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FindingNemo: Finding Your Lost Child in Crowds via Mobile Crowd Sensing

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***Abstract*—Mobile Crowd Sourcing/Sensing (MCS), as a new paradigm for participatory sensing, is suitable for large-scale hard tasks that are costly, or infeasible with conventional methods. Utilizing the ubiquitousness of "crowds" of sensor-rich smartphones, MCS has enormous potential to truly unleash the power of collaborative locating and searching at a societal scale. In this paper, we target the application of finding and locating the lost child in crowds via MCS. Conventional localization approaches require fixed anchor networks or fingerprinting points as references. It is not effective for locating the child in open and uncontrolled areas. We propose MCS-based collaborative localization via nearby opportunistically connected participators. To obtain sufficient measurements, we utilize one-hop and multi-hop assistants to reach more participators. Semidefinite Programming (SDP) based global optimization approaches are proposed to leverage all the location and ranging measurements in a best-effort way. We conduct extensive experiments and simulations in various scenarios. Compared with other classic algorithms, our proposed approach achieves significant accuracy improvement and could locate the "unlocalizable" child.**

***Keywords*-Mobile Crowd Sensing; Finding; Localization;**

I. Introduction

Losing their beloved child is the worst nightmare for every parent. Sometimes after you turn around for just a few seconds, your child is gone when you turn back. If you are at home or some less-crowded small regions, you probably can find your child in some corners or immediate vicinities. But for public areas, like shopping malls, streets, or even your child's favorite Disney World, it is hard to find your child in crowds when lost.

There are so many reasons for your child to get distracted and wander, then lost. In places like Disney theme parks, there is simply so much to see, and so many people attended, especially for events like fast paced parades. Even if your child don't typically wander, kidnapping could happen, making it even harder to find your child. Guarding child in crowded places full of attraction is nontrivial; locating your lost child is mission impossible.

To find your child quickly if you are separated, lots of systems and approaches have been developed. One kind approach is using GPS locator that installed on your child's shoes or clothes, e.g., Amber Alert GPS, PocketFinder, AT&T Family Locator [1]. This kind of device includes GPS and Cellular communication module. If you are separated with your little princess, you could obtain the location updates from this locator and get reunited. One problem for this kind locator is high cost and bulky. GPS and cellular communication are all expensive and power hungry, especially when it works in continuous mode. Providing sufficient battery life for one day use could result in a bulky and heavy device, and not suitable for little kids to carry. For indoor places like castles and shopping malls, GPS may suffer significant performance degradation or even not work due to the signal blockage. For crowded places, the accuracy of current GPS in tens of meters is still hard for parents to pinpoint their children.

Another category of approaches relies on devices with peer-to-peer communication capabilities. The transmitter and receiver pair are carried by parents and child, respectively. If the child goes out of the communication range or pre-determined threshold, parents will get an alert. This kind of approaches leverages the existing low-power communication standard and could be made with high efficient in power and portable in size, e.g., Toddler Tag Child Locator. Newly developed peripherals using Bluetooth Low Energy (BLE) devices that could direct communicate with users' smartphone without additional hardware attachment, e.g., Keeper 4.0, Chipolo [2]. It is convenient for users to use their personal smartphones to locate the BLE peripherals attached in their child's clothing or shoes. The energy efficiency and miniaturization of BLE peripherals make it perfect for tacking the child continuously without significant degradation of the battery life of parents' smartphones. A drawback of this approach lies in its lacking absolute location information, e.g., GPS location. It is impossible for parents to locate their child when the child goes out of the communication range.

In this paper, we propose system solutions for locating the lost child using low-power BLE peripheral via mobile crowd sensing. We focus on the investigation of the smartphone and BLE tag (peripheral) for continuous tracking and locating via transparent peer collaboration. Instead of just relying on the connection information, we propose approaches to derive the absolute location of the BLE tag even with no sufficient measurements from the immediate surroundings. Leveraging the low-power and portable feature of the BLE tag, parents could place one tag to their beloved ones, and paired with their smartphone. If the child goes outside of the warning threshold, the smartphone could wake up automatically and post alert immediately to prevent the child lost. If the child is already lost, our developed App "FindingNemo" installed

