Utilizing Position-based Routing for Data Aggregation in Crowdsensing Systems

Morihiko Tamai, Akio Hasegawa, and Nobuo Suzuki
Adaptive Communications Research Laboratories
Advanced Telecommunications Research Institute International
Kyoto 619-0288, Japan

***Abstract*—In crowdsensing systems, a huge amount of sensory data may be uploaded from the mobile devices participating in a sensing campaign and may lead to the overloading in the network infrastructures of cellular networks or Wi-Fi. In order to reduce the upload traffic volume, we present a distributed data aggregation scheme among mobile devices over the opportunistic network. Using short range communication (e.g., Bluetooth or Wi-Fi Direct), our scheme utilizes position-based routing to forward sensory data to the appropriate mobile devices that can effectively perform the data aggregation on sensory data collected from the other devices so that the aggregation performance is improved. Our simulation results show that the proposed scheme can significantly improve aggregation performance compared with other aggregation schemes.**

***Index Terms*—Crowdsensing, opportunistic networks, data aggregation, position-based routing**

I. Introduction

Mobile crowdsensing [1] has become one of the most viable sensing paradigms for realizing environment data collection campaigns (e.g., noise level [2], traffic condition [3], etc.) through widely scattered mobile devices (e.g, smartphones) and has created a broad range of applications bringing convenience to people's daily life [4]–[6]. For example, a large scale spectrum monitoring [6] can be a promising application and be expected to be utilized for improving spectrum utilization by identifying spectrum opportunities and facilitating spectrum sharing, which is considered as one of key features in future wireless communication systems [7]. In crowdsensing systems, compared to the sensing infrastructures consisting of dedicated sensor nodes deployed in static locations, the system organizers can gather sensory data covering wide urban area by scattered mobile devices without a large cost incurred for maintaining those devices (e.g., battery exchange).

In crowdsensing systems, it is common that the sensory data sampled by mobile devices are uploaded to the cloud servers through the base stations (BSs) of cellular networks (e.g., 3G, LTE) or Wi-Fi access points (APs) that are connected to the Internet [8]. From the user's perspective, however, it is preferable to reduce the total data amount that goes through the cellular networks as much as possible, since the network cost is relatively high [9]. Moreover, it is common for users to choose cellular data plans that limit the usable data volume per a specific timespan (e.g., 3GB per month). On the other hand, since Wi-Fi APs are required to operate on the same frequency bands with the other wireless technologies [10] (e.g., Bluetooth) and to share the scarce wireless resources with these technologies, it is also preferable to reduce the wireless resources consumed by Wi-Fi in uploading sensory data. In addition, since the coverage of Wi-Fi APs are limited [11], there may be no usable Wi-Fi APs at the timing of uploading in the first place.

In this paper, we tackle these challenges by proposing a distributed data aggregation scheme executed on the participating mobile devices to achieve the upload traffic reduction of sensory data. We assume multiple sensory data that were sampled in close proximity and timing have the space and time correlation, and therefore, they can be aggregated into one data, which can be represented with fewer bytes than the total bytes required to represent the original data. In this context, the aggregation performance can be improved by collecting as many correlated sensory data as possible at relatively small number of mobile devices and by performing aggregation on the collected data all together. To facilitate the process of this data gathering, in our scheme, immediate uploading of sensory data after each data sampling is deferred and the opportunistic contacts between mobile devices along with the mobility of users or vehicles are utilized for data exchange between the devices. Specifically, when two mobile devices are located in a direct communication range, they determine which data should be transferred to the other device and the selected data are exchanged between two devices using short range wireless link over Bluetooth, Wi-Fi Direct, etc.

