Energy-Optimal Collaborative GPS Localization with Short Range Communication
- Technical Report -

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***Abstract*—Localization in mobile devices has been intensively studied in both perspectives of localization-accuracy and energy-efficiency. The key issue of the localization study is that how we can minimize the energy consumption of devices with guaranteeing high degree of accuracy. In this paper, we show that the collaboration among proxy devices is helpful to energy-efficiently localize their positions in time-average sense by analyzing the device proximity including real GPS trace of students in KAIST and NCSU campuses. Next, we deliberate what is the best method for selfish mobile users to collaborate for the energy-efficient localization, and formulate an optimization problem which considers the energy-efficiency and/or user fairness. However, optimizing this problem is tricky since it requires a global knowledge of sets of proxy devices and also solving a NP-hard problem for localization. This paper makes a contribution towards presenting a practical and fully distributed location sharing protocol and an optimal algorithm by only controlling mean waiting time for competition with proxy devices in order to turn off GPS. Through the extensive simulations under several sample topologies and real mobility trace in KAIST campus, we obtain the following interesting observations: *(i)* (in sample topologies) our scheme achieves a near-optimal performance of proposed problem in terms of energy efficiency and fairness (up to 27.2% power saving with 35.8% higher fairness than existing heuristic algorithms), *(ii)* (in real mobility trace) our scheme well adapts at unpredictably changing mobility environment (65.5% power saving than no collaboration, 27.4% or more power saving with 25% higher fairness than the existing algorithms).**

I. INTRODUCTION

A. Motivation

Recently, the number of applications which demand consecutive and accurate positions in smart phones/pads are increasing [1]–[3]. For example, Google Now [2] continuously senses your position to provide appropriate service based on the location. Moreover, in the next generation networks using the technique of location based beamforming [4], base stations should know consecutive positions of every associated device for network management. To the best of our knowledge, GPS is the most accurate localization technique in outdoor environment. However, the GPS modules in mobile devices consume significant amount of energy compared to the other modules (e.g., *(i)* a GPS-enabled device consumes more than sevenfold time-average power compared to a GPS-disabled one. *(ii)* Keeping GPS continuously activated drains the 1200mAh battery in less than 11 hours on an N95 smartphone [5]). To reduce localization energy, there have been several researches, e.g., [5]–[9] which use WiFi/cellular infrastructures or adscititious sensors. However, some of energy-efficient schemes which do not use GPS such as WPS (WiFi-based positioning system from SkyHookWireless [6]), or GSM-based positioning system had sacrificed the degree of accuracy by reducing the energy (e.g., accuracy of GPS: 8.8m, WPS: 32.44m, GSM:176.7m in open sky environments [5]). Since the recent applications [1]–[4] demand consecutive positions with guaranteeing high degree of accuracy, we need a localization solutions to satisfy both of localization accuracy and energy efficiency.

B. Summary & Main Contributions

Key idea of this paper is sharing position information among proxy devices to reduce localization energy with short range communication (SRC) such as Bluetooth or Zigbee [10] which use less energy than GPS (e.g., average GPS power consumption: 440mW [5], average Bluetooth power consumption: 110.5mW [11]). For example, if there are 9 devices around a certain within a few meters and the all 10 devices should consecutively know their own location, the certain device can measure its location using GPS and share the location information with the other 9 devices using the SRC. Then the 10 devices can obtain their locations with consuming high GPS power of only one device plus low Bluetooth power of all devices while guaranteeing accuracy of GPS plus SRC range (e.g., average range of Bluetooth is 10m [12]). In this idea, energy efficiency depends on the number of proxy devices within the coverage of the SRC.

Since the human beings are social creatures, they spend a lot of time with other people. For example, students taking the same class are likely to be closely located in the campus, and soldiers having the same mission are likely to move together in the battlefield. Moreover, relationless people also happen to be closely located when they are in the crowed places such as downtown in the city. The recent human mobility studies, see, e.g., [13] and references therein, also have told that the moving of the human being reflects the social proximity with other people. At this point, we define two proximity natures: *(i)* Temporal proximity, i.e., how long stay with other people, *(ii)* Spatial proximity, i.e., how close stay with other people.

According to the American time use survey in [12], a person had enjoyed social relationship with acquaintances for 8.5

hours in average. Also, an analysis of MIT reality mining data told that if a person once meets other people, they had enjoyed the meeting during over 1 hour for 47% and over 30 minutes for 65%. These studies show the temporal proximity of general human beings is long enough. To observe the spatial proximity, we first statistically analyze the proximity of the human being based on real GPS trace data of students in the KAIST (Korea Advanced Institute of Science and Technology), Korea and NCSU (North Carolina State University), USA campuses. The key result of the analysis is that approximately 5-10 number of people are located within the 10m coverage which is average Bluetooth range [12].

However, there are rising questions from the idea of the collaborative localization: *(i)* Who measures GPS among proxy devices? *(ii)* How long the device should measure GPS? If total devices can share their locations with minimum number of devices who turn on GPS, they maybe achieve the highest energy efficiency. On the other hand, if total devices can turn on GPS with the same time portion, probably they fairly share the location. Since the owners of the smartphones/pads are selfish, they may not want to spend all of the energy alone for localization. Therefore, considering fairness among devices is no less important than energy-efficiency. However, since the devices cannot satisfy both of the highest energy efficiency and complete fairness simultaneously, the answers of above two questions are directly connected to strike a balance between the energy efficiency and fairness of devices. Therefore, we formulate long-term problem which strives to reduce time-average GPS power consumption of all devices and controls the fairness of the devices.

As a solution of the proposed problem, we should find a sequence of GPS-on device sets that average GPS-on/off time portion of each device asymptotically approaches to an optimal solution. This notion of optimality was similarly considered in the concept of clustering in sensor networks [14]–[16]. However, the clustering cannot directly be applicable in localization due to the different objectives, e.g., maximizing network lifetime. Also, optimizing our problem requires *(i)* a global knowledge of SRC connectivity, and also *(ii)* solving an NP-hard problem of maximum weighted independent set selection form. To resolve these two non practicality, we present *(i)* a distributed location sharing (DLS) protocol which is operated by proxy device sensing and waiting time to turn off GPS, and *(ii)* an optimal mean waiting time decision (OWD) algorithm which makes DLS protocol to achieve an optimal GPS-on/off time portion of each device using only past GPS-on/off statistics. The key mechanism of DLS protocol is that proxy devices compete to turn off GPS with random waiting time whose average value is updated by OWD algorithm.

