Ubiquitous Transmission of Multimedia Sensor Data in Internet of Things

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***Abstract*—The Internet of Things (IoT) enables environmental monitoring by collecting data from sensing devices, including cameras and microphones. The popularity of smartphones enables mobile users to communicate and collect data from their surrounding sensing devices. The mobile devices can obtain useful environmental data from nearby sensors through short-range communication such as Bluetooth. Nevertheless, the limited contact time and the wireless capacity constrain the amount of data to be collected. With the increasing amount of multimedia big data such as videos and pictures from cameras, it is crucial for mobile users to collect prioritized data that can maximize their data utility. In this paper, we propose a distributed algorithm to provide information-centric ubiquitous data collection of multimedia big data by mobile users in the IoT. The algorithm can handle transmissions of multimedia big data recorded by the surrounding cameras and sensors, and prioritize the transmissions of the most important and relevant data. The mobile users construct data collection trees adaptively according to their dynamic moving speeds and the value of information carried by the multimedia and sensor data. The distributed algorithm can support smooth data collection and coordination of multiple mobile users. We provide both numerical analysis and extensive simulations to evaluate the information value, energy efficiency and scalability of our solution. The results showed that our distributed algorithm can improve the value of information up to 50% and reduce energy consumption to half compared with existing approach. Our algorithm also scales perfectly well with increasing number of mobile users and dynamic moving speeds.**

***Index Terms*—Data collection, energy efficiency, mobile devices, quality of information (QoI), wireless sensor networks (WSNs).**

I. Introduction

THE INTERNET of Things (IoT) has been widely deployed and utilized for environmental monitoring and sustainable development. The smart sensing devices, such as cameras, microphones, and chemical sensors, enable better understanding of climate change, pollution, and habitats from natural environment to water system and transportation in urban life [1]–[3]. With the advancement of mobile devices, mobile users can collect data from their nearby sensors using their mobile devices, such as PDAs or smartphones, anytime and anywhere [4]–[6]. This architecture increases the flexibility of sensor network deployment and offers a cost-effective solution for sensor data collection and data sharing [7], [8]. Giordano and Puccinelli [9] have offered a rich overview of various commercial efforts in pervasive sensing, current trends, and possible future directions. For example, street cameras are common nowadays for monitor traffic flows and road conditions in smart cities. Similarly, wildlife cameras are deployed in rural areas to capture still images at specific intervals or record images/videos when they detect motion of animals [10].

Mobile users can support data collection in many sensing applications including environmental monitoring, healthcare, transportation, safety, etc. For example, personal environmental impact report is a mobile sensing application developed to calculate personalized estimates of environmental impact and exposure [11]. Since the available sensor types are limited on mobile phones, mobile users can collect sensing data with more variety by communicating with wireless sensors in their surroundings. In the GreenOrbs project [12], forest rangers can use their PDAs to collect scientific data, such as temperature, humidity, and concentration of carbon dioxide, from the wireless sensors deployed in the forest. As multimedia sensors are getting more common, there is an increasing need of transmitting multimedia data (e.g., videos, pictures, and audio) from sensors to mobiles, though the transmission of multimedia data is a challenge with the limited contact time and bandwidth [13].

In the IoT, wireless sensors are communicating with each other through short range wireless communication. Multiple sensors may form a wireless sensor network (WSN) which is connected to the Internet through one or multiple gateways. The communication between the sensors to the gateway(s) in the sensor network can be via single hop or multihop wireless communications [14]. Evolved from traditional WSNs, ubiquitous data collection enables mobile devices to collect sensing data from their surrounding sensors [15]. For example, a mobile phone on a bike can collect sensor data from the air quality monitoring station deployed on the roadside. In ubiquitous data collection, the data collection opportunities may occur anytime and anywhere when the mobile devices and the wireless sensors are within their communication range. This form of short-range communication provides a lot of flexibility in sensor deployment without the need of any fixed Internet

Manuscript received May 28, 2017; revised August 21, 2017; accepted September 30, 2017. Date of publication October 13, 2017; date of current version February 9, 2018. This work was supported in part by the Swedish Governmental Agency Vinnova under Grant 2015-00347 for the project GreenIoT: An Energy-Efficient IoT Platform for Open Data and Sustainable Development. The work of J. Liu was supported in part by the Qatar National Research Fund (a member of Qatar Foundation) under NPRP Grant 8-519-1-108. *(Corresponding author: Edith C.-H. Ngai.)*

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Digital Object Identifier 10.1109/JIOT.2017.2762731

connection. The mobile devices can collect data from nearby sensors as data consumers. At the same time, they can serve as data collectors and upload the collected data to the Internet when network connectivity is available. The uploaded data can then be accessed by other Internet or mobile users who have not visited the sensing areas.

Data collection using smartphones carried by mobile users is different from data collection using mobile sinks with predefined mobility patterns. For example, the routes of the mobile elements (MEs) are under controlled to optimize their data collection performance in WSNs [16]. On the contrary, the mobile users are free to move around, so their mobility patterns are not under control [17], which poses new challenge in ubiquitous sensor data collection especially for multimedia data. In particular, the contact time between the mobiles and the sensors can be short considering the limited wireless communication range. It also depends on the activities of the mobile users. For example, the contact time could be really short if they are running, biking or even in a vehicle. The limited wireless capacity constrains the amount of data to be transmitted from the sensors to the mobile devices. Considering the limited contact time and wireless capacity, it is crucial for the mobile users to maximize their information gain by collecting the most significant multimedia data from the nearby sensors.

Quality of information (QoI) captures the utility of information delivered to the users, which can be computed by the accuracy, timeliness, relevance, and provenance of data [18]. The QoI of sensor data represents the importance of various observations carried by the collected sensing data [19], [20]. Sensing data of unusual events are considered to be more significant and valuable to the users compared with routine data. For example, it will be of interest to prioritize data transmissions of pictures and videos from field cameras that capture movements of animals than regular static scenes. The data transmissions result in higher QoI if the users can collect more important and relevant sensing data. Achieving high QoI in ubiquitous data collection is very challenging, since it has to handle the dynamic topology and the limited contact time due to mobility of users. Energy efficiency is another major concern for both mobile devices and wireless sensors. Mobile users always want to save the batteries of their smartphones. The batteries of the wireless sensors are even more constrained as they are seldom recharged after deployment. The goal of this paper is to improve QoI and reduce energy consumption in multimedia big data transmissions in IoT with ubiquitous data collection.

Although data collection for WSNs with MEs has been studied, most of the studies assume that the MEs move along predefined paths and stop at rendezvous points to collect data. However, the mobility patterns of mobile users are uncontrollable and continuously. The mobile users may not stop, which implies that data collection has to be done on the fly. The data collection trees need to be constructed and adapted quickly to the mobility of users. Global data collection trees have been widely adopted by the MEs in existing work [4], [21]–[23]. The idea is to broadcast HELLO messages to the sensor nodes in the network for tree construction. Nevertheless, it is difficult to determine how far the messages should be broadcast. A common way to limit the size of the data collection tree is by predefining a maximum hopcount h in broadcast. However, this approach cannot adapt to the dynamic moving speed of the mobile user, since the predefined maximum hopcount may be overestimated or underestimated. To address this problem, we propose to construct the data collection trees dynamically according to the moving speeds of the mobile users. We provide a distributed solution for constructing the data collection trees and schedule the collection of sensing data to maximize the information value.

The contributions of this paper are as follows. First, we propose a distributed algorithm, called EQRoute, to provide information-centric ubiquitous data collection with mobile users. It coordinates data collection for multiple mobile users with uncontrollable mobility in a distributed manner. Second, the mobile users can estimate the available capacity dynamically according to their moving speeds. Our algorithm provides energy-efficient and smooth data collection that maximizes the information value with low energy consumption. Finally, we evaluate performance of EQRoute by both analysis and simulations with multiple mobile users and variable speeds. Compared with the most advanced existing approach, EQRoute improves the information value and reduces the energy consumption significantly. Our results also demonstrated the scalability of our solution with multiple mobile users and high moving speeds.

The rest of this paper is organized as follows. The related work is presented in Section II. We describe the challenges and design goals of information-centric ubiquitous data collection in Section III. In Section IV, we present the problem formulation and propose a centralized optimal approach to solve the problem. We present our distributed ubiquitous data collection algorithm in Section V. We provide numerical analysis and extensive simulations to evaluate the performance of our solution in Sections VI. We conclude this paper in Section VII.