To improve the aggregation performance, it is important to consider how to route each sensory data over the opportunistic network. To this aim, in our aggregation scheme, position-based routing [12] is utilized. Specifically, when a pair of devices meet, they exchange their locations acquired with a positioning system (e.g., Global Positioning System (GPS)). Then, each sensory data is forwarded to the other device if the distance from the location where the data was sampled is decreased compared with the case without forwarding. By doing so, we can expect that each sensory data is held by the mobile device that is currently locating at near the position where the data was sampled. This increases the possibility that the multiple sensory data with high spatial correlation are held by relatively small number of devices, resulting in improvement of aggregation performance.

The simulation results demonstrate that our scheme can achieve high aggregation performance compared with the other

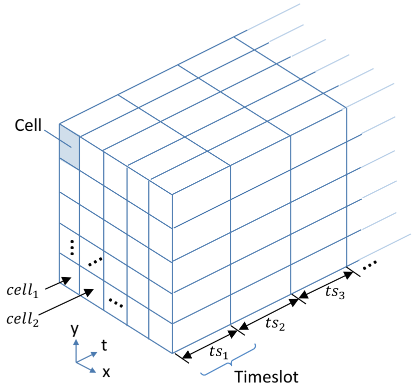

Fig. 1. Division both in space and time domains.

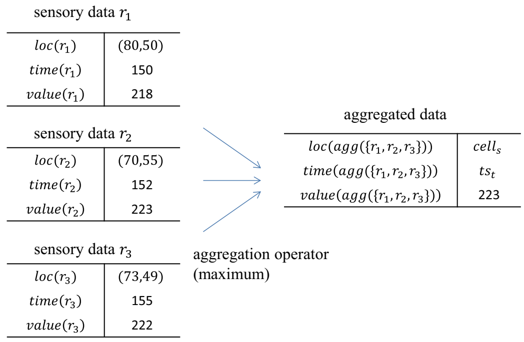

Fig. 2. An example of applying an aggregation operator.

schemes that utilize contact history [13].

II. System Model

We consider a mobile crowdsensing system that consists of mobile devices and communication infrastructures providing mobile Internet access (3G BS, LTE BS, Wi-Fi AP, etc.). As for the mobile devices, we suppose that the devices such as smartphones, tablets, and in-vehicle electronic devices. At various locations and timings, each mobile device samples sensory data (e.g., noise level, wireless signal strength, etc.) with embedded sensors or external sensors connected to the mobile device. We suppose that the mobile devices can obtain the longitude and latitude coordinates of their current location using a positioning system (e.g., GPS). The acquired location information is used to attach the location where a sensing is performed to each sampled data and is used for position-based routing in our aggregation scheme. The sampled data are deferred from immediate uploading to the server and are stored in the local storage of the mobile device for a certain period of time. During the period, when two mobile devices meet (i.e., when they are located within the direct communication range of a short range wireless link), they transmits a subset of data to the peer device based on the algorithm described in Section III. After some time, each device uploads all of the sensory data held in own storage to the server using cellular network or Wi-Fi.

In the following, the set of the mobile devices is denoted by $U = \{u_1, u_2, ..., u_N\}$, where N is the number of the mobile devices. Each device periodically (each T_{sen}) performs sensing and acquires a sensory data. Also, each device periodically (e.g., every 3 hours) uploads all of the sensory data currently held in own storage to the server located on the Internet. Each sensory data contains the time and the latitude and longitude coordinates at which the sensing was performed, and the value (e.g., noise level) sampled by a sensor. For a sensory data r, we denote the location coordinates, the time, and the value by $loc(r)$, $time(r)$, and $value(r)$, respectively.

