Energy-Efficient Collaborative Localization for Participatory Sensing System

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***Abstract*—Location based services are getting increasingly popular in participatory sensing systems. They make use of location information on the mobile devices to support applications that improve personal health, object search, and entertainment. However, GPS positioning consumes a lot of energy, which can drain a mobile device's battery. Although WiFi localization and cell tower localization have been suggested as alternatives, they have lower localization accuracy and limited coverage. In this paper, we suggest a novel solution for multiple mobile devices to perform collaborative localization to reduce energy consumption and provide accurate localization. We divide the mobile devices into two groups, the aggregator group and the collector group. The aggregator group turns on their GPS periodically, while the collector group uses the locations of the aggregators to estimate their own locations. We formulate the aggregator set selection problem and propose two novel algorithms to minimize the energy consumption in collaborative localization. Simulations with real traces showed that our proposed solution can save up to 88% of the energy of the entire network.**

I. Introduction

Participatory sensing system [1] supports a large number of mobile users to collect sensor data and share information about their environment. The data of the environment and the services provided are usually location oriented. For example, a drive may want to know the gas price from nearby gas stations, and information of traffic jam in the area. Potential applications of location-based services in participatory sensing range from personal healthcare, object search to entertainment. However, obtaining location information could be very energy consuming, which threatens many mobile participants. As the mobile devices have limited batteries, it is crucial to minimize the energy consumption in localization.

GPS localization is known as a major source of energy consumption in mobile devices. It can easily drain the battery of a mobile device in five to six hours [2]. Unfortunately, many participatory sensing applications require the mobile devices to turn on their GPS all the time in order to collect sensor data with corresponding locations. Even though alternative localization methods, such as cell-tower based localization and WiFi-based localization, have been suggested, they fail to provide satisfactory accuracy in localization.

Recently, device-to-device localization method [3] has been proposed to reduce energy consumption and improve accuracy in localization. The key idea is to use only small number of mobile devices to collect real-time location and motion information, and allow other devices to calculate their relative locations based on this information. Such approach requires only small number of mobile devices to turn on their GPS and motion sensors, which can save a lot of energy. In this paper, we extend the idea of device-to-device localization for collaboration localization in participatory sensing system. We address an important problem on how to select mobile devices to provide GPS readings for the others, so that the overall energy consumption of all devices is minimized. This work makes collaborative localization feasible to be implemented for participatory sensing systems. The mobile devices are coordinated adaptively according to their mobility in the dynamic environment.

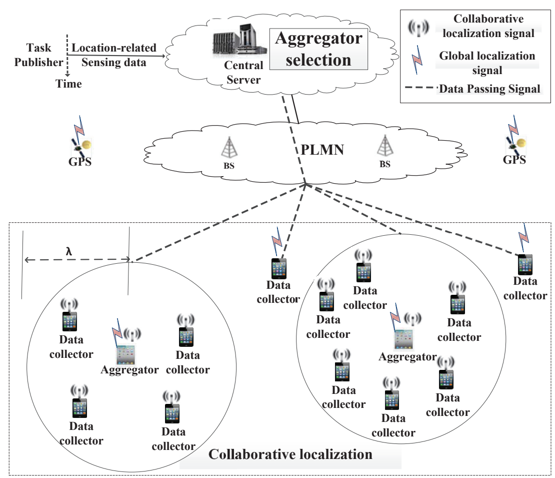

Fig. 1. System overview

Our research is motivated by the application scenario shown in Fig.1, which is derived from the setting of a common participatory sensing system [4]. The figure shows a population of mobile users collecting location-based sensor data collaboratively for a certain task. In this paper, we focus on minimizing the overall energy consumption of all mobile devices on localization. First, we build an energy consumption model to measure the total energy consumption from GPS and communication for the aggregators and the collectors.

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Then, we formulate an optimization problem for aggregator set selection using this energy model and propose two heuristic algorithms to solve the problem.

The contribution of this paper is summarized as follows:

- We derive a mathematical model to measure the total energy consumption on localization for the aggregators and the collectors, which enables flexible adjustment on the localization accuracy according to the application requirement.
- We formulate the Aggregator Set Selection Problem (ASSP), which aims at minimizing the energy consumption of the entire network.
- We propose two novel algorithms to solve ASSP, which is a NP-hard problem.
- The performance of the proposed solution has been evaluated thoroughly by simulations using real mobility traces. The results showed that our proposed algorithms can save up to 88% of the total energy in localization.