II. Related Work

IoT combines future Internet and ubiquitous computing, and envisions interactions between smart objects consisting of stationary sensors and mobile devices [3]. Perera *et al.* [24] proposed an IoT middleware solution that can work on resource constrained mobile devices allowing them to collect and process data from sensors easily. Mobile sinks and mobile relays have been suggested for improving the performance of data collection in WSNs. Shah *et al.* [23] presented an architecture using moving entities, called *data mules*, to collect sensing data. Gu *et al.* [25] proposed a partitioning-based algorithm to schedule the movement of MEs, which minimizes the required moving speed and eliminates buffer overflow. Bisnik *et al.* [26] studied the problem of providing quality coverage using mobile sensors and analyzed the effect of controlled mobility on the fraction of events captured. Xu *et al.* [27] further studied delay tolerant event collection in sensor networks with mobile sink which considers the spatial-temporal correlation of events in the sensing field.

He *et al.* [28] analyzed the performance of data collection theoretically to evaluate service disciplines of MEs through a queueing model. Mehrabi and Kim [29] addressed the problem of maximizing data collection throughput on a path in energy harvesting sensor networks using a mobile sink with fixed mobility pattern. Nevertheless, the above works focus on controlling the movement of mobile sinks for data collection, which are different from the mobile users with independent and uncontrollable mobility in this paper.

Studies have been conducted for MEs without any fixed trajectory. Kusy *et al.* [30] presented an algorithm to predict the mobility pattern of the mobile sinks from the training data. They computed and maintained the mobility graph of the mobile sinks to improve routing reliability in data collection. Similarly, Lee *et al.* [31] presented a routing scheme that exploits the mobility pattern of the mobile sinks to minimize energy consumption and network congestion. However, the above works emphasize on predicting the movement of MEs to improve routing efficiency. Recently, ubiquitous data collection with mobile users has been studied for mobile users to collect data from WSNs. Li *et al.* [4] proposed a ubiquitous data collection scheme that can efficiently form a new data collection tree by locally modifying the previously constructed data collection tree. Similarly, Cheng *et al.* [13] proposed a streaming data delivery protocol for multihop cluster-based WSNs with MEs, with focus on supporting mobility for continuous data delivery in hierarchical networks. Recently, Yang *et al.* [32] investigated low-delay and high-throughput opportunistic data collection in WSNs with MEs. They proposed a novel routing metric, called Contact-Aware ETX, to estimate the packet transmission delay caused by both packet retransmissions and intermittent connectivity. However, the above works have been focusing on reliability and energy efficiency in data collection. The information value carried by the sensing data has not yet been fully considered in data collection for mobile sensor networks.

QoI has been studied by Bisdikian *et al.* [18] to measure attributes like accuracy, timeliness, reliability, completeness, and relevance of the sensing information [33], [34]. Gelenbe and Ngai [35] proposed an adaptive routing protocol that can detect the presence of unusual events and provide better QoI for the high priority traffic. Mathew and Weng [36] further studied the problem of co-optimizing energy efficiency and information quality for WSNs. They proposed a novel quality/energy efficient metric, which models the relationship of sensing, processing, and transmitting with quality and energy. Based on the metrics, a quality-energy adapting system has been developed to exploit base station scheduling priority and adaptive sampling to optimize both energy efficiency and overall information quality. Singh and Al-Turjman [37] studied the use of heuristically accelerated learning techniques for improving the data delivery success rate in information-centric sensor networks. It examined the performance in terms of impact on the network lifetime, average success and failure rates, energy consumption, and the QoI at the sink. Recently, opportunistic routing with data compression has been explored to further reduce the data size and energy consumption in WSNs [38]. Nevertheless, QoI-aware data collection for mobile sensor networks has not yet been fully explored. In particular, collaboration among multiple mobile users for information-centric ubiquitous data collection in a distributed manner remains to be further investigated.

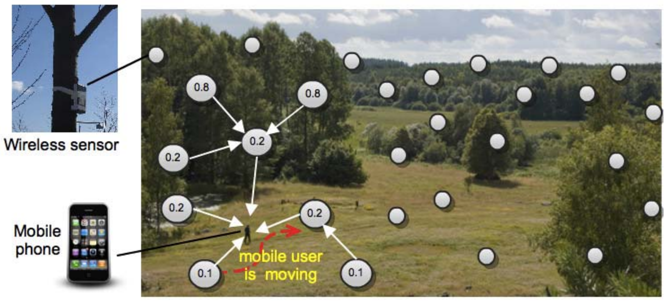

Fig. 1. Mobile user is walking in a sensing field to collect data from his surrounding sensors. The numbers in the figure indicate the information value carried by the sensing data. The data with higher information value are prioritized for data collection to maximize the information gain.

III. Preliminary

A. System Model

We consider a number of wireless sensors deployed in an open field for environmental monitoring. These wireless sensors (e.g., cameras) collect sensor data, which may include multimedia data (e.g., videos and pictures) of wild animals, plants, and nature scenes. The sensors are equipped with short-range wireless communication capability, such as IEEE 802.15.4 or Bluetooth, so that they can communicate with other sensors and mobile devices within the communication range. This setup enables rangers and visitors who walk in the field with hand-held devices to communicate and collect data from the nearby sensors. The wireless sensors can also form a data collection tree, so that the mobile user can collect sensor data from multiple sensors outside its communication range. However, there is limited contact time between the mobile user and the wireless sensors. This problem is particularly critical when the wireless sensors collect and transmit multimedia data. The data size of multimedia is much bigger than the size of traditional sensor data like temperatures and humidity. It is important to prioritize the transmission of multimedia sensor data with higher information value considering the limited contact time.

For this reason, the data collection tree cannot be extended without a limit. The tree has to be built and reconstructed based on the available communication capacity and the moving speed of the mobile user. This paper focuses on maximizing the information value of sensor data collected by the mobile users in the field, considering the importance of sensor data, the available communication capacity, and communication overhead.

B. Application Scenarios

Fig. 1 shows a mobile user walking in a sensing field to collect sensor data. The wireless sensors take sensor measurements and store the data in their buffers. The data can be picked up by the mobile users when they pass by the sensors.

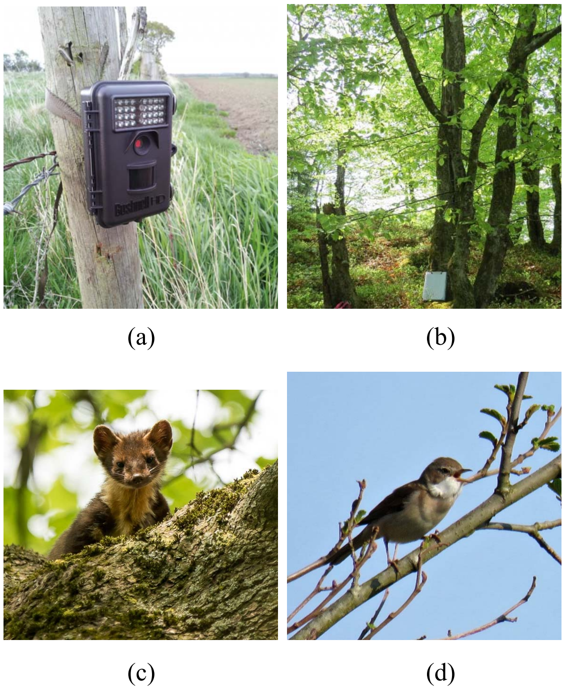

Fig. 2. (a) Wildlife camera and captured pictures. (b) Normal forest scene without detecting any wild animals (low information value). (c) Picture capturing a marten (high information value). (d) Photograph capturing a bird (high information value).

We use *information value* to indicate the importance of various observations carried by the sensing data [20]. For instance, the information value of a piece of data, w, can be measured by the importance and relevance of the environmental observation being carried. The information value is high if the data carry information of unusual events, for example, abnormal temperature or detection of wild animals. Intuitively, the mobile users want to maximize the information value of the collected data from the wireless sensors. For simplicity, we normalize the information value of the data packets, such that $0 \leq w \leq 1$. In Fig. 1, the mobile user decides to collect data with $w = 0.8$ rather than data with $w = 0.1$ if he has only limited contact time with the sensors.

An example of wildlife camera is shown in Fig. 2(a), which can be mounted on a tree. The camera takes pictures for routine field monitoring and for detecting the activities of wild animals. Fig. 2(b) shows a photograph of a normal forest scene without detecting any wild animals, which may carry lower information value. In contrast, Fig. 2(c) and (d) captures the movement of a marten and a bird, which could be very interesting for rangers and visitors.