Through the simulations under the several location topologies and real mobility trace in KAIST campus, we find the following key observations. *(i)* We verify our DLS protocol and OWD algorithm (DLS+OWD) can obtain a near-optimal performance in terms of GPS energy-efficiency and device fairness by comparing with an optimal centralized algorithm. *(ii)* Our DLS+OWD achieves up to 27.2% power saving with 35.8% higher fairness, and *(iii)* uses 15-22% of fewer numbers of message passing with proxy devices than the existing heuristic algorithms under the sample topologies. *(iv)* Our DLS+OWD achieves 65.5% power saving than no collaboration, and 27.4% or more power saving with 25% higher fairness than the existing algorithms under real mobility trace. This shows that our scheme well adapts at even unpredictably changing mobility environment.

In the rest of this paper, we begin with the observation of device proximity in Section II. Next, in Section III, we develop a collaborative localization protocol and an optimal distributed algorithm. Next, in Section IV, we discuss about the reasonable problems of DLS protocol. In Section V, we evaluate our proposed scheme under the several environments including real mobility trace. In Section VI, we take a review of related works. Finally, we conclude this paper in Section VII.

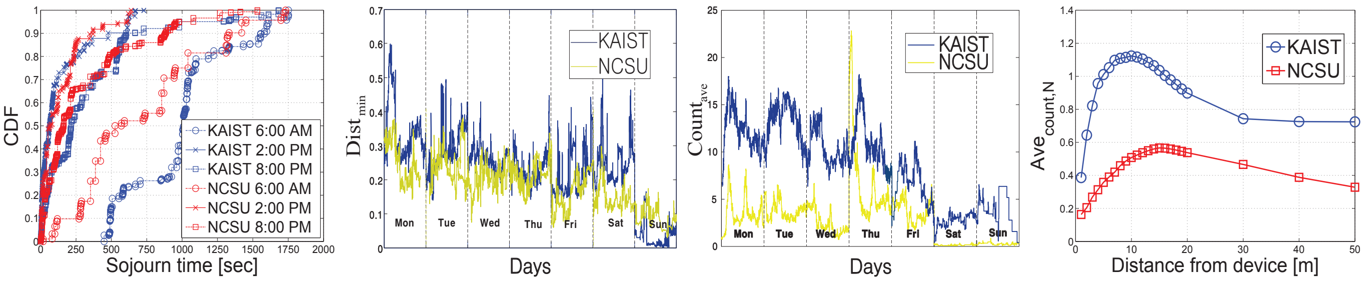
II. Device Proximity Analysis

A. Environment and Metrics

We had collected the GPS traces of 93 and 99 students with 5 second granularity for 7 days in the KAIST and NCSU campuses, respectively. The areas of campuses are $2 \times 2\text{km}^2$ (KAIST) and $8.5 \times 8.5\text{km}^2$ (NCSU), and the total numbers of students and faculties are approximately 10000 (KAIST) and 40000 (NCSU), respectively. We assume that the distributions of the experimental volunteers are the same as distributions of all the people in each campus, respectively. So, we scaled down the distance between two devices to factor of $\sqrt{\frac{\text{\# of experimental volunteers}}{\text{\# of all the people in the campus}}}$ in this analysis. For the analysis, four kinds of metrics are considered. Sojourn time is continuous retention time of a device within 10m coverage from a reference user, $\text{Count}_{ave}(t)$ is average number of devices within 10m coverage in time t, Dist_{min} is average scaled distance with the closest device, $\text{Ave}_{count,N}(r) = \frac{\text{Ave}_{count}(r)}{r}$ where $\text{Ave}_{count}(r)$ is time-average number of devices within rm coverage. Finally, we define an information sharing gain as the number of total devices divided by the number of devices who measures some information and shares it with proxy devices using SRC.

B. Trace Analysis

From the trace analysis, we made five interesting observations. *(i)* Sojourn time depends on the attribute of human mobility. Therefore, estimating the event of future mobility is maybe difficult. For example, at 2:00PM and 8:00PM, sojourn time is relatively shorter (average 1 min in KAIST, NCSU (2:00PM), 2min 30sec in KAIST, 3 min 30 sec in NCSU (8:00PM)) than dawn (16min 30sec in KAIST, 9min 30sec in NCSU (6:00AM)) since people more actively move around campus at afternoon and evening than dawn. Nevertheless, the observed time scale of sojourn time can be considered in the design of a localization scheme. *(ii)* Dist_{min} is within 1m in both of KAIST and NCSU campuses at every time. This implies that there exists at least one device to estimate location together in the very near position.



(a) Sojourn time

(b) Minimum distance with the closest device

(c) Average number of devices within 10m for days

(d) Distance-normalized time-average number of devices within distance

Fig. 1: KAIST & NCSU trace analysis

(iii) In weekdays, there exist approximately 10 Count$_{ave}$ in KAIST, and 5 Count$_{ave}$ in NCSU, respectively. This implies that average 10 number of devices in KAIST, 5 number of devices in NCSU can collaboratively share some information within 10m coverage. However, keep in mind that it does not mean that an information sharing gain is 10 or 5 because the number of information measuring devices varies depending on the SRC connectivity and the selection of sharing device. Our clear objective is to maximize information sharing gain and we will handle this issue in this paper. The reason why NCSU has fewer number of devices than KAIST is that the density of people in the NCSU campus (40000persons/75.25km^2 = 531persons/km^2) is lower than KAIST campus (10000persons/4km^2 = 2500persons/km^2). *(iv)* In weekends (Saturday, Sunday), there exist fewer number of devices within 10m than weekdays. This is because there exist fewer students in the campus as well as more actively moving students in weekends than weekdays. *(v)* Using only short range (e.g., 0-20m) communication may be enough to obtain the information sharing gain. In both campuses, Ave$_{count,N}$ of a long range is smaller (e.g., KAIST with 50m distance: 0.7242, NCSU with 50m distance: 0.3282) than short range (e.g., KAIST with 10m distance: 1.123, NCSU with 10m distance: 0.508). In summary, we could obtain a motivation that the average energy consumption of devices can be significantly reduced when we collaboratively measure their locations with proxy devices from the proximity analysis in both campus scenarios. Although our analysis is carried out in the limited scenarios, the other environments such as crowed hotspot at downtown or the movement of soldiers with the same mission are expected to have the similar proximity properties. From this motivation, we develop an energy efficient collaborative localization scheme in the next section.

III. Energy Optimal Collaborative Localization

In this section, we formulate a convex optimization problem considering energy efficiency and device fairness, and propose a distributed location sharing protocol and an optimal algorithm to solve the problem.

