energy consumption was studied at different sensing intervals, i.e., the user determined the sampling rate in advance and thereafter fixed it throughout the recording duration. In contrast, Aquiba adjusts the sampling and uploading rates according to the current number of nearby Human Probes.

Researchers are interested not only in movement by walking but also in other modes of movement in urban areas. BikeNet [30] allows cyclists to share information on themselves and the paths they traverse. Bicycles are equipped with a Nokia N80 mobile phone and Moteiv Tmote Invent motes and other necessary sensors. The sampling rate in the continuous sensing mode is set according to the cyclist's preference profile. CarTel [31] is a mobile sensor system designed to collect data from sensors located on automobiles. A CarTel node is a custom-made device built from a commodity Wi-Fi access point with additional enhancements for other sensors. In the presence of opportunistic wireless networks (e.g., Wi-Fi and Bluetooth), each node delivers the sensor readings to a central portal.

Some commercial and voluntary-based services [5], [32] employ a similar participatory means to capture data. In particular, Weathernews [5] has conducted a number of participatory campaigns to capture detailed data on temperature, rain acidity, rainfall, snowfall, earthquake, cherry blossoms, autumn leaves, etc. using mobile phone-based services. The participants in these campaigns received messages on their mobile phones asking them to use inexpensive, ordinary instruments such as a thermometer and a ruler to capture data relating to their local environments and report the observations to the company. The data are collected from thousands of participants without ensuring efficiency in terms of redundancy, energy efficiency, and quality.

7. Conclusion

Systems that tightly integrate human activities and sensing, such as mobile phone-based Human Probes, introduce a novel mode of cooperation that blends human-to-human and device-to-device interactions. We have proposed Aquiba protocol that exploits such cooperation to enable energy-efficient Human Probes. We have conducted a simulation-based study of Human Probes and investigated two performance metrics, i.e., sensing resolution and energy saving, by exploiting three movement patterns of pedestrian. The study has further focused on a realistic simulation of pedestrian dynamics based on the social force model. Overall, the proposed Aquiba protocol can substantially reduce energy consumption in a very crowded as well as less crowded scenarios while still achieving high sensing resolution.

Existing participatory campaigns to capture and share sensor data, such as the trials by Weathernews [5], are designed for the world in which sensors are the scarce resource, and therefore they pay little attention to redundancy and cooperation. However, in designing Human Probes, which exploits the ubiquity of mobile phones, we must consider the sensor-rich world in which energy and human attention are the resources of scarcity. Our study of the Aquiba protocol is a first step towards providing an effective Human-Probe sensing in urban environments through cooperative mechanisms that take energy consumption and sensing resolution into consideration. Our future works also include prototype implementation, field experiments, and a comprehensive examination of various qualitative factors besides sensing resolution and energy consumption.

References

[1] International Telecommunication Union, "Worldwide mobile cellular subscribers to reach 4 billion mark late 2008," http://www.itu.int/newsroom/press_releases/2008/29.html (Accessed: May 31, 2010)

[2] J. Burke, D. Estrin, M. Hansen, A. Parker, N. Ramanathan, S. Reddy, and M.B. Srivastava, "Participatory sensing," Proc. Workshop on World-Sensor-Web (WSW 2006), pp.6–10, Boulder, Colorado, USA, Nov. 2006.

[3] 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 Comput., vol.12, no.4, pp.12–21, July/Aug. 2008.

[4] D. Cuff, M. Hansen, and J. Kang, "Urban sensing: Out of the woods," Commun. ACM, vol.51, no.3, pp.24–33, March 2008.

[5] Weathernews Inc., "Weathernews," http://weathernews.com/ (Accessed: Feb. 9, 2010)

[6] 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," Proc. 4th ACM International Conference on Mobile Computing and Networking (MobiCom 1998), pp.85–97, Dallas, Texas, USA, Oct. 1998.

[7] 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, vol.1, no.4, pp.383–403, Nov. 2003.

[8] D. Helbing and P. Molnár, "Social force model for pedestrian dy-

namics," Phys. Rev. E (Statistical Physics, Plasmas, Fluids, and Related Interdisciplinary Topics), vol.51, no.5, pp.4282–4286, May 1995.

[9] D. Helbing, L. Buzna, A. Johansson, and T. Werner, "Self-organized pedestrian crowd dynamics: Experiments, simulations, and design solutions," Transportation Science, vol.39, no.1, pp.1–24, Feb. 2005.

[10] "Network simulator — ns-2," http://www.isi.edu/nsnam/ns/ (Accessed: July 3, 2009)

[11] 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

[12] C.Y. Wan, S.B. Eisenman, A.T. Campbell, and J. Crowcroft, "Overload traffic management for sensor networks," ACM Trans. Sensor Networks, vol.3, no.4, p.18, Oct. 2007.

[13] Casio Computer Co.,Ltd., "G'zOne W62CA," http://k-tai.casio.jp/products/w62ca/ (Accessed: July 3, 2009)

[14] P. Mohan, V.N. Padmanabhan, and R. Ramjee, "Nericell: Rich monitoring of road and traffic conditions using mobile smartphones," Proc. 6th International Conference on Embedded Networked Sensor Systems (SenSys 2008), pp.323–336, Raleigh, North Carolina, USA, Nov. 2008.

[15] W.Z. Song, R. Huang, M. Xu, A. Ma, B. Shirazi, and R. LaHusen, "Air-dropped sensor network for real-time high-fidelity volcano monitoring," Proc. 7th Annual International Conference on Mobile Systems, Applications, and Services (MobiSys 2009), pp.305–318, Krakow, Poland, June 2009.