The rest of the paper is organized as follows. Section II presents the related work. Section III shows the energy model and formulates the Aggregator Set Selection Problem (ASSP). Section IV describes our proposed aggregator set selection algorithms. Section V evaluates the performance of our proposed algorithms by simulations using real mobility traces. Finally, Section VI concludes the paper.

II. Related work

Energy efficiency has been widely explored in participatory sensing systems from different perspectives. A number of approaches have been proposed to reduce the sampling rates of sensors to save energy [5], [6]. The techniques can be applied for reducing sampling rate of the GPS, but it may lead to lower accuracy and granularity in localization. Other approaches utilized additional sensors such as accelerometers and orientation sensors to determine when to turn on the GPS [7]. Nevertheless, the existing methods have rarely explored the possibility of sharing location information with neighboring devices.

Other than GPS, some mobile networks have suggested to use location beacons as localization references [8], which require either fixed or mobile beacons to estimate their own locations. Similarly, Zhang and Yu [9] have proposed a beacon selection method that selects equilateral triangle nodes to be beacons. Unfortunately, the location beacons may constrain the energy saving performance and increase the deployment and maintenance cost.

Johnson and Seeling [10] have proposed a scheme based on Bluetooth friendly device names to enable power-optimized ad-hoc localization of mobile devices. However, this work has focused on the naming scheme, while the potential of collaborative localization among mobile devices remains to be further investigated. In this paper, we suggests coordination among the mobile users to minimize the energy consumption for localization without deploying any beacons nodes.

TABLE I
List of notations

Notation	*Explanation*
$\mathcal{M}$	The set of all the participants.
$\mathcal{A}$	The set of aggregators.
$\mathcal{C}^*$	The set of data collectors.
d^i	The distance between aggregator B and collector C at time i.
r^i	The RSSI between aggregator B and collector C at time i.
$\vec{m_i}$	The movement of collector C from t_i to t_{i+1}.
a_i	Boolean to indicate aggregators.
b_{ij}	Boolean to indicate connection between $\mathcal{A}_i$ and $\mathcal{M}_j$.
c_{ij}	Energy consumption for $\mathcal{M}_j$ to communicate with $\mathcal{M}_i$.
$\mathcal{C}$	The cost matrix of c_{ij}.
d_{ij}	The distance between $\mathcal{M}_i$ and $\mathcal{M}_j$.
p_{ij}	The physical connectivity between $\mathcal{M}_i$ and $\mathcal{M}_j$.
g_i	Boolean to indicate whether participant $\mathcal{M}_i$ need to turn on GPS.
r_{ij}	The RSSI $\mathcal{M}_j$ received from $\mathcal{M}_i$.
$\mathcal{R}$	The RSSI Matrix of r_{ij}.
E	The total energy consumption.
M	The number of all paticipates.
A	The number of aggregators.
e_a	Energy consumption of data aggregator.
e_g,	Energy consumption of GPS.

III. System Model and Problem Formulation

A. Motivating Scenario for Collaborative Localization

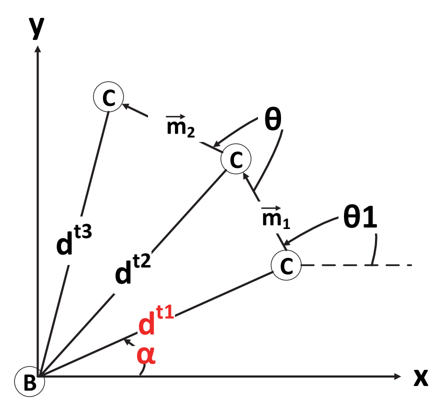


Fig. 2. Device-to-Device localization

We consider a participatory sensing system in Fig.1. It consists of a central server and a set of M smartphone users $\mathcal{M} \triangleq \{1, 2, ..., M\}$ moving in the region. Among the participants in $\mathcal{M}$, a subset of A smartphone users $\mathcal{A}$ are selected as data aggregators, while the remaining participants $\mathcal{C}^*$ work as data collectors. Both the data collectors and data aggregators collect sensor data periodically and upload them to the server through cellular network, but only the data aggregators turn on their GPS. Besides, the data aggregators also broadcast their locations and movement information to their surrounding data collectors. The surrounding data collectors can calculate their locations using the device-to-device localization method proposed in our previous work [3]. If a data collector can not communicate with any data aggregator, it has to turn on its GPS to obtain its location. Nevertheless, it will consume more energy.