A. Model and Problem Formulation

Model. We consider a set $\mathcal{N}$ of devices who require consecutive location information and are capable of short range communication (SRC). We define neighbors as two devices who can communicate each other, i.e., bidirectional communication link. Then, the SRC connectivity is represented by a conflict graph $\mathcal{G}$ in which each node represents a device and an edge between two nodes represents a communication link if corresponding two devices are neighbors. Let a device n be a G-leader (GPS leader) if it measures GPS[1] and broadcasts location value. Each G-leader has G-members (GPS members) receiving G-leader's location value. We denote the sharing set of G-leader n by S_n, i.e., $S_n = \{m \in \mathcal{N} \mid n, m \text{ are neighbors}\}$. Note that one G-member can be belonged to multiple sharing sets and some G-leaders may have an empty sharing set.

Let's consider a vector $x \in \{0,1\}^{|\mathcal{N}|}$ where nth element of x is 1 ($x_n = 1$) if device n is a G-leader, and $x_n = 0$ otherwise. We say that x is a feasible G-leader set if it satisfies a following condition.

Definition 1. *(Feasible G-leader set condition): Since all devices should consecutively know their locations for all time, the feasible G-leader set condition of x is given by:*

$$\bigcup_{n:x_n=1} (S_n \cup \{n\}) = \mathcal{N}. \quad (1)$$

This definition means that every device is contained at least one sharing set or turns on GPS. Then, we can define a set I of feasible G-leader set condition where $(x^i, i \in \mathcal{I})$ satisfies the condition (1) for given conflict graph $\mathcal{G}$.

Problem Formulation. Our two questions in Introduction for collaborative localization were as follows: *(i)* Who measure GPS among proxy devices? *(ii)* How long the device should measure GPS? To deal with two questions, our objective is to find the time portion of G-leader of each device n, $\theta_n \in \boldsymbol{\theta}$, which is the solution of an optimization problem with the constraints on feasible G-leader condition. All possible vector sets of $\boldsymbol{\theta}$ satisfying feasible G-leader sets are given by:

$$\mathcal{F} = \{\boldsymbol{\theta} \in R^{|\mathcal{N}|} | \theta_n \geq \sum_{i\in\mathcal{I}} x_n^i \phi_i, \forall n, \sum_{i\in\mathcal{I}} \phi_i = 1, \ \phi_i \geq 0\} \quad (2)$$

where $\phi_i \in \boldsymbol{\phi}$ is the time portion of x^i.. The optimization problem **[P-EOL]** is chosen such that

[1] Although we consider the GPS as location measuring method, it can be generalized into the other localization methods.

TABLE I: Decomposed Problems and Solutions

	Dual problem [DP]	Primal problem1 [PP1]	Primal problem2 [PP2]
Problems	$\max_{\lambda_n} \lambda_n\left(\sum_{i\in\mathcal{I}} x_n^i\phi_i^* - \theta_n^*\right), \forall n$	$\min_{\boldsymbol{\theta}} \sum_{n\in\mathcal{N}} ((P_n\theta_n)^\alpha - \lambda_n^*\theta_n))$	$\min_{\boldsymbol{\phi}} \sum_{i\in\mathcal{I}} \left(\phi_i\left(\sum_{n\in\mathcal{N}} \lambda_n^* x_n^i\right)\right)$, *s.t.* $\sum_{i\in\mathcal{I}} \phi_i = 1$
Solutions for all n	$\lambda_n(t+T) = \lambda_n(t) + \beta(\rho_n(t) - \theta_n^*(t))$	$\theta_n^*(t) = \begin{cases}(\lambda_n(t)/\alpha)^{1/(\alpha-1)}/P_n, & \text{if } \alpha>1,\\ \rho_n(t), & \text{if } \alpha=1,\end{cases}$	Centralized, NP-hard [17]

Energy optimal G leader selection problem [P-EOL]

$$\min_{\boldsymbol{\theta}} \quad \sum_{n\in\mathcal{N}} (E_n)^\alpha = \sum_{n\in\mathcal{N}} (P_n\theta_n)^\alpha, \tag{3}$$

$$\text{subject to} \quad \boldsymbol{\theta} \in \mathcal{F} \tag{4}$$

where P_n is the average power to use GPS of device n, E_n is the average-consumed energy during unit period to use GPS of device n, and $\alpha \geq 1$ is the fairness parameter. When α is 1, we only consider a sum energy minimization. As α is bigger, the problem **[P-EOL]** tends to select less elected devices as G leader to minimize the objective function, which means higher fairness is enforced.

Since actual $\mathcal{G}$ varies depending on the mobility of devices, we should know the future mobility events to solve this problem. Unfortunately, estimating future mobility events is intractable as mentioned at observation *(i)* in section II, so we assume that pursuing the optimal solution under the current $\mathcal{G}$ is the best under the current status. Even in this assumption, our simulation results show enough energy saving under the real mobility scenario.

B. Optimal Solutions

Problem Decomposition. We can solve the **[P-EOL]** problem to find the GPS-on time portion θ_n of each device using primal-dual technique [18]. The Lagrangian function of **[P-EOL]** is given by:

$$L(\boldsymbol{\theta}, \boldsymbol{\phi}, \boldsymbol{\lambda}) = \sum_{n\in\mathcal{N}} \left((P_n\theta_n)^\alpha + \lambda_n\left(\sum_i x_n^i\phi_i - \theta_n\right)\right), \tag{5}$$

where $\lambda_n \in \boldsymbol{\lambda}$ is a dual variable for satisfying the constraint (2). From the primal-dual decomposition, the original problem **[P-EOL]** is divided into the primal-dual problems as shown in Table I. By iteratively solving the three decomposed problems as follows, we can find an optimal G-leader (GPS-on) time portion of each device. Let $t = kT$ for some nonnegative integer $k = 0, 1, 2, ...$ and $T > 0$ is a constant.

1) [DP] solution: Using the form of distributed gradient method [19] in **[DP]**, dual variable λ_n of each device n can be updated per each $t = kT$ as a follow.

$$\lambda_n(t+T) = \lambda_n(t) + \beta(\rho_n(t) - \theta_n^*(t)) \tag{6}$$

where $\rho_n(t)$ denotes the actual GPS-on ratio of device n for last T which is equivalent to $\sum_{i\in\mathcal{I}} x_n^i\phi_i$ in **[DP]**, $\theta_n^*(t)$ is a solution of **[PP1]**, and $\beta > 0$ is a constant.