[16] G. Werner-Allen, K. Lorincz, J. Johnson, J. Lees, and M. Welsh, "Fidelity and yield in a volcano monitoring sensor network," Proc. 7th Symposium on Operating Systems Design and Implementation (OSDI 2006), pp.381–396, Seattle, Washington, USA, Nov. 2006.

[17] J.M. Kahn, R.H. Katz, and K.S.J. Pister, "Next century challenges: Mobile networking for "Smart Dust,"" Proc. 5th Annual ACM/IEEE International Conference on Mobile Computing and Networking (MobiCom 1999), pp.271–278, Seattle, Washington, United States, Aug. 1999.

[18] I.F. Akyildiz, W. Su, Y. Sankarasubramaniam, and E. Cayirci, "A survey on sensor networks," IEEE Commun. Mag., vol.40, no.8, pp.102–114, Aug. 2002.

[19] P. Naik and K.M. Sivalingam, "A survey of MAC protocols for sensor networks," Wireless Sensor Networks, ed. C.S. Raghavendra, K.M. Sivalingam, and T. Znati, ch. 5, pp.93–107, Kluwer Academic Publishers, 2004.

[20] J.N. Al-Karaki and A.E. Kamal, "Routing techniques in wireless sensor networks: A survey," IEEE Wireless Commun., vol.11, no.6, pp.6–28, 2004.

[21] H. Karl and A. Willig, Protocols and Architectures for Wireless Sensor Networks, Wiley, June 2005.

[22] R.N. Murty, A. Gosain, M. Tierney, A. Brody, A. Fahad, J. Bers, and M. Welsh, "CitySense: A vision for an urban-scale wireless networking testbed," Proc. IEEE International Conference on Technologies for Homeland Security (HST 2008), pp.583–588, Waltham, MA, USA, May 2008.

[23] A. Arora, R. Ramnath, E. Ertin, P. Sinha, S. Bapat, V. Naik, V. Kulathumani, H. Zhang, H. Cao, M. Sridharan, S. Kumar, N. Seddon, C. Anderson, T. Herman, N. Trivedi, C. Zhang, M. Nesterenko, R. Shah, S.S. Kulkarni, M. Aramugam, L. Wang, M.G. Gouda, Young-ri Choi, D.E. Culler, P. Dutta, C. Sharp, G. Tolle, M. Grimmer, B. Ferriera, and K. Parker, "ExScal: Elements of an extreme scale wireless sensor network," Proc. 11th IEEE International Conference on Embedded and Real-Time Computing Systems and Applications (RTCSA 2005), pp.102–108, Hong Kong, China, Aug. 2005.

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

[25] T. Spyropoulos, K. Psounis, and C.S. Raghavendra, "Spray and wait: An efficient routing scheme for intermittently connected mobile networks," Proc. ACM Workshop on Delay Tolerant Networking (WDTN 2005), pp.252–259, Philadelphia, Pennsylvania, USA, Aug. 2005.

[26] T. Small and Z.J. Haas, "Resource and performance tradeoffs in delay-tolerant wireless networks," Proc. ACM Workshop on Delay Tolerant Networking (WDTN 2005), pp.260–267, Philadelphia, Pennsylvania, USA, Aug. 2005.

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

[28] Y. Ishida, S. Konomi, N. Thepvilojanapong, R. Suzuki, K. Sezaki, and Y. Tobe, "An implicit and user-modifiable urban sensing environment," Proc. International Workshop on Urban, Community, and Social Applications of Networked Sensing Systems (UrbanSense 2008), pp.36–40, Raleigh, North Carolina, USA, Nov. 2008.

[29] 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," Proc. 6th International Conference on Embedded Networked Sensor Systems (SenSys 2008), pp.337–350, Raleigh, North Carolina, USA, Nov. 2008.

[30] 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," Proc. 5th International Conference on Embedded Networked Sensor Systems (SenSys 2007), pp.87–101, Sydney, Australia, Nov. 2007.

[31] 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," Proc. 4th International Conference on Embedded Networked Sensor Systems (SenSys 2006), pp.125–138, Boulder, Colorado, USA, Nov. 2006.

[32] "USA National Phenology Network," http://www.usanpn.org/ (Accessed: July 3, 2009)

Niwat Thepvilojanapong has since April 2010 became an assistant professor with the School of Engineering at Mie University. Prior to joining Mie University, he worked as a researcher at Tokyo Denki University for two years (2008–2010). Apart from that, he used to work as a research engineer at KDDI R&D Laboratories Inc. from 2006 to 2008. Niwat holds a Ph.D. in Information and Communication Engineering from the University of Tokyo. His research interests include networked sensing, sensor and ad hoc networks, and ubiquitous and pervasive computing. He is a member of the ACM.

Shin'ichi Konomi is a project associate professor of the School of Science and Technology for Future Life, Tokyo Denki University. His research interests include interaction design and social implications of pervasive computing, urban computing, human-computer interaction, RFID applications and databases. He received his Ph.D. in computer science from Kyoto University. He is a member of the ACM, IEEE Computer Society, IPSJ, and DBSJ.

Yoshito Tobe received his Ph.D. in Media and Governance from Keio University in 2000. He is currently a Professor at Tokyo Denki University. His research interests include multimedia communications and sensor networks. He is a member of IEEE Communications Society, ACM, and IPSJ.