C. Challenges and Design Goals

Communication opportunity occurs between the mobile devices and the wireless sensors only when they are within the communication range. Hence, it is challenging to collect data from the wireless sensors when the mobile user is moving with uncontrollable and unpredictable mobility. Due to the limited wireless communication range, i.e., IEEE 802.15.4 or Bluetooth, the mobile user may have *short contact time* to collect sensing data especially when he is moving fast and without any stops. Since the sensors and the mobile device communicate over the same wireless channel, they have to share the *limited wireless capacity* with their neighboring nodes. Bottleneck may occur particularly at the mobile node, since it is the root of the data collection tree that receives and processes maximum amount of traffic. Due to the above reasons, QoI is very important for the users to maximize the total information value from the collected data. Distributed and localized approach is preferred to reduce communication overhead for coordination among multiple mobile users. We highlight the design goals of our solution here.

1) It provides information-centric ubiquitous data collection to maximize the information value of the collected data with low energy consumption.
2) It supports smooth data transmission and adaptive data collection according to the moving speeds of the mobile users.
3) It coordinates data collection with multiple mobile users in a distributed manner.

IV. Information-Centric Ubiquitous Data Collection

In this problem, the sensors generate sensing data periodically and cache them in their buffers. The mobile devices with compatible wireless components, i.e., IEEE 802.15.4 or Bluetooth, can collect data from their surrounding sensors. The collected data can be uploaded by the mobile devices to the server when the Internet connection is available later.

We focus on data collection from the wireless sensors to the mobile users in this paper. Our goal is to maximize the information value and reduce the communication overhead in ubiquitous data collection. The mobile user is similar to an ME with uncontrollable mobility, limited communication range, and variable moving speed. Each sensor can communicate with the MEs and sensors that are within its wireless communication range. Multihop routing is supported to deliver data from the wireless sensors to the mobile users.

A. Problem Formulation

We consider that the sensor data are encapsulated in data packets. We introduce the following notations in our problem formulation.

1) Each mobile user j creates a routing tree T_j.
2) Each data packet d_i has an information value w_i.
3) We use w_H and w_L to represent the information value of high and low priority data, respectively.
4) We use p_H and p_L to represent the packet generation probability of high and low priority data, respectively.
5) We denote μ_j as the maximum service rate (number of packets per second) that j can receive and process data from T_j.
6) We define capacity C_j as the size of data (in number of packets) that can be collected by j in a time slot t, where $C_j = \mu_j t$. Note that this capacity is shared among the neighboring nodes of j and their subtrees.
7) We use hopcount c_{ij} to measure the communication cost for delivering d_i to j.

Variable: $x_{ij} \in [0, 1]$ indicates the amount of data to be collected by tree T_j.

Objective

$$\max U = \sum_{i,j} \frac{w_i}{c_{ij}} x_{ij}. \quad (1)$$

Constraints

$$\sum_j x_{ij} \le 1 \qquad \forall i \quad (2)$$

$$0 \le x_{ij} \le 1 \qquad \forall i, j \quad (3)$$

$$\sum_i x_{ij} \le C_j \qquad \forall j. \quad (4)$$

We consider application scenarios which contain a number of sensors in the sensing field monitoring the environment. These sensors could be wildlife cameras detecting the activities of wildlife animals, or sensors monitoring the environment (e.g., fire). The data collected by the sensors may contain different information values depending on their importance and relevance. For example, cameras which detect animal activities of interest provide data with higher information value than the others. Their data will be given higher priority in data collection compared with sensor data containing less valuable information.

The data packets may contain a series of sensor readings or multimedia data collected by the sensors. We use w to denote the information value, which indicates the importance of various observations carried by the data packet. We use c to indicate the communication cost (in hopcount) for collecting data packet from the sensor to the mobile device. We assume that the data are divided into small packets of the same size for transmission. We consider data packets individually when giving them priority in data collection. The system allows partial collection of sensor data generated by the same sensor. C_j is defined as the number of data packets can be collected by the mobile device in a time slot t.

We measure the information gain per communication cost of the data packet d_i by $u_i = w_i/c_{ij}$, which is the information value of the data divided by its communication cost in hopcount. The value of w_i/c_{ij} indicates the information value per communication cost (transmission in one hop). $w_i/c_{ij} = w_i$ when the data is collected by one hop transmission ($c_{ij} = 1$). If the data needs two hops to reach the mobile device, then $w_i/c_{ij} = w_i/2$ which is less economical than one hop transmission. It is more cost effective to collect data from sources with higher w_i/c_{ij}, since the information value obtained per communication cost is higher. Our objective function is to maximize the sum of u_i from all the collected data, denoted by U. This allows us to maximize the information value from the collected data, while achieving a good balance between the information value and the communication cost.

We define the variable x_{ij} to indicate whether data packet d_i is allocated with capacity for data collection in tree T_j. When $x_{ij} = 1$, it means that the data packet d_i will be sent to mobile j. Constraint 2 enforces a data packet to be sent to only one mobile user. Constraint 3 allows fractional data (down-sampled sensor data or image) to be sent. Constraint 4 ensures that the total amount of data received by mobile user j does not exceed its capacity C_j in a given time slot.

Algorithm 1 Centralized Capacity Allocation

C_j: capacity of mobile j;
w_i: information value of data d_i;
c_{ij}: hopcount for d_i to reach mobile j;

Mobile user j broadcasts to all sensors in the network;
Each sensor replies to j with w_i and c_{ij} of its data;
while $C_j > 0$ **do**
  Choose the data d_i with maximum w_i/c_{ij};
  if $C_j \ge 1$ **then**
    $x_{ij} = 1$;
  else
    $x_{ij} = C_j$;
  end if
  $C_j = C_j - x_{ij}$;
end while

B. Optimal Centralized Algorithm

We suggest a centralized data collection algorithm for mobile user to maximize U from the collected data (see Algorithm 1). The mobile user first floods the network to gather the information value, size and communication cost of the data from the sensors. Then, it assigns capacity to the sensors by selecting data with the maximum information value per communication cost, i.e., w_i/c_{ij}. However, this algorithm works only in a centralized manner. The mobile user has to wait for the information from all the sensors before allocating the capacity to individuals. As discussed before, the mobile user has to flood the whole networks or broadcast to h hops, but h is not easy to decide.

Theorem 1: The above greedy algorithm gives an optimal solution for capacity allocation to sensors.

Proof: We recall that the algorithm allocates the capacity C_j for receiving a limited number of data packets in each time slot t. We use variable x_i to indicate whether each data packet d_i will be allocated with capacity for data collection.

The algorithm allocates the capacity C_j completely for receiving the sensing data. We assumed that the capacity is limited, so that it is not enough to collect all the data in the network. This implies that here exists a q, such that $1 = x_1 = \ldots = x_{q-1} > x_q \ge x_{q+1} = \ldots = 0$, where $x_{n+1} = 0$. We show the optimality of this solution by comparing to any other feasible solution $y_1, \ldots, y_n$ of this problem. Since w_i/c_{ij} are positive for all i, this solution can only be optimal if $\sum_i y_i = C_j$. Let k be the smallest index such that $y_k < 1$, and let l be the smallest index with $k < l$ such that $y_l > 0$. Note that such an l exists, unless the solution $y_1, \ldots, y_n$ is equal to the solution $x_1, \ldots, x_n$ obtained by the above greedy algorithm. We will now increase y_k and decrease y_l, while keeping all other values equal, to obtain a new solution. Let $\epsilon = \min\{1 - y_k, y_l\} > 0$. Increase y_k by ϵ and decrease y_l by ϵ. It is easy to find that this move yields a feasible solution with value not smaller than the value of the solution $y_1, \ldots, y_n$. Moreover, either y_k has become equal to 1, or y_l has become equal to 0. Repetition of this argument eventually yields the solution $x_1, \ldots, x_n$ obtained by the greedy algorithm. ■

However, the energy consumption is very high in this centralized approach. The mobile user has to broadcast to all the sensors in the network and get back their replies. The communication overhead is in the order of $O(N)$, where N is the number of sensors in the network. In the following section, we develop a distributed algorithm for ubiquitous data collection that does not require flooding the whole network.