We assume that sensory data obtained in close proximity and timing have a significant correlation and they can be aggregated by applying an aggregation operator (such as maximum, minimum, or average), which eliminates redundancy. To determine the range of sensory data that can be aggregated together, we discretize the space and the time in which sampling occurs as follows. In space domain, the whole two dimensional area is divided into grid cells, denoted as $cell_i$, as shown in Fig. 1. Similarly, the time is divided into timeslots, denoted as ts_i, of equal length T_{par}, as shown in Fig. 1. Using the notations, the necessary and sufficient condition for a set of sensory data r_i $(i = 1, 2 \ldots, M)$ to be able to be aggregated is that there exist $cell_s$ and a timeslot ts_t that satisfy:

$$loc(r_i) \in cell_s \wedge time(r_i) \in ts_t, \quad \forall i \in \{1, ..., M\}. \tag{1}$$

We denote the aggregated data by $agg(\{r_1, \ldots, r_M\})$. Fig. 2 shows an example of applying the maximum operator to three sensory data. By aggregating M sensory data, the total volume of the sensory data can be reduced to approximately $1/M$ of the total volume before aggregation.

To indicate its presence to the devices within the communication range, each mobile device broadcasts a *hello packet* periodically every T_{hel} seconds. A receiver side of a hello packet establishes a connection with the sender side, and exchanges the *device information*, which includes the location coordinates acquired by a positioning system. After that, based on the device information exchanged, each device transfers a subset of sensory data held in own storage to the peer device. Finally, the connection between two devices is terminated. It is possible to further transmit sensory data received from one device to the other devices. For example, suppose that mobile devices u_1 and u_2 met each other and u_2 received sensory data from u_1. After some time, when u_2 meets another device u_3, u_2 is able to transmit sensory data sampled itself together with the data received from u_1 to u_3.

We suppose that aggregation operators are applied only at immediately before each uploading. This means that, during a meeting, sensory data are forwarded between devices in its original (i.e., raw) form. This is required if we want to use *median* as the aggregation operator [14].

III. Aggregation Scheme

In order to improve aggregation performance, it is important to collect as many correlated data, which can be aggregated

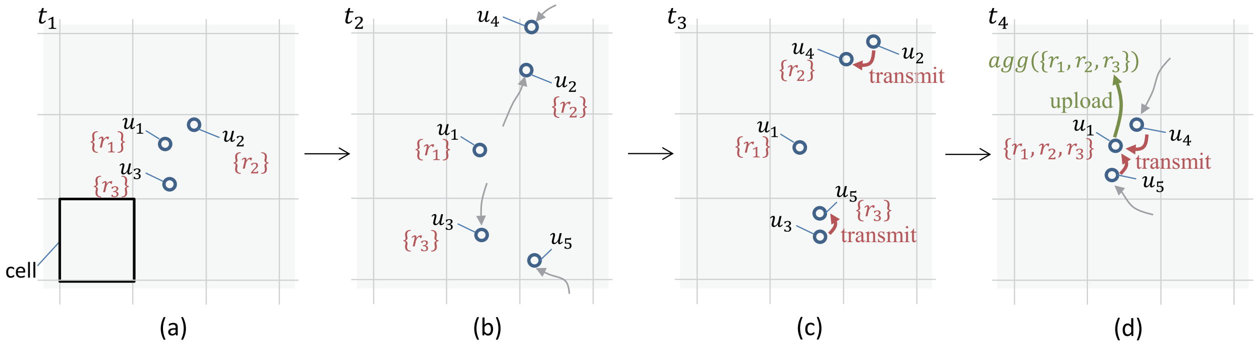

Fig. 3. An example of utilization of position-based routing for data aggregation in opportunistic network.

together, as possible at relatively small number of mobile devices. To achieve this, we utilize position-based routing when a pair of mobile devices meet. In the following, we explain how position-based routing is performed over an opportunistic network using an example illustrated in Fig. 3.