2) [PP1] solution: We can easily derive the $\theta_n^*(t)$ by applying Karush-Kuhn-Tucker (KKT) conditions [20] because **[PP1]** is a convex function. The derived $\theta_n^*(t)$ is as a follow.

$$\theta_n^*(t) = \begin{cases} (\lambda_n(t)/\alpha)^{1/(\alpha-1)}/P_n, & \forall n\in\mathcal{N}, \text{ if } \alpha > 1,\\ \rho_n(t), & \forall n\in\mathcal{N}, \text{ if } \alpha = 1, \end{cases} \tag{7}$$

3) [PP2] solution: **[PP2]** is a problem to find a G-leader set i which makes to minimize sum of virtual queues of all G-leaders at time $t = kT$. Therefore, while **[DP]** and **[PP1]** can be solved by distributed manners, **[PP2]** is centralized problem where the problem is NP-hard [17], and solver of the problem should know all SRC connectivity $\mathcal{G}$ information in order to find ϕ. So in the next subsection, we present a fully distributed algorithm which contains the distributed solution of **[PP2]**.

Solution Mechanism. The dynamics in (6) can be considered as a queueing system (we call a virtual queue) in which the arrival quantity is ρ_n and departure quantity is θ_n^*. When $\alpha > 1$, the virtual queue λ_n is operated to achieve fairness among devices. For example, λ_n increases if device n is sufficiently selected as the G-leader compared to θ_n^*, i.e., $\rho_n > \theta_n^*$. Then, the device is less selected since the solution of **[PP2]** finds devices whose sum of virtual queues is minimum. Then, the GPS-on ratio of the device decreases. This mechanism forms a negative feedback of (6). If α is large, the departure value θ_n^* becomes small by (7), so $\lambda_n(t)$ increases at even small increment of GPS-on ratio, which affects a decrement of GPS-on ratio. Therefore, more fairness is enforced. When $\alpha = 1$, the virtual queue λ_n is the same for all time and all devices. Therefore, $\boldsymbol{\phi}$ in **[PP2]** is selected when the number of G-leaders satisfying a feasible G-leader set condition is minimum (i.e., total energy consumption is minimized). This means that the solution absolutely does not consider fairness.

C. DLS Protocol and OWD Algorithm

In this subsection, we first describe a collaborative localization protocol which is operated by a distributed manners, we called distributed location sharing (DLS) protocol, and design an optimal mean waiting time decision (OWD) algorithm which makes to achieve optimality of the **[P-EOL]** problem. Similar with CSMA/CA, our DLS protocol is operated by the competition for turning off GPS among neighbors based on the different randomized waiting time of each device. By doing so, the selected G-leader set becomes reversible Markov chain which has stationary distribution depending only on the waiting time. In OWD algorithm, we inherit the distributed solutions of **[PP1]** and **[DP]** problems, and develop an distributed optimal solution for remained **[PP2]** problem. This algorithm present an mean waiting time of each device with only the past GPS-on statistics, which makes to find optimal GPS-on time portion of each device.

Distributed Location Sharing Protocol. We inherit the idea from well-known CSMA/CA [21] for the distributed operation, where the key operations are carrier sensing and random waiting time. Similarly, our protocol selects a G-member set (it is complementary G-leader set) by individual operations (neighbor sensing, random waiting time) of each device. *Neighbor sensing:* each device listens location values broadcasted from G-leaders for checking competition devices who are turning on GPS as well as GPS sharing. We assume that each device can know identifications of neighbors using the SRC. Therefore, each device can know the number of competition devices. *Random waiting time:* if there exist neighbors which are G-leaders, the devices compete for turning off GPS with randomly selected waiting time between 0 and maximum waiting times, e.g., the device who selects shorter waiting time is winner. Also, each device has the maximum waiting time which is controlled by an OWD algorithm, and it is updated every T time.

Next, we deal with four practical problems in DLS protocol. *(i) How to communicate among devices with short range communication?* We consider four types of message passings: location value, GPS-on/off, NO message. The location value means longitude and latitude acquired by the GPS measurement. This value is broadcasted by G-leader at every t_{GPS}. The GPS-on/off messages mean that some device informs that the device turns on or off GPS to neighbors. The NO message is used for feasibility condition. *(ii) How to detect device topology?* Since the neighbors content based on hearing of GPS-on/off and location value messages, they do not need additional message passings for topology detection. The devices can know the number of neighbors or competitors based on the location values which are received during past t_{GPS}. *(iii) Which location value is selected if a certain device receives several GPS location data from several GPS-on devices?* Since the devices do not measure signal strengths of SRC, the devices do not know which devices are closer. Therefore, we make a decision that the devices which received location values from several devices calculate their locations as the average of all received location values. *(iv) What happens if the SRC links are broken while the location sharing?* The GPS-off devices turn on GPS and broadcast their location values, then the devices naturally participate in the competition under the newly determined SRC connectivity. In summary, the DLS protocol can be presented by a flowchart as Fig. 2.

In Fig. 2, we consider three states of a device, each of which represents G-leader (GPS-on), G-member (GPS-off) and GPS-off competition state. At G-leader state, each device measures GPS and broadcasts the location value every t_{GPS}. If the device listens location values or GPS-on messages from neighbors during t_{GPS}, (neighbor sensing), the device goes to the GPS-off competition state. At G-member state, each device listens location values from it's G-leaders. Then the device calculates an average location based on receiving location values. If the device receives GPS-off message from it's only one G-leader, the device sends NO message. If GPS-off duration is over, the device broadcasts GPS-on message

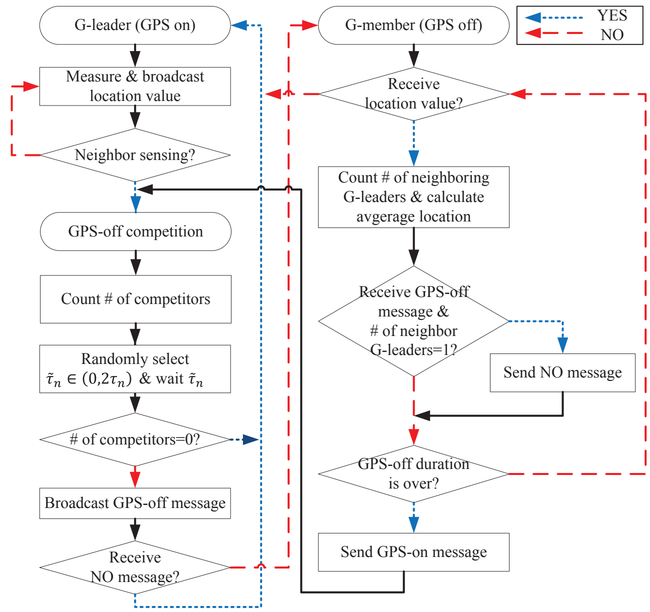
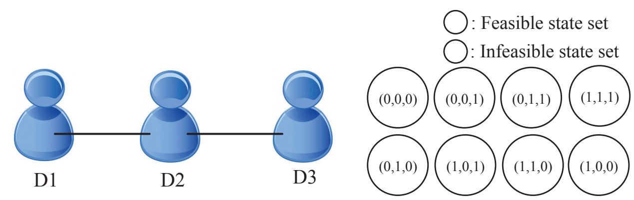