Fig. 2 shows an example of device-to-device localization. Let d^i be the distance between an aggregator B and a data collecor C, and r^i be the RSSI that B receives at time t_i. The movement is measured based on a step detection method, which is commonly used in pedestrian localization [11]. The movement of C from t_i to t_{i+1} is denoted by a vector $\vec{m_i}$.

According to the free space radio propagation model [12], the ratio between d^i and d^j can be calculated by:

$$\frac{d^i}{d^j} = 10^{\frac{r^j - r^i}{10n}} \tag{1}$$

Then, we can obtain the distance between B and C at time t_1 using the following equations:

$$\begin{aligned} &\arccos\frac{({k_{t_2}}^2-1)(d^{t_1})^2+{m_1}^2}{2k_{t_2}d^{t_1}m_1}+\theta = \\ &\arccos\frac{({k_{t_2}}^2-{k_{t_3}}^2)(d^{t_1})^2+{m_2}^2}{2k_{t_2}d^{t_1}m_2}+2\pi \end{aligned} \tag{2}$$

where $k_{t_i} = 10^{\frac{r^1 - r^i}{10n}}$.

Based on above equation, we can obtain the relative angle, α, between B and C using the following equations:

$$\alpha = \arccos\frac{(d^{t_1})^2+{m_1}^2-k_{t_2}^2\times(d^{t_1})^2}{2(d^{t_1})m_1}+\theta_1-\pi \tag{3}$$

B. Energy Consumption Model

We consider that the communication range of WiFi can be adjusted to different levels according to the distance between the aggregators and the collectors. This feature has been implemented in many existing WiFi routers and devices, which is beneficial for energy saving.

Let e_a be the total energy consumption of a data aggregator, including GPS localization and communication with its associated data collectors. Let e_w be the energy consumption of WiFi communication for individual data collector, and e_g be the energy consumption for GPS localization, where $e_a > e_g > e_w$. We use a_i to indicate whether a mobile participant $\mathcal{M}_i$ is an aggregator and use b_{ij} to indicate whether $\mathcal{M}_j$ can communicate with an aggregator $\mathcal{A}_i$. The RSSI $\mathcal{M}_j$ received from $\mathcal{M}_i$ is denoted by r_{ij}, which can be used to calculate the physical distance between $\mathcal{M}_i$ and $\mathcal{M}_j$ denoted by d_{ij}. Based on r_{ij}, M_j can select the appropriate communication range, in which the corresponding energy consumption is c_{ij} (see notations in Table I).

Let $\mathcal{R}$ =$\{R_1, R_2, ..., R_M\}$= $(r_{ij})_{M\times M}$ be the RSSI matrix, and R_j be the set of RSSI that $\mathcal{M}_j$ received from its neighbors, $\forall j \in \{1, 2, ..., |\mathcal{M}|\}$, where

$$\mathcal{R} = \begin{bmatrix} r_{11} & r_{12} & ... & r_{1M} \\ r_{21} & r_{22} & & \\ ... & & ... & \\ r_{M1} & & & r_{MM} \end{bmatrix} \tag{4}$$

and

$$R_j = \begin{bmatrix} R_{1j} \\ R_{2j} \\ ... \\ R_{Mj} \end{bmatrix}, \forall j \in \{1, 2, ..., |\mathcal{M}|\} \tag{5}$$

The overall energy consumption for localization, E, consists of three parts: the energy consumption of the aggregators (E_A), the energy consumption of the collectors connected to any aggregator (E_C), and the GPS localization energy consumption of the collectors without any aggregator ($E_{C'}$). We calculate these three parts in the following.