In Fig. 3 (a), at time t_1, there are three mobile devices (i.e., u_1, u_2, and u_3) located in the same cell, which is called $cell_1$ hereafter. Since each mobile device performed a sensing while staying at $cell_1$, each device holds one sensory data, denoted by r_1, r_2, and r_3, in its storage, and they can be aggregated together if a device acquires some of the three. Although they are located in the same cell, we suppose that they don't meet each other while staying at $cell_1$. Then, at time t_2 (Fig. 3 (b)), u_2 and u_3 move in a direction apart from $cell_1$. In general, without special treatment, correlated sensory data tend to be moved to the locations far away from one another along with the devices' movement, as time passes. On the other hand, we suppose that the other devices, denoted by u_4 and u_5, are approaching $cell_1$. At time t_3 (Fig. 3 (c)), u_2 and u_3 meet u_4 and u_5, respectively. During the meeting, u_2 transmits r_2 to u_4 because the current geographic coordinates of u_4 have a smaller distance from $cell_1$, in which r_2 was sampled, compared with the u_2's current coordinates. Similarly, u_3 forwards r_3 to u_5 because u_5 is currently located at the coordinates that have a smaller distance from $cell_1$ compared with the u_3's current coordinates. By doing so, at time t_4 (Fig. 3 (d)), when u_4 and u_5 meet u_1, they transmit r_2 and r_3 to u_1, respectively. Finally, u_1 can aggregate three sensory data and upload the aggregated data to the server.

The above mentioned example can be generalized and formalized as Algorithm 1. This algorithm is executed individually at each device when a pair of mobile devices meet, to determine the subset of sensory data to be forwarded to the other device during the contact. Before executing Algorithm 1, we suppose that they exchange device information, which includes devices' current coordinates. Then, each device executes the procedure named `subset_data_forwarded` in Algorithm 1, where u_{self} and u_{peer} represent itself and the peer, respectively. In this procedure, S will eventually become the subset of sensory data, all of which will be forwarded to u_{peer}. To compute S, for each sensory data r_i held in the local storage of u_{self}, the device checks if u_{peer} is located at the coordinates closer to the *destination coordinates* of r_i than the u_{self}'s current coordinates. If so, u_{self} adds r_i to S. Here, we adopt the centroid's coordinates of the cell in which r_i was sampled as the destination coordinates of r_i for position-based routing. For example, in the case in Fig. 3, the destination coordinates of r_1, r_2, and r_3 are all set to the centroid's coordinates of $cell_1$. By doing so, we can expect that each sensory data is held by the device that is currently located at the coordinates relatively close from the data's destination coordinates. This increases the possibility that the multiple sensory data that can be aggregated together will be intensively collected by the relatively small number of devices and results in better aggregation performance. In the following, we call the cell in which a data was sampled as *origin cell* of the data.

Algorithm 1 Determining the subset of sensory data to be forwarded to the peer device

procedure `distance_from_origin`(u, r)
  return the Euclidean distance between u's current coordinates and the coordinates of the centroid of the cell in which r was sampled.

procedure `subset_data_forwarded`(u_{self}, u_{peer})
  $S \leftarrow \emptyset$
  for all sensory data r held in u_{self}'s local storage **do**
    $d_{self} \leftarrow$ `distance_from_origin`(u_{self}, r)
    $d_{peer} \leftarrow$ `distance_from_origin`(u_{peer}, r)
    if $d_{peer} < d_{self}$ **then**
      $S \leftarrow S \cup \{r\}$
    end if
  end for
  return S

IV. Experimental Evaluation

We conducted simulation-based experiments to evaluate the aggregation performance of our proposed scheme. To generate mobile devices' mobility, we extracted the road network of a 1.5 km $\times$ 1.5 km area in Kyoto as a graph from the

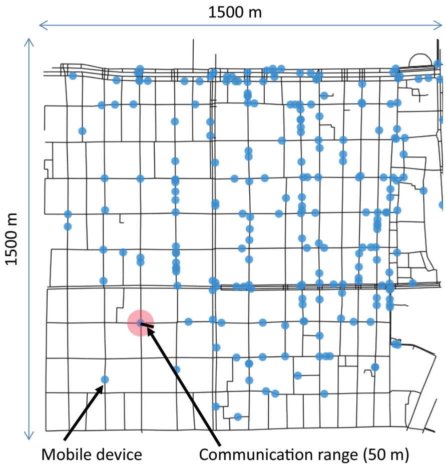

Fig. 4. Simulation area.