Fig. 2: Flowchart of distributed location sharing protocol



(a) Device topology: a line between devices represents that two devices are neighbors

(b) Markov states: 0 denotes GPS-on, 1 denotes GPS-off

Fig. 3: Example: device topology and Markov states

and goes to GPS-off competition state. If the device cannot receive location values, the device goes to the G-leader state. At GPS-off competition state, each device checks the number of neighbors which are G-leaders based on GPS-on messages or location values during t_{GPS}. Then, the device randomly selects waiting time $\tilde{\tau}_n$ between 0 and maximum waiting time τ_n which is updated by OWD algorithm, and waits for $\tilde{\tau}_n$. If the number of competitors becomes zero, the device goes to G-leader state, otherwise, broadcasts GPS-off message. If the device receives NO message after broadcasting GPS-off message, the device loses competition and goes to G-leader state. We present a simple example of the DLS protocol.

In Fig. 3(a), D1-D3 devices are located where D1,D2 are neighbors and D2,D3 are neighbors. This SRC connectivity can be modeled as a Markov chain (MC) whose states are shown in Fig. 3(b). For the feasible G-leader set condition, the probabilities to the infeasible state sets from other state sets in the MC should be zero. To that end, we introduce "NO message" which prevents going to the infeasible state sets. For example, assume that waiting times of D1, D2 and D3 are initially selected by the order of D3 $>$ D2 $>$ D1 as shown in Fig. 4. Then, D1 first broadcasts GPS-off message.

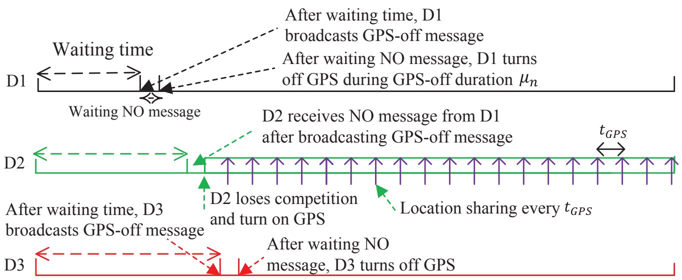


Fig. 4: Example: distributed location sharing protocol

Since D2 is in the GPS-off competition state, D2 does not send NO message. After waiting time, D1 turns off GPS. Next, D2 broadcasts turn off message. Since D1 is turning off GPS, D1 sends NO message to D2 in order to prevent going to the infeasible state. After then, D2 loses competition, and turn on GPS. Finally, after transmitting GPS-off message and waiting NO message, D3 turns off GPS during GPS-off duration.

Optimal mean Waiting time Decision Algorithm. The DLS protocol continuously operates by the fully distributed mechanism depending on the only maximum waiting time, which is double of mean waiting time. To find optimal solution of **[P-EOL]** problem by DLS protocol, we develop an optimal mean waiting time decision (OWD) algorithm. Since **[PP1]** and **[DP]** problems can be solved by distributed manner, the remaining issue is to find distributed optimal solution of **[PP2]** in Table I. From now on, instead of **[PP2]**, we use the complementary maximization form and complementary vectors as follows.

Lemma 1. *Denote by y_n^i the GPS-off indicator of device n in G-leader set i, i.e., $y_n^i = 1$ if device n is in G member state, and $y_n^i = 0$ otherwise. Then,* ***[PP2]*** *is equivalent to*

$$\max_{\boldsymbol{\phi}} \sum_i \left(\phi_i \left(\sum_{n \in \mathcal{N}} \lambda_n y_n^i \right) \right), \qquad \text{s.t.} \sum_i \phi_i = 1. \tag{8}$$

Proof: By the definition of x_n^i and y_n^i, $y_n^i = 1 - x_n^i, \forall n, i$. Then, from **[PP2]**, *we have:*

$$\begin{aligned}
\min_{\boldsymbol{\phi}} & \sum_i \left(\phi_i \left(\sum_{n \in \mathcal{N}} \lambda_n x_n^i \right) \right) \\
&= \min_{\boldsymbol{\phi}} \sum_i \left(\phi_i \left(\sum_{n \in \mathcal{N}} \lambda_n - \sum_{n \in \mathcal{N}} \lambda_n y_n^i \right) \right) \\
&= \min_{\boldsymbol{\phi}} \sum_i \phi_i \sum_{n \in \mathcal{N}} \lambda_n + \max_{\boldsymbol{\phi}} \sum_i \phi_i \sum_{n \in \mathcal{N}} \lambda_n y_n^i \\
&= \sum_{n \in \mathcal{N}} \lambda_n + \max_{\boldsymbol{\phi}} \sum_i \phi_i \sum_{n \in \mathcal{N}} \lambda_n y_n^i
\end{aligned} \tag{9}$$

Since $\sum_n \lambda_n$ is independent of i and $\sum_i \phi_i = 1$, the first term of (9) is $\sum_n \lambda_n$ (constant in terms of ϕ). Therefore, (9) can be represented by (8). This completes the proof. ∎

Let $\tau = [\tau_1, ...\tau_{|\mathcal{N}|}]^T$ be a vector of the mean random waiting time, and $\mu = [\mu_1, ...\mu_{|\mathcal{N}|}]^T$ be a vector of the mean GPS-off duration. If each device n runs a DLS protocol in Fig. 2, the G-member selection procedure follows a Markov chain in which a state is a G-member set. Consider a state y^i and a device n who is a G-leader, i.e., $y_n^i = 0$, and has at least one neighboring G-leader. Then, state y^i transits to state $y^i + e_n$ with rate $1/\tau_n$, and state $y^i + e_n$ transits to state y^i with rate $1/\mu_n$, where e_n is a $|\mathcal{N}|$ vector whose nth value is 1 and other values are 0s. If the device n has no neighboring G-leader, then state y^i cannot transit to state $y^i + e_n$ due to the NO message in Fig.2. Thus, similar to the CSMA Markov chain in [21], the Markov chain of the G-member selection is reversible, and the stationary distribution is given by:

$$\phi_i(\tau) = \frac{\prod_{n: y_n^i = 1} \frac{\mu_n}{\tau_n}}{\sum_{i' \in \mathcal{I}} \prod_{n': y_{n'}^{i'} = 1} \frac{\mu'_n}{\tau_{n'}}}. \tag{10}$$

This equation shows that a G-member set i is more frequently visited in the Markov chain if it contains devices with low waiting time. We assume that μ_n of all devices are constants. We control a parameter τ to solve **[PP2]** for given $\boldsymbol{\lambda}$ as a follow.

$$\tau_n = \exp(-B\lambda_n)\mu_n, \qquad \forall n \in \mathcal{N}. \tag{11}$$

Where $B > 0$ is a constant. Then, the following result is an immediate consequence of the rule in (11).