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in nearby users' smartphones could receive notifications when the "lost" child is passing or near by. To localize the child, opportunistic communication and ranging is performed with nearby peers w/o GPS location in a transparent way without disturbing the users. Depending on the available measurements, one-hop or multi-hop configuration is automatically selected for the best-effort localization. To prevent the algorithm from converging to the local optimality under unreliable crowd sensed measurements, we introduce semidefinite relaxation to convert the initial problem into a *convex* problem. The global optimal solution can be ensured by using the semidefinite programming (SDP) to jointly estimate the "lost" child and nearby mobile phone locations. We introduce *virtual anchor* from participators with better measurements, and utilize this "anchor" location to assist the localization of the true target, i.e., BLE tag on a child. Detailed simulation and experimental results are presented to evaluate the performance.

II. System Overview

A. Design Considerations

Despite substantial research on the localization, why is locating the child still an unsolved problem? The popularity of GPS-enabled devices and smartphones making us think locating any object as granted. While we have been somewhat surprised and exhausted that when we cannot locate our beloved ones in any ways. When the GPS and Cellular communication enabled devices are not cost-effective and prevalent. Tracking any objects without bulky devices and Cellular subscription fee is impossible. Tiny devices based on peer-to-peer communication, e.g., BLE, Zigbee, WiFi, cannot obtain location information without infrastructure or fingerprinting data from site survey.

From literatures, most papers on the localization have attempted to solve this problem in terms of accuracy improvement under specific settings, i.e., w/o infrastructure. Both settings have their distinct drawbacks, especially when the measurement comes from various unreliable sources. Solutions using acoustic anchors [3] could achieve centimeter-level resolution with low-cost, but only works in small areas with infrastructure. For real cases without infrastructure, the central server even cannot collect sufficient measurements, not to say perform localization via trilateration. Fingerprinting based approaches [4], [5] cannot work without site survey, and suffer the problem of collecting RSS fingerprinting data when the child is already lost. Liu et. al [6], proposes location optimization approaches via peer-to-peer ranging without infrastructure. However, this approach requires initial location from GPS module, which does not exist in our application.

Why not giving kids GPS-enabled smartphones for lost prevention? For most cases, GPS-enabled smartphones with Cellular subscription are expensive. Even if you can purchase one for your child, it is not practical for every family members including your pets. Current smartphone is still bulky for embedding in your kid's clothing or shoes. Your child may not be old enough to carry or cannot perform correct operations when they got lost.

Why use BLE tags, what about other devices? BLE seems becoming the most promising solution for connecting peripherals to your smartphone with low-cost and high energy efficiency. WiFi or Cellular solutions are too heavy for low data-rate applications. Zigbee and RFID are also low-cost solutions, but not popular in current smartphones.

Why need crowd sensing, what's the incentive for people participating in lost finding? For locating the lost child in crowds without infrastructure and site survey, collect measurement data via nearby ubiquitous sensor-rich smartphones becomes a flexible and cost-effective solution. The powerful computing/communication capacities of nearby smartphones, huge population in crowds, and the inherent mobility makes Mobile Crowd Sensing (MCS) a fast-growing consumer-centric sensing paradigm.

Incentive mechanism design is one of the key components in MCS. Participatory sensing should be performed in a transparent, energy and privacy preserving way, otherwise users are reluctant to release sensor data. We propose solutions for the background processing of sensory data only for a limited time period. The uploaded data from smartphone utilizes pseudo-ID that is irrelevant to users' personal identification. Moreover, helping others locating the lost child earns "credit", which you can spend when you need crowd sensing services in the future. This could be a beneficial environment for locating the child, and in turn provides incentives for participation.

Why need multi-hops and opportunistic connection? We cannot assume that there are enough participators nearby with sufficient measurements, e.g., GPS location and ranging results. To enable target localization in real cases, we need to leverage multiple sources and perform opportunistic connection. One-hop or multi-hop assistance could make the target localizable and provide sufficient performance improvement.

B. System Design

Fig. 1 shows the key building blocks and connections underlying the "FindingNemo" system for kids or other family members including pets. The overall "FindingNemo" system has three main modules, namely: (1) BLE Tag installed on child's belongings, (2) Smartphone App running in background, and (3) Cloud server for aggregating all the crowd sensed measurements and performing global location optimization.