Given $|\mathcal{A}|$ and e_a, the total energy consumption of all the data aggregators can be calculated by:

$$\begin{aligned} E_A &= |\mathcal{A}|e_a \\ &= \sum_{i=1}^{|\mathcal{M}|} a_i e_a \end{aligned} \tag{6}$$

As described before, the communication range between the data collector and the aggregator is divided into different levels. According to the distance with the associated aggregator, the energy consumption of the data collectors can be calculated by:

$$E_C = \sum_{i=1}^{|\mathcal{M}|}\sum_{j=1}^{|\mathcal{M}|} c_{ij} b_{ij}(1-g_i) \tag{7}$$

For the remaining collectors which do not belong to any aggregators, $\sum_{i=1}^{|\mathcal{M}|}(g_i - a_i)$, their energy consumption can be calculated by:

$$E_{C'} = \sum_{i=1}^{|\mathcal{M}|}(g_i - a_i)e_g \tag{8}$$

where e_g is the energy consumption for the GPS.

Finally, the overall localization energy consumption E can be calculated by:

$$\begin{aligned} E &= E_A + E_C + E_{C'} \\ &= \sum_{i=1}^{|\mathcal{M}|} a_i e_a + \sum_{i=1}^{|\mathcal{M}|}\sum_{j=1}^{|\mathcal{M}|} c_{ij} b_{ij}(1-g_i) + \sum_{i=1}^{|\mathcal{M}|}(g_i - a_i)e_g \end{aligned} \tag{9}$$

C. Problem Formulation

The main goal of this work is to find an optimal aggregator set $\mathcal{A}$ that minimizes energy consumption in collaborative localization. We formulate it as the Aggregator Set Selection Problem (ASSP) in the following:

minimize: E

subject to:

$$a_i = \{0, 1\}, \forall i \in \{1, 2, ..., |\mathcal{M}|\} \tag{10}$$

$$g_i = \{0, 1\}, \forall i \in \{1, 2, ..., |\mathcal{M}|\} \tag{11}$$

$$b_{ij} = \{0, 1\}, \forall i, \forall j \in \{1, 2, ..., |\mathcal{M}|\} \tag{12}$$

$$p_{ij} = \{0, 1\}, \forall i, \forall j \in \{1, 2, ..., |\mathcal{M}|\} \tag{13}$$

$$b_{ij} \leq p_{ij}, \forall i, \forall j \in \{1, 2, ..., |\mathcal{M}|\} \tag{14}$$

$$h_1 \leq \sum_{i=1}^{|\mathcal{A}|} b_{ij} \leq h_2, \forall g_i = 0, \forall j \in \{1, 2, ..., |\mathcal{M}|\} \tag{15}$$

$$c_{ij} = \{c_1, c_2, c_3\}, \forall i, \forall j \in \{1, 2, ..., |\mathcal{M}|\} \tag{16}$$

$$d_{ij} a_i \leq \Theta, \forall g_i = 0, \forall j \in \{1, 2, ..., |\mathcal{M}|\} \tag{17}$$

Eq. (10) to Eq. (13) are the integer constraints. Eq. (14) enforces the connection between $\mathcal{M}_j$ and $\mathcal{A}_i$ subject to physical reachability. Eq. (15) enforces that each data collector connects with at least h_1 aggregators and at most h_2 aggregators. Eq. (16) indicates that the energy consumption of WiFi communication is divided into three different levels. Eq. (17) constrains the maximum distance between the aggregator and the data collector, which is determined by the localization accuracy and the relaxation parameter Θ.

IV. Our Aggregator Selection Algorithms

It can be proved easily that ASSP is an NP-hard problem by reduction. Due to the limited space, the detailed proof is omitted in this paper. We propose two heuristic algorithms to solve the ASSP. The first one is a Greedy based Aggregator Selection (GAS) algorithm. Algorithm 1 shows the pseudocode of the GAS algorithm. In each round, a node with the maximum energy saving will be selected as a new aggregator. The selection of aggregators will continue until the total energy consumption, E, can not be further improved.