Theorem 1. *Fix $\boldsymbol{\lambda}$ and consider a DLS protocol under the waiting time satisfying* (11)*. Then, in steady state, the optimal G-leader set of* ***[PP2]*** *is visited only and all as B goes to infinity.*

Proof: If a distributed location sharing algorithm runs with a waiting time satisfying (11)*, a time fraction (or stationary distribution) of G-member set i, ϕ_i, is given by:*

$$\phi_i(\tau) = \frac{\exp(B \sum_{n \in \mathcal{N}} \lambda_n y_n^i)}{\sum_{i' \in \mathcal{I}} \exp(B \sum_{n \in \mathcal{N}} \lambda_n y_n^{i'})}. \tag{12}$$

Let $U(i) = \sum_{n \in \mathcal{N}} \lambda_n y_n^i$ and I^* be a set of i in which U is to be a global maximum. Note that points in set I^* are one of solutions of ***[PP2]*** *from Lemma 1. Next, divide numerator and denominator of* (12) *by e^{kB} where $k = \max_i U(i)$. Then,*

$$\begin{aligned}
\phi_i(\tau) &= \frac{e^{(B(U(i)-k))}}{\sum_{i' \in \mathcal{I}^*} e^{(B(U(i)-k))} + \sum_{i' \notin \mathcal{I}^*} e^{(B(U(i)-k))}} && (13) \\
&= \frac{e^{(B(U(i)-k))}}{|\mathcal{I}^*| + \sum_{i' \notin \mathcal{I}^*} e^{(B(U(i)-k))}} && (14)
\end{aligned}$$

As B goes to infinity, the time fraction of G-member set i is given by:

$$\lim_{B \to \infty} \phi_i(\tau) = \begin{cases} \frac{1}{|\mathcal{I}^*|}, & \text{if } i \in \mathcal{I}^*, \\ 0, & \text{if } i \notin \mathcal{I}^*, \end{cases} \tag{15}$$

since $e^{B(U(i)-k)}$ goes to 0 if $U(i) < k$ and 1 if $U(i) = k$. Thus, the Markov chain visits only and all the optimal G-member set of ***[PP2]*** *equally likely.* ∎

Now, we can describe our optimal mean waiting time decision (OWD) algorithm by the optimal solutions of three decomposed problems in Table I as follows.

OWD: Optimal mean Waiting time Decision Algorithm

Let $t = kT$ for some nonnegative integer k = 0,1,2,... and $T > 0$ is a constant. Every kT, each device updates mean waiting time $\tau_n(kT)$ by the following mechanisms for all n.

$$\tau_n(t+T) = \mu_n \exp(-B\lambda_n(t)), \tag{16}$$

$$\lambda_n(t+T)=\begin{cases}\left[\lambda_n(t)+\beta\left(\rho_n(t)-\frac{\left(\frac{\lambda_n(t)}{\alpha}\right)^{\frac{1}{\alpha-1}}}{P_n}\right)\right]^+, & \text{if } \alpha>1\\ \lambda_n(t), & \text{if } \alpha=1,\end{cases} \tag{17}$$

where $\rho_n(t)$ is the GPS-on ratio of device n for T.

The mean waiting time τ_n is operated to achieve a fairness among devices. For example, the virtual queue $\lambda_n(t)$ increases when the device n is sufficiently selected as G-leader by (17). Then, $\tau_n(t)$ decreases by (16), so the device n try to turn off GPS with high probability. This forms a negative feedback mechanism. Note that the DLS protocol continuously operates with neighbor sensing and random waiting time even though mean waiting time update by OWD algorithm is slotted.

IV. Discussion

In this section, we discuss about four reasonable problems of DLS protocol. First, Bluetooth [10] is very suitable for short range communication (SRC) due to its coverage and energy-efficiency. For communication, Bluetooth should initially make connections among master node and slave nodes, and master node can be connected with up to 7 slave nodes. Actually, this connection procedure and the limitation of number of slave nodes can be a disturbance for cooperative localization in terms of delay and power consumption. Fortunately, however, Bluetooth system provides a device discovery protocol [22] which does not need connection procedures, but just discovers proxy devices. Moreover, the device discovery protocol provides class of device (CoD) which classifies cooperative localizing devices with other Bluetooth devices. We can exchange location values or side information such as “NO message” or GPS-off message among devices by a inquiry header.

Second, the power consumptions of a commercial Bluetooth discovery device [11] can be found in Table II. Compared to average GPS power consumption (440mW) in N95 smartphone [5], idle power of Bluetooth discovery (6.6mW) can be negligible. However, inquiry power should be essentially considered in the total power consumption for the collaborative localization. Therefore, we check the message passing of DLS protocol compared to lowest ID (Low-ID), highest connectivity (High-C), LEACH [23] and HEED [16]. Table III summarizes the type of message passing where (O,X) means that the type of message passing is used or not. LEACH has no message passing to share location information. Thus, it cannot guarantee feasibility condition under fixed SRC range. Low-ID and High-C and HEED need to broadcast a cost and a G leader declaration per each G leader selection phase. DLS protocol need to broadcast GPS-on/off indicator per each GPS-off duration, but sending NO message can be varied depending on the feasible G-leader set condition.

Third, the location sharing among devices can be provoked privacy problem. Indeed, knowing the identity of well known proxy devices is critical for security. Therefore, DLS protocol suggests that devices use encoded ID. The device discovery protocol use the parameter called “Friendly name” which is defined by the owner of the Bluetooth device [11]. Thus, we use this parameter as encoded ID for each device.