BLE Tag. BLE peripherals enjoys substantial growth over past three years, since the launch of the iPhone 4S in 2001, which is the first smartphone that natively support BLE technology. The recent launch of the *iBeacon* by Apple, even made for *iBeacon* certificate, further promotes the prosperity of BLE peripheral devices. Even the new category

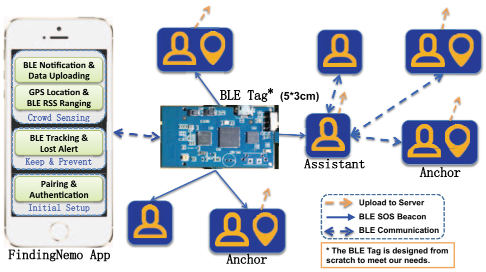


Figure 1. System architecture.

of *Smartwatch*, e.g., Samsung Gear, could be acted as a BLE tag for locating the child. Using ubiquitous hardware for MCS lowers the barriers of participants.

We also designed a BLE tag from scratch as shown in Fig. 1 that dedicated for child or family member tracking and locating with additional features like low-cost, portable, auto-sleep, privacy-preserving, and secure pairing and authentication.

FindingNemo App. The FindingNemo App continuously tracks the BLE tag even in sleep mode with low-duty-cycle for better energy efficiency. If the feedback signal from BLE tag is lost for a period of time, the App will be launched to the front and the "lost" alert will be sent to the user. Performing background BLE scan and tracking in an App is lightweight. The latest version of iOS can handle this process via the OS, a.k.a., through iBeacon API. Even the App is switched off from the background, the OS could still launch the App automatically when the BLE notification is received. The native support from modern mobile OS provides an essential reason for using BLE for child tracking.

The participators have their own choice of involvement. They can choose to allow GPS localization assistance, or only allow BLE communication assistance. As shown in Fig. 1, the users with "location" icon means the GPS location is available for this participator, a.k.a., Anchor. Other users without "location" icon could participate via BLE communication and ranging. We assume all the participators have internet connection, and they could upload their sensed information to the central server.

Cloud Server. Due to the inconsistent, error-prone, and opportunistic feature of crowd sensing, one central cloud server for optimizing all the available measurements is necessary. Most algorithms proposed in this paper run on this cloud server. The cloud server consists of the pub/sub messaging module Kafka, the stream processing module (Storm), and the persistent datastore with efficient writing/reading and flexible query mechanisms Cassandra [7]–[9].

III. Mobile Crowd Sensing via Semidefinite Programming

A. Definitions and Models

Early Prevention via BLE Ranging. If no child or any family member is lost, the locations of parents and other participators are all unknown for privacy concerns. The BLE tag broadcasts its unique UUID via BLE broadcast channel. The parents' paired smartphone continuously scans and recognizes this UUID, and extracts the received-signal-strength (RSS) as the closeness indication.

When the App lost the "heart beat" of the tracked BLE tag, i.e., the RSS value is below than the pre-defined threshold or completely lost, the FindingNemo App will send notification to parents. If parents could not find or locate their child in the physical surroundings, they could request crowd sensing and locating their lost child via the App. The cloud server will launch this task and start receiving reports and measurements from potential participators.

Smartphone and BLE Tag Location. The location from the GPS module of a smartphone is at Geodetic coordinates (latitude ϕ, longitude λ, height h), e.g., WGS 84 datum. To convert the Geodetic coordinates to the *navigation* coordinate, we first convert it to the earth-centered earth-fixed (ECEF) coordinate, then convert the ECEF to ENU frame via the formula in [6]. By subtracting the reference point O_R, the GPS location is mapped to the *navigation* coordinate (n-frame) for more intuitive and practical analysis.

Assume the position of the BLE tag in the n-frame is $\mathbf{y}^n \in \mathbb{R}^d$, i.e., 2-D coordinate ($d = 2$) of $\mathbf{y}^n$. For notation simplicity, we refer $\mathbf{y} = [x, y]^T$ as $\mathbf{y}^n$ in the navigation coordinate without the superscript.