OpenStreetMap (OSM)[1] repository. The graph extracted is shown in Fig. 4, which consists of 1,614 vertices and 2,124 edges. In the experiments, 225 mobile devices are deployed within the area. The initial position of each mobile device is randomly determined from the set of vertices in the graph. The mobility of the devices are generated as follows: (i) At the beginning of a simulation run, each mobile device selects its destination vertex randomly from the set of vertices and (ii) moves to the destination along the shortest path from the current location, with a speed determined randomly from $[0.5, 1.5]$ m/s; After reaching the destination vertex, (iii) the device stays at the destination for a duration randomly selected from $[60, 300]$ s; Then, (iv) the device selects a new destination vertex randomly and goes to the step (ii). The sensing period T_{sen} is set to one second, which means that for each mobile device one sensory data is generated every T_{sen}. The width of a cell and the length of a timeslot are set to 250 m and 100 s, respectively. The hello period T_{hel} is set to 10 s. The communication range between devices is set to 50 m. The warmup time and simulation time are set to 2,000 s and 5,000 s, respectively. Table I shows the parameters and their values used in the simulations. For each experiment, the simulation is executed for 10 times with different random seeds and the results are averaged over the 10 runs.

In the experiments, in order to measure the aggregation performance, we assume that the data volume of a single sensory data is regarded as 1. We also assume that the data volume of one aggregated data generated by aggregating multiple sensory data has the same data volume as a single sensory data. Thus, by aggregating $n (\in \mathbb{N})$ sensory data, the data volume of the aggregated data is regarded to be 1. Similar to a measure used in the area of data compression [15], we introduce *aggregation ratio*, which measures the aggregation performance. The aggregation ratio is defined as:

$$\text{aggregation ratio} = \frac{\text{data volume before aggregation}}{\text{data volume after aggregation}}. \quad (2)$$

[1]https://www.openstreetmap.org

TABLE I
THE PARAMETERS USED IN THE SIMULATIONS.

Parameter	Value
Number of mobile devices	225
Simulation time	5,000 s
Communication range	50 m
Area size	1.5 km $\times$ 1.5 km
Movement speed	$[0.5, 1.5]$ m/s
Pause duration at destination	$[60, 300]$ s
Sensing period	1 s
Hello period	10 s
Cell width	250 m
Timeslot length	100 s

A. Aggregation performance

We first examine aggregation performance of various aggregation schemes. We compared the following schemes:

(a) *Inner aggregation only*. No communication link available between devices and each mobile device performs aggregation only on the sensory data sampled by itself.

(b) *Ranking-based*. In ranking-based aggregation scheme, each mobile device is assigned a rank and when two mobile devices meet, the mobile device that has a lower rank forwards all of the sensory data held in own storage to the peer. There exist three types in this scheme:

  (1) *ID-based*. Each mobile device is assigned a randomly selected unique identifier, which is fixed throughout a simulation run, and the identifier is regarded as its rank.

  (2) *CH-fixed*. By utilizing the contact history among mobile devices, ranks are assigned to the mobile devices so that the relatively higher ranks are assigned to the devices that tend to meet the other devices more frequently. In CH-fixed, one fixed rank is assigned for each mobile device throughout a simulation run.

  (3) *CH-dynamic*. The mobile devices are assigned ranks in the similar manner to CH-fixed, but the ranks are dynamically changed based on the dynamics of the contact pattern recorded in the contact history.

  More details on ranking-based aggregation scheme can be found in [13].

(c) *Position-based routing*. This is the aggregation scheme explained in Section III. There exist two types in the scheme for the purpose of investigating the impact on the destination setting in position-based routing.

  (1) *PR-origin*. The destination coordinates of each sensory data is set as the centroid's coordinates of the origin cell, as described in Section III.