V. Distributed Algorithm Design

We propose a distributed and information-centric ubiquitous data collection algorithm, called EQRoute. In this distributed approach, a mobile user does not need to flood the network to h hops. Instead, it estimates the amount of available capacity for the data collection tree. This amount of capacity can be delegated from the root to its children to form a data collection tree with multiple layers. The data collection tree is extended from one layer to another as long as there is remaining capacity available. With this distributed approach, we do not have to determine the parameter h or flood the whole network. It reduces the communication overhead in tree construction.

The main idea of our approach is to utilize the estimated available capacity C_j and the sensor demands to automatically determine the maximum layer in the data collection tree. This distributed design also supports collaborative data collection with multiple mobile users. We present our design with three components.

1) Construction of data collection tree.
2) Migration of data collection tree.
3) Selection among multiple mobile users in the following.

A. Construction of Data Collection Tree

We consider that each sensor holds high priority and low priority data with probabilities p_H and p_L, where $p_H + p_L = 1$. Their information values are denoted by w_H and w_L, respectively, where $w_H > w_L$. Similar to most of the studies, the construction of a data collection tree starts with a HELLO message from the mobile user. However, unlike existing approaches, we do not flood the whole network or broadcast to a predefined hopcount. Instead, each sensor node decides whether to extend the tree to the next layer by checking its remaining capacity in a distributed manner.

In our algorithm, the capacity of mobile j, C_j, has to be updated according to its moving speed for energy-efficient and smooth data transmission. It is much easier if we know the coordinates of each sensor and the trajectory of the mobile user. However, we do not make these assumptions, since we want to give more freedom and flexibility for the mobile users to explore new areas. To handle the unpredictable mobility, we introduce ΔD as an approximation of the average moving distance that a mobile user can walk without losing the connection with its neighboring sensors. We pick ΔD as the communication range R in this paper to ensure that the tree is updated before mobile user losing connection with its neighboring nodes. Then, we estimate the available capacity of the mobile user in the time interval $\Delta t = (\Delta D / v_j)$ by

$$C_j = \frac{\mu_j \Delta D}{\upsilon_j} \tag{5}$$

Algorithm 2 Distributed Capacity Allocation

d_i^H: required capacity for high priority data from node i;
d_i^L: required capacity for low priority data from node i;
f_j: free capacity of node j; initially $f_j = C_j$;

Procedure CapacityAllocation(j, f_j)
Broadcasts Hello message to 1-hop neighbours;
Each neighbouring node i replies with d_i^H and d_i^L;
{//Allocate capacity for H data}
for each reply from neighbouring nodes i **do**
  if $f_j + d_j^L > 0$ **then**
    Allocate capacity for d_i^H;
    $f_j = f_j - \min(f_j + d_j^L, d_i^H)$;
  end if
end for
{//Allocate capacity for L data}
for each d_i^L **do**
  if $f_j > 0$ **then**
    Allocate capacity for d_i^L;
    $f_j = f_j - \min(f_j, d_i^L)$;
  end if
end for
Assign remaining capacity to each i by $f_i = f_j / N(j)$;
{//Extending the tree}
for each neighbouring nodes i **do**
  if $f_i > 0$ **then**
    Run **CapacityAllocate(i, f_i)**;
  end if
end for
End Procedure

where μ_j is the service rate and υ_j is the moving speed of j.

The mobile user j estimates its available capacity according to its moving speed from time to time. It begins the data collection process by running the CapacityAllocation(j, C_j) algorithm (see Algorithm 2). It first broadcasts to its one-hop neighbors to obtain their capacity requests including the size of high and low priority data, d_i^H and d_i^L, respectively. Then, it assigns capacity first to the high priority data according to the received requests. The neighboring nodes start transmitting the high priority data immediately after the capacity is allocated. Next, the mobile user assigns the remaining capacity f_i to the low priority data of its neighboring nodes. If there is still remaining capacity, the mobile user will assign the capacity evenly to its $N(j)$ neighbors, i.e., $f_i = f_j / N(j)$. The neighboring nodes will extend the tree T_j to the next layer by running the CapacityAllocation procedure. Similar to j, each node i broadcasts to its one-hop neighbors m to receive replies of d_m^H and d_m^L. The capacity allocation process is repeated until there is no remaining capacity left in the data collection tree. Note that the high priority data can preempt the low priority data in the previous layer if there is not enough capacity in the data collection tree.

The message broadcasts for tree construction are limited to the level of nodes with capacity allocated in the data collection tree. Let h be the height of the data collection tree. The number of broadcasts in data collection tree construction will be $1 + N(1) + +N(h-1)$, where $N(h-1)$ equals to the number of nodes in level $h-1$ of the tree.

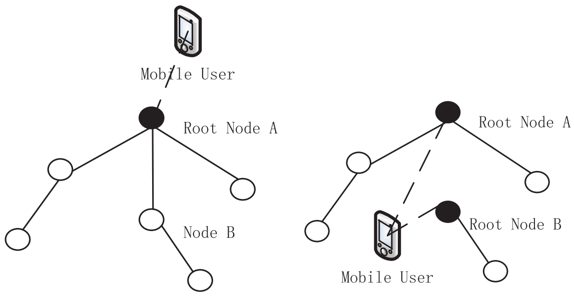

Fig. 3. Data collection tree is reconstructed when the mobile user is moving from the root node to another node inside the tree.

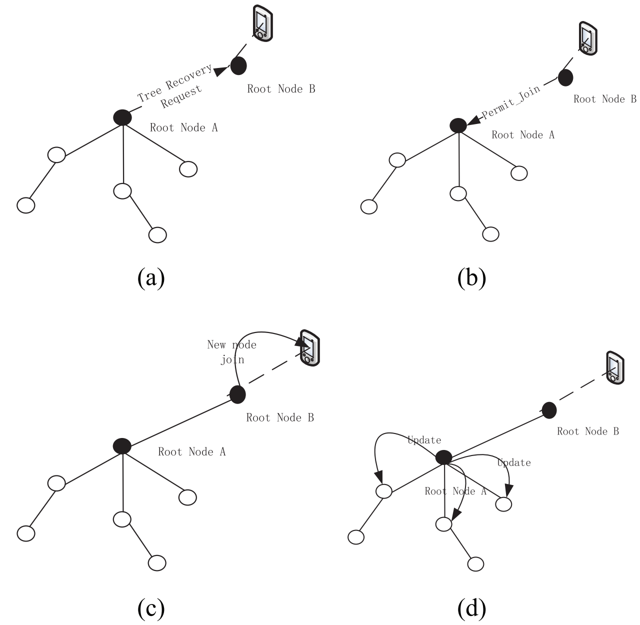

Fig. 4. Data collection tree is recovered when the root node detects a disconnection with the mobile user. (a) A sends tree recovery request. (b) B permits the joining of A. (c) B notifies the mobile user to update the capacity. (d) A updates capacity information to its children.

B. Migration of Data Collection Tree

As discussed before, the mobile user estimates the new capacity of the data collection tree every Δt. However, unexpected disconnections may still occur between the mobile user and the sensors due to its changing speed and moving direction. Hence, the mobile user broadcasts a "MobileHere" maintenance message periodically to its neighboring sensors to notify them of its existence. In general, the sensors wait passively for the maintenance message. However, they can also check actively for the existence of the mobile user if they do not receive any maintenance messages. Thus, the overhead to broadcast maintenance message small, which is only one broadcast message every δt.

In addition, the MobileHere message can be used for updating the tree structure according to the new location of the mobile user. For example, sensor node i may observe that the mobile user is getting very close if it can receive the maintenance message directly from the mobile user. Sensor node i can then connect directly to mobile user rather than taking a longer path via a relay node. This scenario can be handled formally by a tree migration process. For better illustration, we divide these migration processes into two types, namely *inner-tree migration* and *tree recovery*.

Fig. 3 demonstrates an example of inner-tree migration. At the beginning, the mobile user is connected only to root node A in the data collection tree. Then, it moves to a new location, where it can communicate directly with some other sensors. When sensor node B receives the tree maintenance message from the mobile user, it knows that the mobile user is nearby. Then, node B becomes the root of its subtree and connects directly to the mobile user. After updating the route, node B notifies its previous relay node A and the mobile user to update the capacity assignment accordingly. In inner-tree migration, the overhead of data collection migration is only one broadcast from the new root.

Fig. 4 shows the tree recovery process. Once root node A detects a disconnection with the mobile, it sends out a "FindMobile" tree recovery message to its neighbors and tries to recover the connection. Any nodes which do not belong to the subtree of A can help relaying the message to the mobile user. In this example, node B relays the message for node A, so that A is reconnected to the mobile user. Similar to inner-tree migration, it is necessary to update the capacity accordingly after tree recovery.