Algorithm 1: GAS Algorithm

Input:
  $\mathcal{R}$: the RSSI matrix of r_{ij};
  $Accuracy$: the required localization accuracy;
Output:
  $\mathcal{A}$: the approximate optimal aggregator set;
  E_{min}: the approximate optimal energy consumption;

- $Calculate\ (c_{ij})_{M \times M}$;
- $\mathcal{C}^*$=$\mathcal{M}$; $Init\ E_{min}$; $Init\ \Theta$;
- **while** $M > 0$ **do**
  - $C^* = |\mathcal{C}^*|$;
  - **for** $(i = 1; i \leq C^*; i++)$ **do**
    - **if** $Satisfy\ all\ the\ constraints$ **then**
      - $Add\ \mathcal{C}^*_i\ to\ \mathcal{A}$;
      - $Calculate\ E$;
      - **if** $E \leq E_{min}$ **then**
        - $E_{min} = E$;
        - $postion = i$;
        - $Selectionflag = 1$;
      - **end**
      - $Remove\ \mathcal{C}^*_i\ from\ \mathcal{A}$;
    - **end**
  - **end**
  - **if** $Selectionflag == 0$ **then**
    - **break**;
  - **end**
  - $Add\ \mathcal{C}^*_{position}\ to\ \mathcal{A}$;
  - $Selectionflag = 0$;
  - $M--$;
- **end**
- **return**($E_{min}, \mathcal{A}$)

Algorithm 2: SubSAAS Algorithm

Input:
  $\mathcal{C}$: the cost matrix of c_{ij};
  A: the number of data aggregators ;
  Θ: the relaxation parameter determined by localization accuracy;
Output:
  E_{min}: the approximate optimal energy consumption;

- $Init\ temperature\ T$; $Init\ reduce\ ratio\ \xi$;
- $Init\ E_{min}$; $Init\ Max\_iteration\_num$;
- $Init\ global\ vector\ \mathcal{A}$;
- **while** $Max\_iteration\_num > 0$ **do**
  - **if** $Satisfy\ all\ the\ constraints$ **then**
    - $Calculate\ E$;
    - $\Delta energy = E_{min} - E$;
    - **if** $\Delta energy \geq 0$ **then**
      - $E_{min} = E$;
      - $T = T * \xi$
    - **else**
      - **if** $rand(0, 1) < exp(-\Delta energy/T)$ **then**
        - $E_{min} = E$;
        - $T = T * \xi$
      - **end**
    - **end**
    - **if** $T \leq \epsilon$ **then**
      - **break**;
    - **end**
  - **end**
  - $\mathcal{A} = \mathcal{A}_{next}$;
  - $Max\_iteration\_num--$;
- **end**
- **return**(E_{min});

Algorithm 3: SAAS Algorithm

Input:
  $\mathcal{R}$: the RSSI matrix of r_{ij};
  $Accuracy$: the required localization accuracy;
Output:
  $\mathcal{A}$: the set of data aggregators ;
  E_{min}: the approximate optimal energy consumption;

- $Calculate\ (c_{ij})_{M \times M}$;
- $A_S = 1$; $A_E = |\mathcal{M}|$; $Init\ \Theta$;
- **while** $A_E - A_S > 1$ **do**
  - **if** ***SubSAAS***$(\mathcal{C}, A_S, \theta) >$ ***SubSAAS***$(\mathcal{C}, A_E, \theta)$ **then**
    - $A_{TS} = (A_E + A_S)/2$;
    - **while** ***SubSAAS***$(\mathcal{C}, A_{TS}, \theta) \leq$ ***SubSAAS***$(\mathcal{C}, A_{TS} + 1, \theta)$ **do**
      - $A_{TS} = (A_{TS} + A_S)/2$;
    - **end**
    - $A_S = A_{TS}$;
  - **else**
    - $A_{TE} = (A_E + A_S)/2$;
    - **while** ***SubSAAS***$(\mathcal{C}, A_{TE}, \theta) \geq$ ***SubSAAS***$(\mathcal{C}, A_{TE} + 1, \theta)$ **do**
      - $A_{TE} = (A_E + A_{TE})/2$;
    - **end**
    - $A_E = A_{TE}$;
  - **end**
- **end**
- **if** ***SubSAAS***$(\mathcal{C}, A_S, \theta) \leq$ ***SubSAAS***$(\mathcal{C}, A_E, \theta)$ **then**
  - **return(SubSAAS**$(\mathcal{C}, A_S, \theta), \mathcal{A}$**)**;
- **else**
  - **return(SubSAAS**$(\mathcal{C}, A_E, \theta), \mathcal{A}$**)**;
- **end**

We also propose an improved Simulated Annealing (SA) [13] based Aggregator Selection (SAAS) algorithm. SA is a probabilistic algorithm that makes a good approximation to the global optimal solution of the optimization problem in a large search space.