  (2) *PR-random*. The destination coordinates of each sensory data is set as the centroid's coordinates of a randomly selected cell among all the cells (i.e., 36 cells) in the simulation area.

Fig. 5 shows the aggregation performance of each scheme during the simulation time from 0 to 5,000. From Fig. 5, we can see that the aggregation ratios of the aggregation

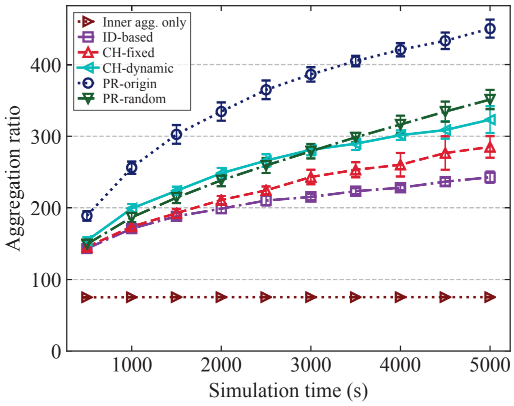

Fig. 5. Comparison of the aggregation performance for different aggregation schemes. The error bars show the standard deviation.

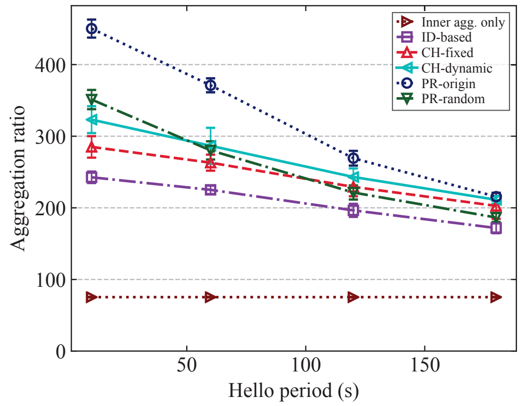

Fig. 7. Impact of the hello period on the aggregation performance. Each data point represents the aggregation ratio at time 5,000 after the beginning of the simulation. The error bars show the standard deviation.

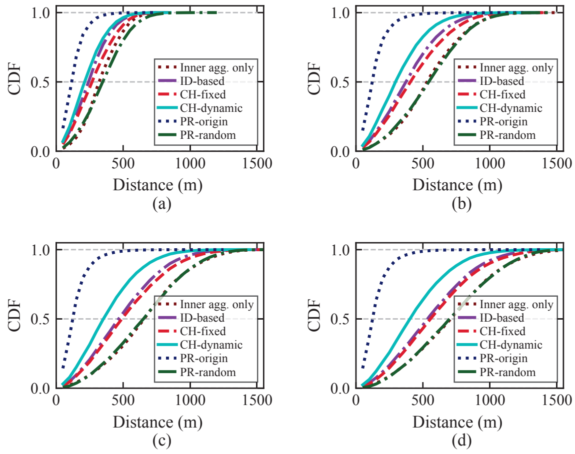

Fig. 6. CDF of the distance between the location of the device that currently stores a sensory data and the location where the data was sampled at elapsed time (a) 500 s, (b) 1,000 s, (c) 1,500 s, and (d) 2,000 s since the data was sampled.

schemes increase with the time elapsed since the beginning of the simulation. This means that a larger uploading period can lead to an increase in the aggregation performance. We also observe that PR-origin achieves the highest aggregation ratio among the six schemes. For instance, the aggregation ratio of PR-origin is about 40 percent higher than that of CH-dynamic at time 5,000. Interestingly, PR-random even outperforms CH-dynamic when the elapsed time is larger than 3,000. This indicates that position-based routing is still effective in some extent to improve aggregation performance even when the destination coordinates of sensory data are set to the coordinates that are not related to their origin cell.