Otherwise, the mobile user may think that A has finished transmitting data, while A is still in the tree and has more to send. If the tree recovery process fails, node A may join the data collection trees of other mobile users if they have free capacity. To avoid routing loop, we include the root ID of the subtree that is connecting directly to the mobile user in the tree recovery message. Only the nodes with different subtree IDs will response to the tree recovery request. In tree recovery, the overhead is two broadcasts from the original root node, and two unicasts from the relay node.

C. Selection Among Multiple Mobile Users

In the scenario with multiple mobile users, the sensor node has to choose one of the mobile users to report its data. It can compare the performance of different mobile users to select the best route. We suggest a metric, ρ_j, to evaluate the performance of each mobile user j considering its available capacity and communication cost as follows:

$$\rho_j = \frac{\mu_{ij} \Delta t_j}{c_{ij}} \tag{6}$$

where μ_{ij} and c_{ij} are the available service rate and the hop-count for the mobile user to receive data d_i, and Δt_j is the available transmission timespan. Initially, ρ_j is set to -1, so that node i shows interest to any HELLO messages. Node i computes the performance metric ρ_j for each newly arrived HELLO message. It changes to a new route only if the new metric ρ_j is greater than the existing one (see Algorithm 3).

We observe that frequent switching between routes may cause unnecessary energy consumption and reduce the packet delivery rate. To avoid this, node i will change its route only if the new ρ_j is better than the current ρ_{j*} with a

Algorithm 3 Evaluation of Alternative Routes

μ_{ij}: service rate of j for receiving data d_i;
c_{ij}: hopcount for reporting data d_i to j;
Δt_j: timespan can be used for transmitting data to j;

Procedure SensorEvaluation $(\mu_{ij}, c_{ij}, \Delta t_j)$
$\rho_j = \frac{\mu_{ij}\Delta t_j}{c_{ij}}$;
if $\frac{\rho_j}{\rho_{j^*}} > \gamma$ **then**
  Update the route to report data to j;
  Send request message for new capacity;
  $\rho_{j^*} = \rho_j$;
end if
End Procedure

certain threshold, i.e., $(\rho_j/\rho_{j^*}) > \gamma$, where γ is greater than 1. When the sensor changes its route, it will notify its parent node to request for new capacity. However, it will not stop sending its data through the old route until the new capacity is assigned.

D. Worst Case Analysis for Optimality

We consider a data collection tree with the mobile user as the root. Each node has n children and generates d data packets on average in each time slot. The average number of data packets generated in layer h is $n^h d$. The generated data have probabilities of p_H and p_L to be high priority or low priority, where $p_H + p_L = 1$. The information value of a high priority packet and a low priority packet are denoted by w_H and w_L, where $0 \leq w_L \leq w_H \leq 1$.

We analyze the optimality of our distributed algorithm in terms of U as stated in the objective function of the problem formulation. The analysis aims at comparing the sum of information gain per communication cost between the centralized algorithm and our distributed algorithm. To make a fair comparison, we consider the same amount of capacity for the mobile user when comparing the performance of the two algorithms. However, the capacity of the mobile user may vary from one time slot to another according to the environment such as moving speed and distance between nodes.

Let $\alpha_1, \alpha_2, \ldots, \alpha_k$ and $\beta_1, \beta_2, \ldots, \beta_k$ be the proportion of high and low priority data collected by the mobile user in each layer h, where $0 \leq \alpha_h \leq 1$, $0 \leq \beta_h \leq 1$, and $h = 1, \ldots, k$. The sum of information value per communication cost, U, in the tree can be calculated by

$$U = \sum_{h=1}^{k} n^h d \frac{w_H}{h} p_H \alpha_h + \sum_{h=1}^{k} n^h d \frac{w_L}{h} p_L \beta_h. \tag{7}$$

Given the capacity C_j of mobile j, we also have

$$C_j = \sum_{h=1}^{k} n^h d p_H \alpha_h + \sum_{h=1}^{k} n^h d p_L \beta_h. \tag{8}$$

We then compare the U' obtained by our distributed algorithm with the U^* obtained by the optimal centralized algorithm. We show that the U^*/U' ratio has the following properties.

Theorem 2: The worst U^*/U' ratio occurs when $w_H >> w_L$. It is bounded by $(w_H p_H A(k^*)/w_H p_H A(m') + w_L p_L A(m'))$, where $k^* = \lceil(\log[((C_j/dp_H) + 1)(n-1) + 1]/\log n) - 1\rceil$, $m' = \lfloor(\log[((C_j/d) + 1)(n-1) + 1]/\log n) - 1\rfloor$ and $A(k) = \sum_{h=1}^{k}(n^h/h)$.

Proof: The analysis compares the sum of information gain per communication cost between the centralized algorithm and our distributed algorithm. In particular, it will provide the worst case analysis for optimality.

The capacity is assigned from the top to the bottom of the data collection tree for the same data type due to the property of $w > w/2 > \ldots > w/k$. Hence, $(\alpha_1, \alpha_2, \ldots, \alpha_k)$ is in a pattern of $(1, 1, 1, \ldots, 0)$, such that $1 = \alpha_1 = \ldots = \alpha_{k^*-1} \geq \alpha_{k^*} > \alpha_{k^*+1} = \ldots = 0$. Similarly, the sequence of $(\beta_1, \beta_2, \ldots, \beta_k)$ has the same property. Let k^* and m^* be the number of layers that are granted capacity for high and low priority data in the optimal algorithm. Since $w_H \geq w_L$, we have $k^* \geq m^*$. Consider that partial capacity may be granted in layer k^* and layer m^*, the optimal U^* must be bounded by

$$\begin{aligned} U^* &\leq \sum_{h=1}^{k^*} n^h d \frac{w_H}{h} p_H + \sum_{h=1}^{m^*} n^h d \frac{w_L}{h} p_L \\ &= d w_H p_H A(k^*) + d w_L p_L A(m^*) \end{aligned} \tag{9}$$

where $A(k) = \begin{cases} \sum_{h=1}^{k} \frac{n^h}{h}, & \text{if } k \geq 1 \\ 0, & \text{otherwise.} \end{cases}$

For our distributed algorithm, the capacity is assigned to both high and low priority data from the top layer. Let k' and m' be the number of layers that are granted capacity for high and low priority data. Since preemption for the high priority data occurs only in the lowest layer of the data collection tree, we have $m' \leq k' \leq m' + 1$. If we take the smaller value m', U' must be greater than the following:

$$\begin{aligned} U' &\geq \sum_{h=1}^{m'} n^h d \frac{w_H}{h} p_H + \sum_{h=1}^{m'} n^h d \frac{w_L}{h} p_L \\ &= d w_H p_H A(m') + d w_L p_L A(m'). \end{aligned} \tag{10}$$

Thus,

$$\frac{U^*}{U'} \leq \frac{w_H p_H A(k^*) + w_L p_L A(m^*)}{w_H p_H A(m') + w_L p_L A(m')}. \tag{11}$$

From (11), we observe that (U^*/U') is maximized when k^* is maximized. It occurs when $w_H >> w_L$, i.e., $m^* = 0$. In this case, only high priority data are selected in the optimal algorithm.

We further analyze the worst U^*/U' ratio in this scenario. Considering $m^* = 0$, all the available capacity C_j will be allocated for the high priority data in the optimal algorithm. Due to the capacity constraint, the total amount of high priority data collected must be smaller than C_j, that is,

$$C_j \geq \sum_{h=1}^{k} n^h d p_H = d p_H \left(\frac{n^{k+1} - 1}{n - 1} - 1\right). \tag{12}$$

By solving this equation, we can obtain $k^* = \lceil k \rceil$ by taking the maximum k with

$$k \leq \frac{\log\left[\left(\frac{C_j}{dp_H} + 1\right)(n-1) + 1\right]}{\log n} - 1. \tag{13}$$

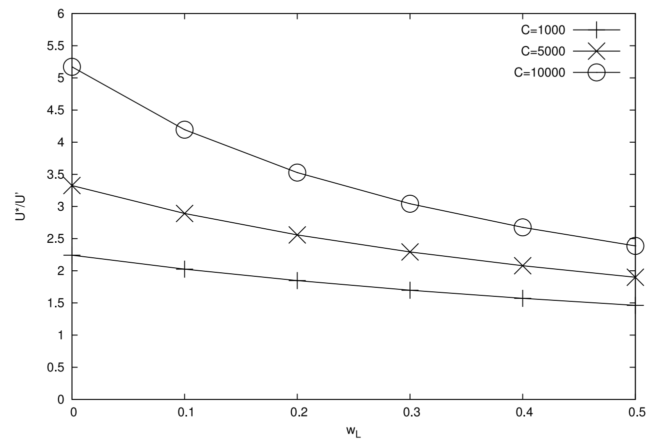

Fig. 5. Analytical results of the U^*/U' ratio varying w_L.