Algorithm 2 shows the pseudo-code of the SubSAAS algorithm. Initially, it generates a feasible $\mathcal{A}$ as the starting point. In each iteration, a neighbour set of $\mathcal{A}$ is generated, which is denoted by $\mathcal{A}_{next}$. If $\mathcal{A}_{next}$ saves more energy than $\mathcal{A}$, then we accept $\mathcal{A}_{next}$ as the set of aggregators. Otherwise, we accept $\mathcal{A}_{next}$ based on a probability of acceptance to avoid falling into a local minimum. The probability of acceptance is an exponentially decreasing function with parameter $exp(-\Delta energy/T))$, where T is the current temperature. After each iteration, the probability of acceptance decreases. It can compute the optimal E given a specific A. This result will be used in the SAAS algorithm. Algorithm 3 shows the pseudo-code of the SAAS algorithm. It varies the number of aggregators A and computes the optimal E by calling the SubSAAS algorithm. Even though the optimal A is not known in advance, the SAAS algorithm can approximate E by calling the SubSAAS algorithm $O(log_2^{|\mathcal{M}|})$ times.

V. Performance evaluation

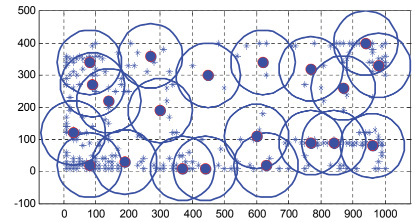
We evaluate the performance of the proposed collaborative strategy using the (Microsoft Research Asia) GeoLife dataset [14]. The GeoLife project has collected the trajectories of volunteers (ordinary citizens) in Beijing for three consecutive years. Each trajectory is marked by a sequence of GPS locations with time stamps. We store all the trajectories in a geographical MySQL database and select two regions with highest movement density in our simulation (named as dataset 1 and dataset 2). There are 300 and 390 mobile participants the two datasets, respectively. We set the parameters in our energy model according to [15], where e_a=550(mW) and e_g=500(mW) and e_w=50(mW).

Fig. 3 shows the best aggregator set obtained by the SAAS algorithm in the two datasets. Each dot represents an aggregator with the circle indicating its coverage. Each cross mark indicates a data collector (or non-aggregator). From the figure, 21 participants are selected as aggregators in dataset 1 and 18 participants are selected in dataset 2.

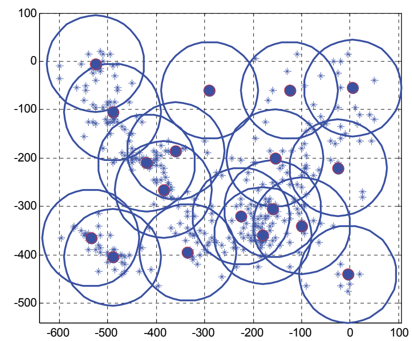
We evaluate the energy consumption varying the ratio of aggregators in Fig. 4. We observe that increasing the aggregator ratio reduces the energy consumption initially. However, the energy consumption increases after reaching an optimal point, since excessive aggregators consume more energy for GPS localization.

Fig. 5 compares the energy consumption of our approaches with traditional GPS sampling. In the traditional approach, all mobile participants turn on their GPS to perform localization periodically [16]. We vary the number of participants by selecting a subset of participants randomly from the two datasets. We find that our approach can up to 88% of the energy compared with the traditional approach. We also see that the SAAS algorithm can save more energy than the GAS.

Next, we evaluate the accuracy on localization in our proposed solution. Table II shows the mean error in localization considering different distances between the aggregator and the collector. We further study the relationship between the required localization accuracy of applications and the energy consumption.



(a) Dataset 1



(b) Dataset 2

Fig. 3. Optimal aggregator sets resulted from collaborative localization

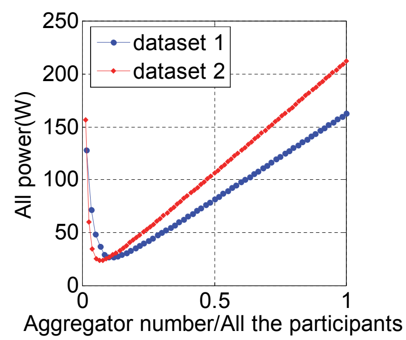
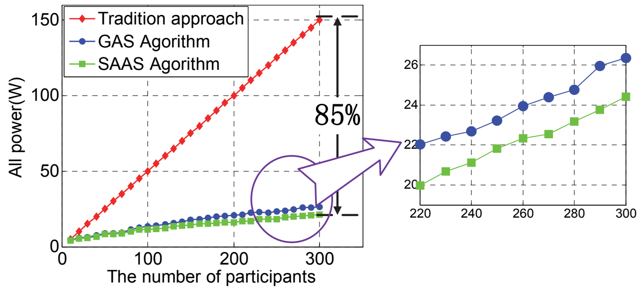