When the child is lost, the BLE tag will broadcast the BLE beacon in "SOS" mode with the communication range as R_B. Assume the nearby m-th participator within the range R_B is a_m, where m is the index number in total M participators. The location of the m-th participator (a.k.a, the smartphone's location) are denoted as $\mathbf{x}_m \in \mathbb{R}^d$. For most of the cases, the dimension could be simplified as $d = 2$, thus each element of $\mathbf{x}_m$ is a 2-D coordinate as $[x_m, y_m]^T$, $m = 1, \ldots, M$. The location of other participators $\mathbf{x}_m$ is unknown for most cases. If the participator allows the App to access the GPS location, then $\mathbf{x}_m$ could be estimated by the GPS result as $\hat{\mathbf{x}}_m$, with the total number as M_a. Since the GPS module is power hungry, and computationally heavier than the BLE communication, we could not require every participators to open their GPS location. Thus, the location of m-th participator is denoted as $\hat{\mathbf{x}}_m$ only if available, and the set of GPS-enabled participators are defined as a subset of $\mathbb{R}^d$ as $\mathbb{R}^d_a$.

Localization Problem Formulation. The objective of finding the lost child via crowd sensing is to estimate $\mathbf{y}$ if the BLE tag goes out of the range of parents' smartphone. Since the BLE tag only equipped with radio communication, the estimation of $\mathbf{y}$ without anchor deployment is challenging. The measurements available are the BLE RSS distance measure and the GPS location available in the subset of participators $\mathbb{R}^d$. Denote the BLE RSS ranging to the m-th participators as $\hat{\mathrm{r}}_m$, where r_m denotes the ground truth distance. Each element of r_m is r_m, from the BLE Tag to the m-th participator, can be written as $r_m = ||\mathbf{y} - \mathbf{x}_m||_2$, where $||\cdot||_2$ calculates the 2-norm and obtains the Euclidean distance. Then, the distance measure from the m-th participator can be written as

$$\hat{\mathrm{r}}_m = ||\mathbf{y} - \mathbf{x}_m||_2 + \delta_m + n_m \tag{1}$$

where δ_m is the drift or bias for the BLE tag and smartphone ranging pair, n_m is the measurement noise. Since r_m should be non-negative, we use $\hat{\mathrm{r}}_m = |\hat{\mathrm{r}}_m|$ to prevent the negative value due to the noise. We define the unknown parameter vector as $\theta = [\mathbf{y}]^T$. The localization process is to estimate θ by using approaches like Bayesian or Maximum-Likelihood (ML) estimation techniques.

The result of ML can be achieved by searching over possible parameters that maximize the log-likelihood. For noise distribution with zero mean and a known covariance matrix, the ML solution can be simplified as

$$\hat{\theta}_{ML} = \arg\min_{\theta} (\hat{\mathbf{r}} - \mathbf{f}(\theta))^T \mathbf{\Sigma}^{-1} (\hat{\mathbf{r}} - \mathbf{f}(\theta)) \tag{2}$$

where $(\hat{\mathbf{r}} - \mathbf{f}(\theta))$ represents the estimation error, and $\mathbf{\Sigma}^{-1}$ can be represented as the weighting coefficient for each independent measurement. (2) is also the form of a non-linear least-squares (NLS) estimator. The steepest descent, Gauss-Newton and Taylor series based method can be used to solve the problem. These kinds of methods require a good initial value in calculation to avoid converging to the local minima of (2), or need to calculate the computational complex of the matrix inverse operation [10].

B. Locating the Target via Multi-hop Participants

For locating the child via crowd sensing, the available measurements from nearby participants are not sufficient for the normal localization process in (2). For 2-d coordinates, the number of participants with GPS location should be $M_p \geq 3$ for localization, a.k.a., trilateration. Since the BLE communication only covers limited areas, the available participants with GPS location may not meet this requirement. For the extreme cases, if none of the participants allows releasing GPS location, the lost child could never be located. How to locate the child with insufficient measurements poses a stringent challenge.