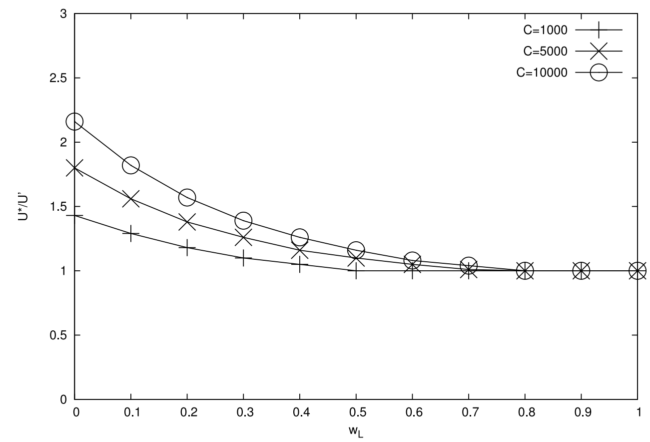

Fig. 6. Simulation results of the U^*/U' ratio varying w_L.

Similarly, the total amount of high and low priority data collected must be smaller than C_j in our distributed algorithm. We can obtain $m' = \lfloor m \rfloor$ by taking the maximum m with

$$m \leq \frac{\log\left[\left(\frac{C_j}{d} + 1\right)(n-1) + 1\right]}{\log n} - 1. \tag{14}$$

By substituting k^* and m' into (11) with $m^* = 0$, we can obtain a bound for the ratio U^*/U'. ■

As mentioned before, our distributed algorithm constructs the data collection tree adaptively according to the available capacity. The mobile user does not flood the whole network or broadcast with a fixed hopcount. In our approach, the size of the tree has maximum k^* layers, which is determined by the available capacity and the information value of the sensing data.

VI. Performance Evaluations

A. Numerical Results

We show the U^*/U' ratio with $p_H = 0.3$, $p_L = 0.7$, $n = 3$, $w_H = 1$, and varying w_L in Fig. 5. The results indicate that U^*/U' approaches to one when w_L increases. This is because the capacity is more evenly distributed among the high priority and low priority data in the optimal approach, so that it achieves similar performance as our distributed approach. We also notice that U^*/U' increases when capacity C_j increases from 1000 data packets to 10 000 data packets. The reason is that the data collection tree becomes bigger when C_j increases. The increased number of nodes makes the difference between U^* and U' larger in the two algorithms.

In order to validate the analysis, we conduct a simple simulation in Fig. 6 to compare the result with the analytical result. We generate the data collection trees based on the centralized and the distributed algorithms and compare their U^*/U ratio. As we can see, the simulation result validates that the U^*/U ratio is the worst when w_L is low. This leads to the biggest difference between the data collection trees in the centralized algorithm and the distributed algorithm. The curves in Figs. 5 and 6 follow the same trend, while the simulation result in Fig. 6 shows lower U^*/U ratio than the worst case analytical result in Fig. 5.

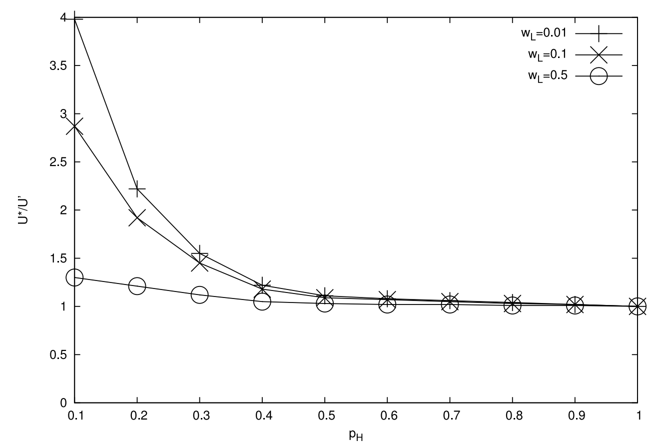

Fig. 7. Analytical results of the U^*/U' ratio varying p_H.

We also show the U^*/U' ratio varying p_H in Fig. 7. Note that $p_L = 1 - p_H$, which indicates the proportion of high and low priority data generated. When p_H increases, the distributed approach allocates more capacity to the high priority data in each layer. This may lead to closer performance compared with the optimal approach. Again, the result shows that the U^*/U' ratio is higher (worse) when w_L is small.

B. Simulation Results

We evaluate the performance of our distributed algorithm, EQRoute, in OMNet++ simulator [39]. OMNeT++ is an extensible, modular, component-based C++ simulation library and framework, primarily for building network simulations. Network in this case is meant in a broader sense that includes wired and wireless communication networks, on-chip networks, queueing networks [40], [41]. It provides commonly used radio transmission models and reliable wireless models. The sensors and the mobile devices communicate with IEEE 802.15.4 in nonbeacon mode. There are 100 sensors uniformly deployed in a 1000 m $\times$1000 m sensing field. The communication range R of the wireless sensors is set to 100 m. We set $\Delta D = 100$ m, which is the same as R in our experiments. The mobile users move independently following the random waypoint model, but we do not include any pause times to model continuous and uncontrollable mobility.

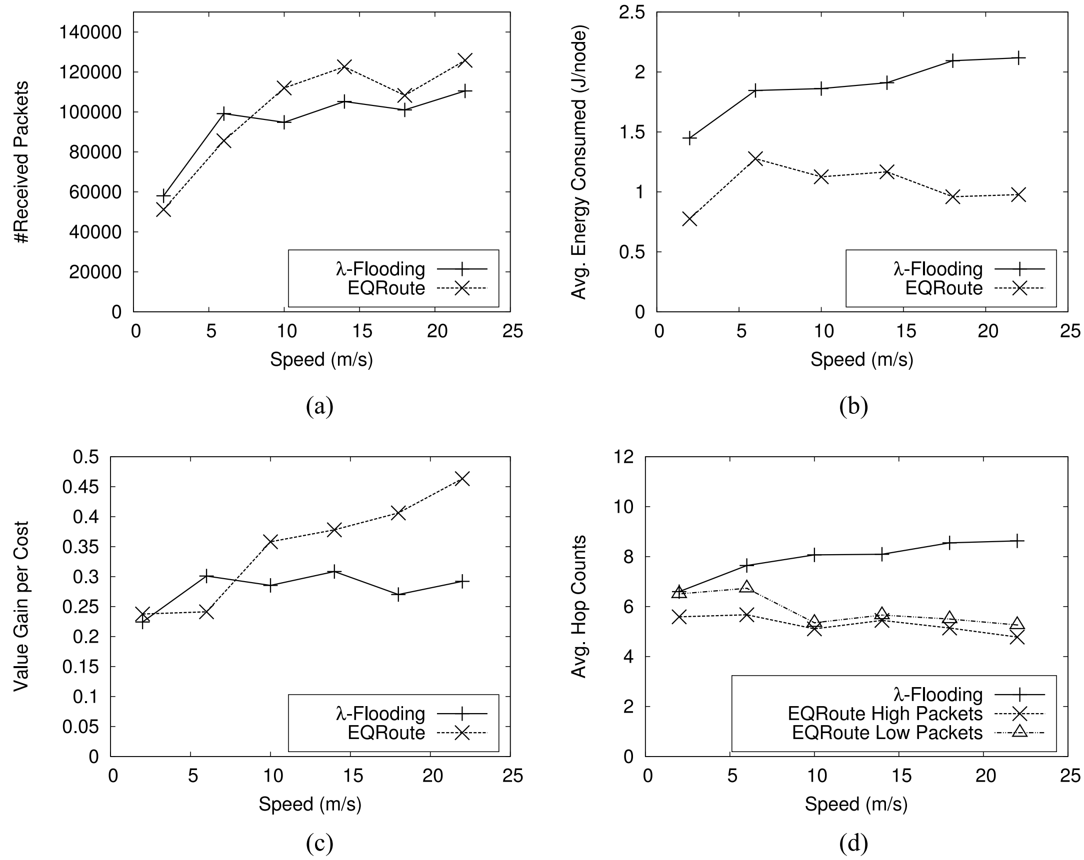

Fig. 8. Simulation results with single mobile user. (a) Total number of received packets. (b) Avg. energy consumption. (c) Information value per cost. (d) Avg. hopcount.