Finally, the time scale of location sharing and GPS-off duration should be considered due to the dynamics of the device mobility. As mentioned in Section II-B observation *(i)*, average sojourn time of devices within 10m is the order of minutes for different time zones. As the speed of mobility is slower, the longer time scale of location sharing and GPS-off duration is good for energy efficiency. Also, A-GPS’s fastest turning on time in hot start mode is known for within 1 second [24], and Bluetooth inquiry’s minimum turn around time is known for within 0.6 second [22]. Therefore, we should carefully select GPS-off duration in the light of these parameters.

TABLE II: Power consumption for Bluetooth discovery device

Estate	Power consumption
Idle(listen)	6.6mW
Inquiry at minimum power	110.5mW
Inquiry at maximum power	120.45mW

TABLE III: Message passing of different algorithms

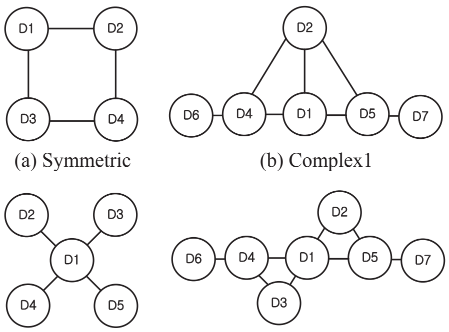
Algorithms	Message passing				
	Location value	NO	Cost	GPS-on/off	CH value
DLS+OWD	O	O	X	O	X
Low-ID	O	X	O	X	O
High-C	O	X	O	X	O
LEACH	O	X	X	X	X
HEED	O	X	O	X	O

V. Evaluation

To verify the optimality of our scheme (DLS protocol and OWD algorithm), and compare with existing algorithms in specific scenario, we first consider fixed topology scenarios. After then, we verify the performance of DLS+OWD and the other algorithms under real mobility trace in KAIST campus.

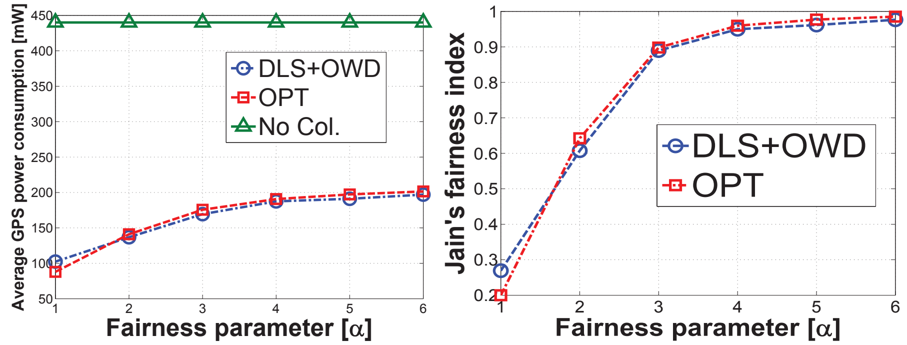
A. Verification under Sample Topologies

Setup. We consider four topologies, each of which has different connectivity (within short range communication (SRC) coverage) among devices as shown in Fig. 5. Symmetric and Star is the basic topologies that each device easily knows an energy minimal solution by exchanging the number of neighboring devices with the neighbors. However, in Complex1 and Complex2 topologies, each device cannot knows an energy minimal solution with the neighboring information. For example, in Complex2 topology, D1 may turn on GPS since the device has maximum number of connectivity among neighbors. And D6 and D7 should have to turn on GPS for



(a) Symmetric (b) Complex1 (c) Star (d) Complex2

Fig. 5: Device topologies



(a) Average GPS power consumption vs. fairness parameter α (b) Jain's fairness index vs. fairness parameter α

Fig. 6: Verification of optimality

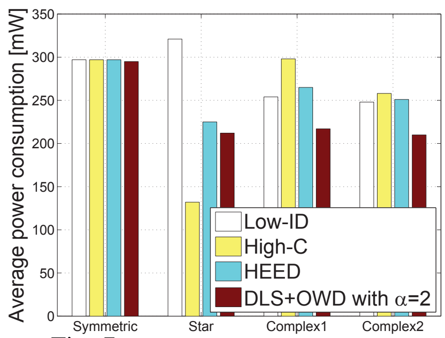


Fig. 7: Average power consumption

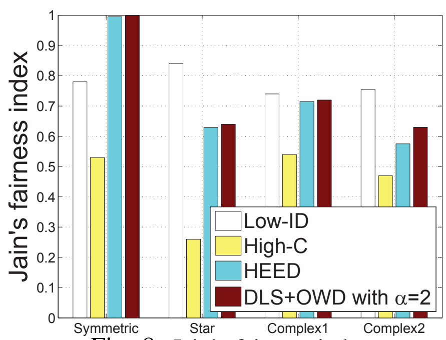


Fig. 8: Jain's fairness index

Topologies	Average number of messages	
	Low-ID, High-C, HEED	DLSA with α=2
Symmetric	1	0.8481
Star	1	0.7785
Complex1	1	0.8536
Complex2	1	0.7978

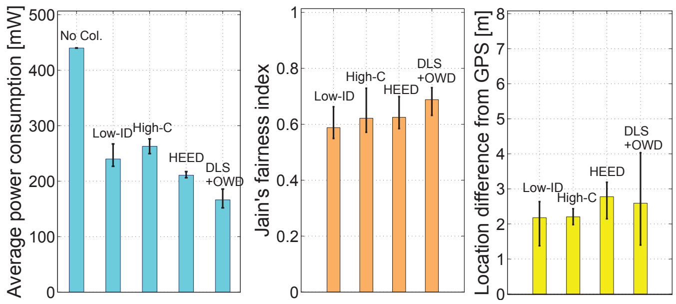
Fig. 9: Average number of message passing

feasible G-leader set condition. However, it is not energy minimal solution. The energy minimal solution is to turn on D4 and D5. Also, we use a Bluetooth inquiry protocol for SRC, and the average power consumption for transmit/receive of Bluetooth signal is 110.5mW [11] which is shown in Table IV. A reference GPS power consumption is 440mW (Nokia N95 smartphone [5]). First, we verify an optimality of our DLS protocol and OWD algorithm under the star topology in Fig. 5 (c). For the comparison, we define an optimal centralized solution (OPT) which finds optimal ϕ in **[PP2]** problem with a global knowledge of topology. In OWD algorithm, β, B and a initial virtual queue are set to be 0.1, 0.1 and 50, respectively. We establish GPS-off duration as 10 seconds, and location sharing period is 1 second, i.e., G-leaders broadcast their location value each second. Actually, turning on time of A-GPS in hot start mode is known for within 1 second [24], and round trip time of Bluetooth inquiry is known for within 0.6 second [22]. However, they can be negligible for our GPS-off duration setting. Also, since the sojourn time defined in Section II is approximately more than 1 minute in general time zone, this is a reasonable GPS-off duration. As performance metrics, the average GPS power consumption and Jain's fairness index [25] are considered. Jain's Fairness index is calculated as follows.

$$\mathcal{J}(a_1, a_2, ...a_n) = \frac{(\sum_{i=1}^{n} a_i)^2}{n \cdot \sum_{i=1}^{n} a_i^2} \tag{18}$$

Verification of Optimality. We verify an optimality of DLS+OWD under a star topology (Fig. 5 (c)). Figs. 6(a), 6(b) show the average GPS power consumption and Jain's fairness index for the fairness parameter α: DLS+OWD comes close to OPT for all fairness parameters (α=1-6) in both terms of average GPS power consumption and fairness.