One possible solution is using multiple hops of communication and connection to cover more participants. Specifically, if the immediate surroundings of the BLE tag does not have enough participants with location information, relying on the participants' nearby as one-hop could provide a higher probability of location access. More hops could be involved for better localization probability. Using one-hop via m'-th participant as an example, the accessible participants with locations for the m'-th participant can be denoted as $a_{m',n}$, where $n = 1, \cdots, N_a$. The available location measurements in these N_a participants is included in vector $\mathbf{x}_{m',n}$. Among all these second-hop participants, the set of participants with GPS location can be written as $\mathbb{R}^d_{a,m'}$. Thus the measurement model can be rewritten as

$$\begin{aligned} \hat{\mathrm{r}}_m - ||\mathbf{y} - \mathbf{x}_m||_2 &= \delta_m + n_m, \quad m \in \mathbb{R}^d_a \\ \hat{\mathrm{r}}_{m'} - ||\mathbf{y} - \mathbf{x}_{m'}||_2 &= \delta_{m'} + n_{m'}, \quad m' \notin \mathbb{R}^d_a, m' \in \mathbb{R}^d \\ \hat{\mathrm{r}}_{m',n} - ||\mathbf{x}_{m'} - \mathbf{x}_{m',n}||_2 &= \delta_{m',n} + n_{m',n}, \quad n \in \mathbb{R}^d_{a,m'} \end{aligned} \tag{3}$$

where the second added equation in (3) means the ranging between the BLE tag and the m'-th participant that does not contain GPS location; the third added equation means the ranging measurements between the m'-th participant and its own nearby accessed participants with locations. Through this one-hop via $a_{m'}$, more location-enabled participants are available, the probability of locating the target $\mathbf{y}$ is increased.

Denote the residue vector in (3) as $\varepsilon_m = [\delta_m + n_m, \cdots]$, $\varepsilon_{m'} = [\delta_{m'} + n_{m'}, \cdots]$, and $\varepsilon_{m',n} = [\delta_{m',n} + n_{m',n}, \cdots]$, respectively. We define ε as a summation of $\varepsilon = [\varepsilon_m, \varepsilon_{m'}, \varepsilon_{m',n}]$. The vector of unknown parameter is $\theta = [\mathbf{y}, \mathbf{x}_{m'}]$. The Maximum Likelihood (ML) estimate of θ is

$$\hat{\theta}_{ML} = \arg\min_{\theta} (\sum_{\forall m, m', (m',n)} \varepsilon^2) \tag{4}$$

The solution $\hat{\theta}_{ML}$ of (4) is optimal in the ML sense with constraints in (3). However, the ML optimization problem in (4) is highly nonlinear, nonconvex and hard to solve.

C. Problem Formulation for Semidefinite Programming

Least squares (LS) based methods are often used to obtain approximate solutions of ML by linearizing the initial *non-linear* problem. Due to the implicit assumption of Gaussian noise during approximation, and the requirement of good initial values to ensure convergence, LS based approaches can only achieve local optimal solutions and are typically sensitive to large errors.

For problems of using unreliable and insufficient crowd sensing results, convert the nonconvex problem (4) into convex one via Semidefinite Programming (SDP) is a feasible approach to approximate the initial ML solution. Compared with optimal results, SDP approach has been demonstrated to have a tight bound with the initial *non-convex* problem and tend to achieve global optimal results [11]. Our approach is to use semidefinite relaxation to convert the initial localization problem (4) into a convex problem, and jointly estimates the target $\mathbf{y}$ and nearby mobile phone positions $\mathbf{x}_{m'}$ by leveraging multi-hop measurements.

Instead of using the square errors in (4), we can modify the problem formulation before SDP relaxation. Using the first equation in (3) as an example, we can rewrite it into $\hat{\mathrm{r}}_m = ||\mathbf{y} - \mathbf{x}_m||_2 + \varepsilon_m$. Perform square operation in both sides will lead to $\hat{\mathrm{r}}_m^2 = (||\mathbf{y} - \mathbf{x}_m||_2 + \varepsilon_m)^2$, where the right side is $||\mathbf{y} - \mathbf{x}_m||_2^2 + 2{\varepsilon_m}^T||\mathbf{y} - \mathbf{x}_m||_2 + {\varepsilon_m}^T\varepsilon_m$. ε_m is the variance vector of the ranging error. Assume ranging measurements are independent, we will have ${\varepsilon_m}^T\varepsilon_m = 0$; $2\varepsilon_m||\mathbf{y} - \mathbf{x}_m||_2$ will be the new noise term as ε'. Thus, for all three equations in (3), (4) can be rewritten as