Fig. 4. The impact of the ratio between the aggregators and all the participants

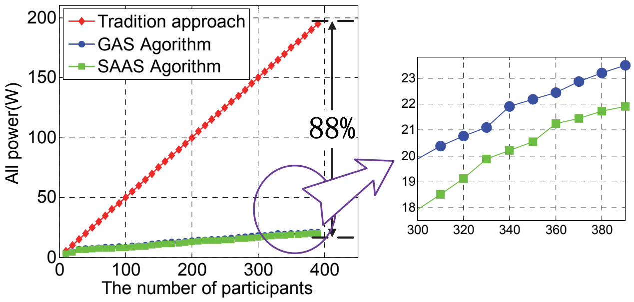
TABLE II
LOCALIZATION ACCURACY

Distance between devices	20 m	30 m	40 m	50 m	60 m
Localization mean error	9 m	13 m	18 m	20 m	25 m

Fig. 6 shows the energy consumption varying the required localization accuracy in the two datasets. Even considering localization accuracy of less than 10 meters (like GPS), our approach can save 48% and 58% of the energy compared with the traditional approach in dataset1 and dataset2. For applications that require lower localization accuracy, our approach can save far more energy (up to 88%) compared with the traditional approach. In addition, our solution enables flexible adjustment on the localization accuracy according to the application requirement, so as to minimize the energy consumption for localization.

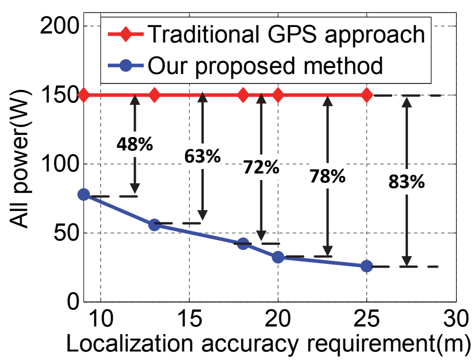


(a) dataset 1

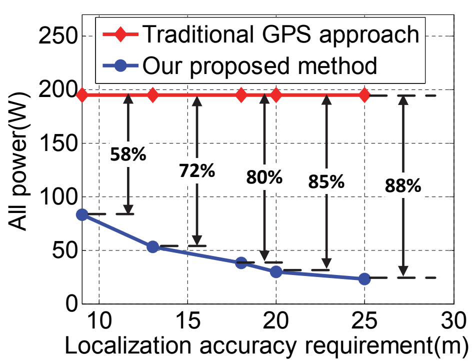


(b) dataset 2

Fig. 5. Comparison with traditional GPS approach



(a) dataset 1



(b) dataset 2

Fig. 6. Relationship between localization accuracy requirement and energy consumption

VI. Conclusions and Future Work

In this paper, we presented a mathematical model to measure the total energy consumption on localization for the aggregators and the collectors, which enables flexible adjustment on the localization accuracy according to the application requirement. We formulated the Aggregator Set Selection Problem (ASSP) and proposed two novel algorithms to minimize the energy consumption of the entire network by coordinating between the data aggregators and the data collectors. We evaluated the performance of our proposed SAAS algorithm and GAS algorithm through extensive simulations using real mobility traces. The results showed that our proposed localization strategy can save up to 88% of the total energy and achieve high localization accuracy. In the future, we would like to take trajectory prediction into consideration to further reduce the energy consumption and enhance the stability of the system.

Acknowledgment

This work is partially supported by the National Natural Science Foundation of China (Grant No. 61370197, No. 61271041), the National High Technology Research and Development Program (863 Program) of China (Grant No. 2013AA013301), the Vinnova GreenIoT project, the SSF Mobility grant, and SSF ProFuN project from Sweden.

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