1) Single Mobile User: We first evaluate EQRoute in a single mobile user scenario with $p_H = 0.3$ and $p_L = 0.7$. The data generation rate of the sensors is set to 8 byte/s. We vary the mean moving speed of the mobile user from 2 to 22 m/s in our experiments with a standard deviation of 0.5 m/s. We compare our EQRoute algorithm with a recently proposed λ-flooding algorithm [4] for ubiquitous data collection. In λ-flooding, the mobile user builds a global data collection tree and updates the tree according to a predefined threshold λ to reduce energy consumption in data collection.

Fig. 8(a) shows the total number of received packets from EQRoute and λ-flooding. We can see that both algorithms receive comparable number of packets. However, our EQRoute algorithm consumes only half of the energy compared with λ-flooding as shown in Fig. 8(b). We believe that the energy consumption increases in λ-flooding due to its prolonged paths to keep the connection with the mobile user. This is further verified by the increasing average hopcount in λ-flooding as the speed increases [see Fig. 8(d)].

Fig. 8(c) shows the average information value per communication cost (hopcount) of the collected data. EQRoute can achieve much higher information value per communication cost than λ-flooding, since the highly valued data are given higher priority for collection. We also find that the information value per cost increases with the speed in EQRoute. This is because the mobile user builds smaller data collection trees with small hopcounts when it is moving fast.

2) Multiple Mobile Users: Next, we evaluate our EQRoute algorithm with multiple mobile users. We keep the same p_H and p_L settings as in the single user experiment. The data generation rate is increased to 800 byte/s to explore the full utilization of available capacity from multiple mobile users. We test with 1, 5, and 9 mobile users in the sensing field varying their average moving speeds.

Fig. 9(a) shows the total number of packets received by the mobile users. Obviously, more packets can be collected when there are more mobile users in the field. We show the average energy consumption of the sensors in Fig. 9(b). Since the sensors find more opportunities to report data to multiple mobile users, they consume more energy than reporting data to only single mobile user. We measure the information value per communication cost in Fig. 9(c). It shows that EQRoute can achieve higher information value per communication cost when the number of mobile users increases. However, the value per cost does not increase as much as expected with nine mobile users at high moving speed. We believe that some capacity is wasted for the sensors to switch their routes among different mobile users. Fig. 9(d) shows the average delay for transmitting high priority packets from the sensors to the mobile users. We can see that the average delay is the smallest with nine mobile users. This is because the mobile users can divide the sensing field and construct smaller data collection trees. The data collection trees become even smaller when the mobile users are moving in high speed.

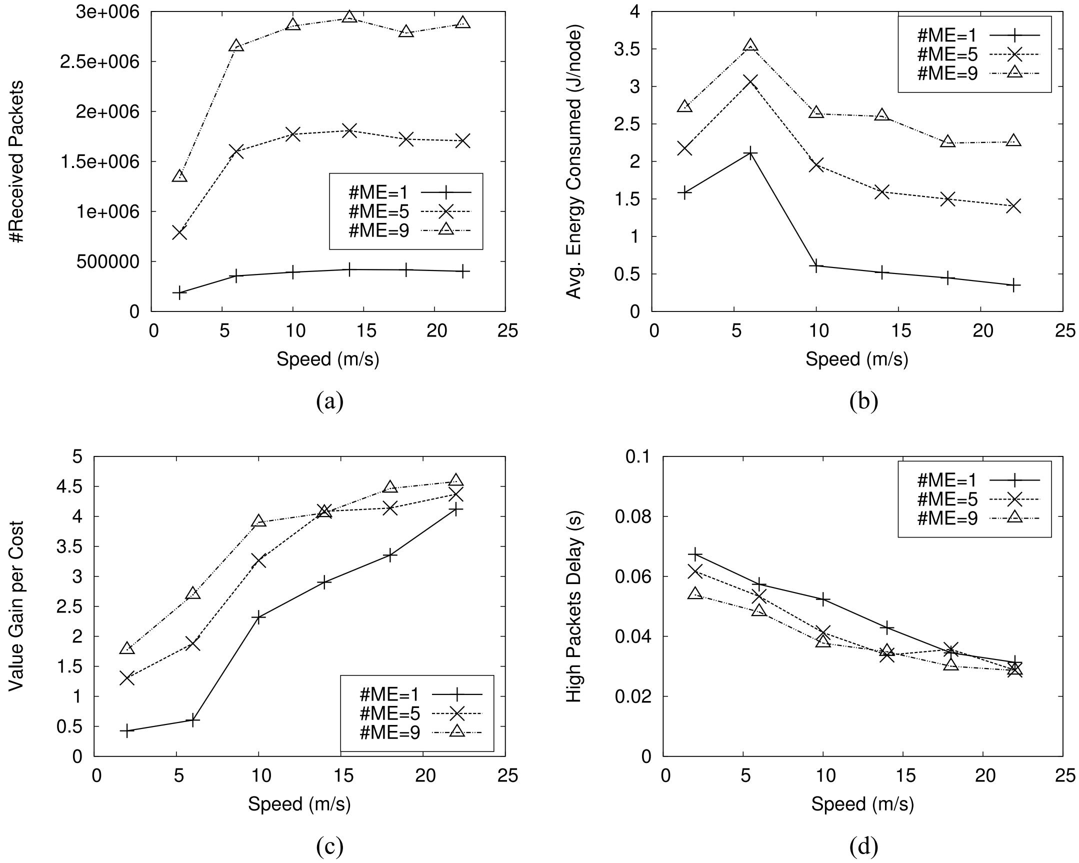

Fig. 9. Simulation results with multiple mobile users. (a) Total number of received packets. (b) Avg. energy consumption. (c) Information value per cost. (d) Avg. packet delay.

VII. Conclusion

In this paper, we proposed an information-centric ubiquitous data collection algorithm, called EQRoute, for collecting multimedia sensor data using mobile devices in the IoT. It supports collection of multimedia sensor data through short-range communication between mobile devices and wireless sensors with limited contact time. EQRoute is a distributed algorithm that allows mobile users to construct the data collection trees dynamically according to their moving speeds. It can control the size of the data collection trees adaptively to reduce packets losses. EQRoute obtains high information value by prioritizing the collection of data carrying more important information. It supports mobile users to make local decisions on data collection without sending any coordination messages among them. Numerical analysis and simulation results demonstrated that our distributed solution can improve information value up to 50% and reduce energy consumption by 50% compared with the latest approach. It can handle any number of mobile users with variable moving speeds.

For future work, we would like to explore mobility prediction to further improve information value and reduce communication overhead in ubiquitous data collection. We also plan to reduce the resolution of pictures and frame rates of videos to reduce the size of multimedia sensor data according to their information value.

References

[1] R. K. Rana, C. T. Chou, S. S. Kanhere, N. Bulusu, and W. Hu, "Ear-phone: An end-to-end participatory urban noise mapping system," in *Proc. IPSN*, Stockholm, Sweden, 2010, pp. 105–116.

[2] V. Dyo *et al.*, "Evolution and sustainability of a wildlife monitoring sensor network," in *Proc. Sensys*, Zürich, Switzerland, 2010, pp. 127–140.

[3] H. Ma, L. Liu, A. Zhou, and D. Zhao, "On networking of Internet of Things: Explorations and challenges," *IEEE Internet Things J.*, vol. 3, no. 4, pp. 441–452, Aug. 2016.

[4] Z. Li, Y. Liu, M. Li, J. Wang, and Z. Cao, "Exploiting ubiquitous data collection for mobile users in wireless sensor networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 24, no. 2, pp. 312–326, Feb. 2013.

[5] E. C.-H. Ngai, M. B. Srivastava, and J. Liu, "Context-aware sensor data dissemination for mobile users in remote areas," in *Proc. INFOCOM*, Orlando, FL, USA, 2012, pp. 2711–2715.

[6] X. Tong and E. C.-H. Ngai, "A ubiquitous publish/subscribe platform for wireless sensor networks with mobile mules," in *Proc. DCOSS*, Hangzhou, China, 2012, pp. 99–108.