Comparison with Other Algorithms. We compare the performance of DLS+OWD with the existing algorithms (Low-ID [14], High-C [15] and HEED [16]) in four different topologies as shown in Fig. 5. In Low-ID and High-C, devices exchange costs which are random numbers (Low-ID) or inverse of the number of connectivity (High-C) with neighboring devices and select a device having the lowest cost as a cluster head which turns on GPS. In HEED, devices exchange costs which are inverse of the number of connectivity and a cluster head is determined depending on the cost and residual energy of each device. Figs. 7, 8 show the total average power consumption (GPS+Bluetooth) and the Jain's fairness index of different algorithms under four different topologies: *(i)* DLS+OWD with α=2 outshines than HEED in complex topologies Fig. 5 (b), (d) in both terms of power consumption and fairness. This is because our OWD algorithm can find optimal feasible sets which minimize sum of square of GPS power in α=2 whereas HEED cannot find this optimal feasible sets in these kinds of topologies. *(ii)* For all cases, High-C cannot achieve high fairness since it selects a cluster head only depending on the neighboring topology. Further, High-C consumes up to 27.2% higher energy than DLS+OWD despite of 35.8% lower fairness since it also cannot find optimal feasible sets in complex topologies. Fig. 9 shows the average number of



(a) Average power (b) Jain's fairness index (c) Accuracy

Fig. 10: Performance under real mobility trace in KAIST campus: a black line denotes a variation of each bar between Monday to Thursday.

messages when the other algorithms use the constant number of messages: *(iii)* For all topologies, DLS+OWD uses 15-22% of fewer number of message passing (NO message, GPS-on/off message) than the other algorithms.

B. Verification under Real Mobility Trace

Setup. We delegate mobility trace data of 93 students in KAIST campus at Wednesday PM 1:00 to PM 8:00 (for seven hours). The other assumptions are the same as the device proximity analysis in Section II. Also, the GPS-off duration and location sharing period as well as the GPS and Bluetooth settings are same as toy topology simulation in Section V-A. Fairness parameter α is set to be 2. As performance metrics, we consider average power consumption (GPS+Bluetooth) of all devices, Jain's fairness index and average location difference from GPS, i.e., degree of accuracy of localization scheme.

Performance Comparison with Other Algorithms. Fig. 10 shows the average power consumption, Jain's fairness index and average location difference from GPS of 93 students: *(i)* our DLS+OWD with α=2 reduces the average power consumption by 65.5% compared to no collaboration, and by 27.4% compared to HEED with 25% higher fairness. *(ii)* Location difference from GPS of all algorithms are below 8.8m which is the accuracy of GPS [5]. This implies that the estimated location using our scheme is not far from real location even though we do not consider accuracy in the design of DLS+OWD.

VI. Related Work

Localization. There was a localization approach based on the fingerprint in cellular or WiFi networks without GPS [7], [26], [27]. For example, in the WiFi-based fingerprint or war-driving [27], regular users collect a set of WiFi signals, and they collaboratively aggregate the signals to make up its signal map. Next, a device estimates the WiFi signals and matches with the signal map to obtain its location. However, these techniques require prior signal information and are available only for given WiFi or cellular infrastructures.

Localization methods using adscititious sensors of the mobile device were also considered in literatures [8], [9]. The authors in [8] use the velocity history information at the same location and the same time-of-day to determine the GPS activation period, i.e., if the velocity is lower under the same location and time, then the GPS is more sparsely activated. Also, [9] recognizes the logical location using many sensing modules in the mobile devices, e.g., light, sound and color recognizers, accelerometers, geoniometers. This paper shows that 87% of accuracy can be achieved for 51 different logical locations. However, these schemes also consume the energy for using sensors, and still provide low accuracy than the continuous GPS positioning. On the other hand, proposed technique in this paper do not require prior signal information, network infrastructure and additional sensors.

Cooperative communication. There were clustering studies in the context of sensor networks which objective is prolonging network lifetime. Most of the optimal clustering solution in this objective is known for NP-hard [17]. Therefore, several heuristic distributed algorithms have been suggested [14]–[16], [23]. Baker *et al.* [14] and Parekh [15] exchange proxy device information and select devices having lowest ID or highest number of proxy devices or weights as cluster head. However, these methods cannot use energy fairly among sensors. LEACH [23] suggests fully fair clustering algorithm, but it completely cannot guarantee energy-optimality in localization. HEED [16] considers both of energy-efficiency and residual energy of each device. However, there is still no criterion about the fairness among selfish devices in this clustering algorithm. Recently, Lee *et al.* [12] presented a cooperation sensing technique between two proxy devices. However, they considered only contract-based cooperation between two devices, but did not consider the energy efficiency and fairness of the total proxy devices.

VII. Conclusion

The main contributions of this paper are three-folds. First, we define spatial and temporal proximity of human beings and give a motivation that collaboration with proxy devices for localization maybe achieve high energy efficiency by analyzing human mobility traces in KAIST and NCSU campuses. Second, we formulate an optimization problem which considers energy efficiency and/or user fairness for collaborative localization. However, solving this problem is hard because it requires a global knowledge of SRC connectivity and also solving a NP-hard problem. Therefore, finally, we suggest DLS protocol and OWD algorithm (DLS+OWD) which practically solve the optimization problem. The DLS protocol operates with only passive neighbor sensing and waiting time for competition to turn off GPS, and the OWD algorithm presents mean waiting time which makes the DLS protocol to find an optimal solution of the problem. Also, we verify that DLS+OWD well adapt even at the unpredictably changing SRC connectivity through the real mobility trace simulation. Additional benefit of our scheme is that it can be generally applied in other sensing data sharing such as dust/UV sensors or activity observations.

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