To investigate how the position-based routing affects the distribution of the sensory data over the simulation area, we calculated the Cumulative Distribution Function (CDF) of the distance between the location of a sensory data (i.e., the current location of the device that stores the data) and the location where the data was sampled. The result is shown in Fig. 6, where sub-figures (a), (b), (c), and (d) represent CDFs at elapsed time 500 s, 1,000 s, 1,500 s, and 2,000 s since the data was sampled, respectively. From Fig. 6, we observe that almost all the sensory data are located within 500 meters in PR-origin for all cases, whereas, in other schemes, the sensory data are located at much broader range of the locations in the simulation area. This suggests that spatially correlated data can be gathered more effectively by the devices located near the origin cell of those data in PR-origin than the other schemes.

B. *Impact of the length of hello period*

Lastly, we demonstrate how the length of hello period affect the aggregation performance. In the experiment, we vary the length of hello period from 10 s to 180 s and measure the aggregation ratio for each length at time 5,000 after the beginning of the simulation for all schemes.

The results are shown in Fig. 7. From Fig. 7, we can see that the aggregation ratio decreases with the increase of the length of hello period in all schemes, because the communication opportunities between devices are lost. Although the aggregation ratio in PR-origin decreases at faster rate than the other schemes, PR-origin still achieves better aggregation performance than the others.

V. Related Work

Various types of crowdsensing (or participatory sensing) systems has been proposed in the literature [2], [3], [16]–[18]. However, in these systems, a general framework achieving the upload traffic reduction has not been explored enough.

In [19], [20], crowdsensing systems that exploit direct communications between mobile devices are proposed to achieve privacy preserving data gathering. In these systems, the sensor readings are exchanged among participating nodes [19] or collected along the tree-like paths [20] so that the users' privacy is preserved without sacrificing data utility.

COUPON [21] utilizes opportunistic contacts between devices and performs data aggregation on these devices, aiming to reduce the data volume of the sampled data. In COUPON, similar to the problem setting in traditional wireless sensor networks, some *sink* nodes are deployed in the network, and the sampled data are opportunistically forwarded to the sink nodes through the data aggregation performed on the forwarding nodes. Our problem setting differs from COUPON in that there are no special sink nodes in the network and that any mobile device can upload sensory data directly to the server through cellular networks or Wi-Fi.

The authors of [22], [23] propose a data gathering scheme for Floating Car Data (FCD), where sensory data are collected and aggregated by moving vehicles using direct vehicle-to-vehicle communication in vehicular networks. The scheme is mainly focused on collecting data from vehicles within relatively short period of time (e.g., 10 seconds [23]). Thus, opportunistic contacts that occur during much longer timespan (e.g., from several minutes to several hours) are not intended to be utilized. In our proposed scheme, the utilization of opportunistic contacts is a key factor to improve aggregation performance.

In our previous work [13], we proposed a data aggregation scheme of utilizing the contact history among mobile devices. As shown in Section IV, contact history-based schemes exhibit lower aggregation performance compared with the schemes that utilize position-based routing. However, contact history-based schemes do not need to know the exact locations of mobile devices but need only a contact information (i.e., a pair of node identifiers). Thus, contact history-based schemes are still beneficial in the situations that prevent the organizers of crowdsensing systems from acquiring the mobile devices' locations due to some reasons (e.g., concerns on battery consumption by GPS).

VI. Conclusion

In this paper, we proposed a distributed data aggregation scheme to mitigate the traffic load generated for uploading sensory data acquired by the mobile devices participating in a crowdsensing campaign. Experimental results based on simulations with a map-based mobility model show that the proposed aggregation scheme, which utilizes position-based routing, improves the aggregation performance over the contact history-based aggregation schemes.

This paper focused on the reduction in the traffic volume that traverses the cellular networks or Wi-Fi AP. It is also important to reduce the traffic incurred by the data transfer between devices, especially when the node's resource such as battery power and wireless bandwidth is limited. We will consider the case as a future direction.

Acknowledgments

This research was conducted under a contract of R&D for radio resource enhancement, organized by the Ministry of Internal Affairs and Communications, Japan.

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