[7] X. Hu *et al.*, "A survey on mobile social networks: Applications, platforms, system architectures, and future research directions," *IEEE Commun. Surveys Tuts.*, vol. 17, no. 3, pp. 1557–1581, 3rd Quart., 2015.

[8] C. Zhu *et al.*, "A survey on communication and data management issues in mobile sensor networks," *Wireless Commun. Mobile Comput.*, vol. 14, no. 1, pp. 19–36, 2014.

[9] S. Giordano and D. Puccinelli, "When sensing goes pervasive," *Pervasive Mobile Comput.*, vol. 17, pp. 175–183, Feb. 2015.

[10] A. T. Ford, A. P. Clevenger, and A. Bennett, "Comparison of methods of monitoring wildlife crossing-structures on highways," *J. Wildlife Manag.*, vol. 73, no. 7, pp. 1213–1222, 2009.

[11] M. Mun *et al.*, "PEIR, the personal environmental impact report, as a platform for participatory sensing systems research," in *Proc. MobiSys*, Kraków, Poland, 2009, pp. 55–68.

[12] L. Mo *et al.*, "Canopy closure estimates with GreenOrbs: Sustainable sensing in the forest," in *Proc. Sensys*, Berkeley, CA, USA, 2009, pp. 99–112.

[13] L. Cheng *et al.*, "Seamless streaming data delivery in cluster-based wireless sensor networks with mobile elements," *IEEE Syst. J.*, vol. 10, no. 2, pp. 805–816, Jun. 2016.

[14] Z. Sheng *et al.*, "A survey on the ietf protocol suite for the Internet of Things: Standards, challenges, and opportunities," *IEEE Wireless Commun.*, vol. 20, no. 6, pp. 91–98, Dec. 2013.

[15] Z. Li, M. Li, J. Wang, and Z. Cao, "Ubiquitous data collection for mobile users in wireless sensor networks," in *Proc. INFOCOM*, Shanghai, China, 2011, pp. 2246–2254.

[16] F. H. Bijarbooneh, P. Flener, E. Ngai, and J. Pearson, "Optimising quality of information in data collection for mobile sensor networks," in *Proc. IEEE/ACM 21st Int. Symp. Qual. Service (IWQoS)*, Montreal, QC, Canada, Jun. 2013, pp. 1–10.

[17] R. Lent, M. Minero, R. North, and J. Barria, "Evaluating mobility models in participatory sensing," in *Proc. 1st ACM Int. Workshop Mission Oriented Wireless Sensor Netw.*, Istanbul, Turkey, 2012, pp. 3–8.

[18] C. Bisdikian *et al.*, "Building principles for a quality of information specification for sensor information," in *Proc. 12th Int. Conf. Inf. Fusion (FUSION)*, Seattle, WA, USA, 2009, pp. 1370–1377.

[19] C. Bisdikian, M. Sensoy, T. J. Norman, and M. B. Srivastava, "Trust and obfuscation principles for quality of information in emerging pervasive environments," in *Proc. IEEE Int. Conf. Pervasive Comput. Commun. Workshops (PERCOM Workshops)*, Lugano, Switzerland, 2012, pp. 44–49.

[20] J. Kho, A. Rogers, and N. R. Jennings, "Decentralized control of adaptive sampling in wireless sensor networks," *ACM Trans. Sensor Netw.*, vol. 5, no. 3, pp. 1–35, Jun. 2009.

[21] H. S. Kim, T. F. Abdelzaher, and W. H. Kwon, "Minimum-energy asynchronous dissemination to mobile sinks in wireless sensor networks," in *Proc. Sensys*, Los Angeles, CA, USA, 2003, pp. 193–204.

[22] J. Luo and J.-P. Hubaux, "Joint sink mobility and routing to maximize the lifetime of wireless sensor networks: The case of constrained mobility," *IEEE/ACM Trans. Netw.*, vol. 18, no. 3, pp. 871–884, Jun. 2010.

[23] R. C. Shah, S. Roy, S. Jain, and W. Brunette, "Data MULEs: Modeling a three-tier architecture for sparse sensor networks," in *Proc. IEEE Workshop Senosr Netw. Protocols Appl. (SNPA)*, Anchorage, AK, USA, May 2003, pp. 30–41.

[24] C. Perera, P. P. Jayaraman, A. Zaslavsky, P. Christen, and D. Georgakopoulos, "MOSDEN: An Internet of Things middleware for resource constrained mobile devices," in *Proc. 47th Hawaii Int. Conf. Syst. Sci.*, Waikoloa Village, HI, USA, Jan. 2014, pp. 1053–1062.

[25] Y. Gu, D. Bozdag, E. Ekici, F. Ozguner, and C.-G. Lee, "Partitioning based mobile element scheduling in wireless sensor networks," in *Proc. SECON*, Santa Clara, CA, USA, Sep. 2005, pp. 386–395.

[26] N. Bisnik, A. Abouzeid, and V. Isler, "Stochastic event capture using mobile sensors subject to a quality metric," in *Proc. ACM MobiCom*, Los Angeles, CA, USA, Sep. 2006, pp. 98–109.

[27] X. Xu, J. Luo, and Q. Zhang, "Delay tolerant event collection in sensor networks with mobile sink," in *Proc. INFOCOM*, San Diego, CA, USA, Mar. 2010, pp. 1–9.

[28] L. He, Z. Yang, J. Pan, L. Cai, and J. Xu, "Evaluating service disciplines for mobile elements in wireless ad hoc sensor networks," in *Proc. INFOCOM*, Orlando, FL, USA, 2012, pp. 576–584.

[29] A. Mehrabi and K. Kim, "Maximizing data collection throughput on a path in energy harvesting sensor networks using a mobile sink," *IEEE Trans. Mobile Comput.*, vol. 15, no. 3, pp. 690–704, Mar. 2016.

[30] B. Kusy, H. Lee, M. Wicke, N. Milosavljevic, and L. Guibas, "Predictive QoS routing to mobile sinks in wireless sensor networks," in *Proc. IPSN*, San Francisco, CA, USA, 2009, pp. 109–120.

[31] H. Lee, M. Wicke, B. Kusy, O. Gnawali, and L. Guibas, "Data stashing: Energy-efficient information delivery to mobile sinks through trajectory prediction," in *Proc. IPSN*, Stockholm, Sweden, 2010, pp. 291–302.

[32] S. Yang, U. Adeel, Y. Tahir, and J. A. McCann, "Practical opportunistic data collection in wireless sensor networks with mobile sinks," *IEEE Trans. Mobile Comput.*, vol. 16, no. 5, pp. 1420–1433, May 2017.

[33] C. H. Liu, C. Bisdikian, J. W. Branch, and K. K. Leung, "QoI-aware wireless sensor network management for dynamic multi-task operations," in *Proc. IEEE SECON*, Boston, MA, USA, Jun. 2010, pp. 1–9.

[34] E. C.-H. Ngai and P. Gunningberg, "Quality-of-information-aware data collection for mobile sensor networks," *Pervasive Mobile Comput.*, vol. 11, pp. 203–215, Apr. 2014.

[35] E. Gelenbe and E. Ngai, "Adaptive random re-routing for differentiated QoS in sensor networks," *Comput. J.*, vol. 53, no. 7, pp. 1052–1061, Sep. 2010.

[36] M. Mathew and N. Weng, "Quality of information and energy efficiency optimization for sensor networks via adaptive sensing and transmitting," *IEEE Sensors J.*, vol. 14, no. 2, pp. 341–348, Feb. 2014.

[37] G. T. Singh and F. M. Al-Turjman, "Learning data delivery paths in QoI-aware information-centric sensor networks," *IEEE Internet Things J.*, vol. 3, no. 4, pp. 572–580, Aug. 2016.

[38] X.-Y. Liu *et al.*, "CDC: Compressive data collection for wireless sensor networks," *IEEE Trans. Parallel Distrib. Syst.*, vol. 26, no. 8, pp. 2188–2197, Aug. 2015.

[39] A. Köpke *et al.*, "Simulating wireless and mobile networks in OMNeT++ the MiXiM vision," in *Proc. Simutools*, Marseille, France, 2008, pp. 1–8.

[40] A. Varga and R. Hornig, "An overview of the OMNeT++ simulation environment," in *Proc. 1st Int. Conf. Simulat. Tools Tech. Commun. Netw. Syst. Workshops*, Marseille, France, 2008, pp. 1–10.

[41] A. Varga, "The omnet++ discrete event simulation system," in *Proc. ESM*, Prague, Czech Republic, 2001, pp. 1–7.

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