$$\mathbf{y} = \arg\min_{\mathbf{y}} \max_{m,m'} \underbrace{\left\{\left|||\mathbf{y} - \mathbf{x}_m||_2^2 - \hat{\mathrm{r}}_m^2\right| + \left|||\mathbf{y} - \mathbf{x}_{m'}||_2^2 - \hat{\mathrm{r}}_{m'}^2\right|\right\}}_{\xi_1} + \arg\min_{\mathbf{y}} \max_{m',n} \underbrace{\left|||\mathbf{x}_{m'} - \mathbf{x}_{m',n}||_2^2 - \hat{\mathrm{r}}_{m',n}^2\right|}_{\xi_2} \tag{5}$$

(5) calculates $\mathbf{y}$ by minimizing the maximum residual error, where the $\sum$ in (4) becomes $\max$ operation, i.e., using *minimax* approximation. Among existing relaxation criteria, *minimax* approximation and semidefinite relaxation can find the global minimum value without the "inside convex hull" requirement [12].

D. Location Optimization via Semidefinite Programming

The objective function in (5) can be converted to minimize ϵ at the constraint of an inequality expression $-\epsilon < \xi_1 + \xi_2 < \epsilon$, while ξ_1 and ξ_2 are the residual error in (5) for the first and second term.

The term $||\mathbf{y} - \mathbf{x}_m||_2^2$ in ξ_1 of (5) can be written into a matrix form of

$$\begin{aligned} ||\mathbf{y} - \mathbf{x}_m||_2^2 &= \begin{bmatrix} \mathbf{y}^T & 1 \end{bmatrix} \begin{bmatrix} \mathbf{I}_d & -\mathbf{x}_m \\ -\mathbf{x}_m^T & \mathbf{x}_m^T\mathbf{x}_m \end{bmatrix} \begin{bmatrix} \mathbf{y} \\ 1 \end{bmatrix} \\ &= \mathrm{tr}\left\{ \begin{bmatrix} \mathbf{y} \\ 1 \end{bmatrix} \begin{bmatrix} \mathbf{y}^T & 1 \end{bmatrix} \begin{bmatrix} \mathbf{I}_d & -\mathbf{x}_m \\ -\mathbf{x}_m^T & \mathbf{x}_m^T\mathbf{x}_m \end{bmatrix} \right\} \\ &= \mathrm{tr}\left\{ \begin{bmatrix} \mathbf{Y} & \mathbf{y} \\ \mathbf{y}^T & 1 \end{bmatrix} \begin{bmatrix} \mathbf{I}_d & -\mathbf{x}_m \\ -\mathbf{x}_m^T & \mathbf{x}_m^T\mathbf{x}_m \end{bmatrix} \right\} \end{aligned} \tag{6}$$

where $\mathbf{Y} = \mathbf{y}^T\mathbf{y}$, $\mathrm{tr}\{\cdot\}$ calculates the trace of the matrix, $\mathbf{I}_d$ is an identity matrix of order d. From step 1 to step 2 in (6), we utilized the property of matrix trace $\mathrm{tr}\{\mathbf{x}\mathbf{x}^T\mathbf{A}\} = \mathbf{x}^T\mathbf{A}\mathbf{x}$.

Using the same process in (6), $||\mathbf{x}_{m'} - \mathbf{x}_{m',n}||_2^2$ in ξ_2 of (5) can be written into

$$\begin{aligned} &||\mathbf{x}_{m'} - \mathbf{x}_{m',n}||_2^2 = (\mathbf{x}_{m'} - \mathbf{x}_{m',n})^T(\mathbf{x}_{m'} - \mathbf{x}_{m',n}) \\ &= \begin{bmatrix} \mathbf{0}_{1\times d} & 1 & -1 \end{bmatrix} \begin{bmatrix} \mathbf{I}_d & \mathbf{x}_{m'} & \mathbf{x}_{m',n} \\ \mathbf{x}_{m'}^T & \mathbf{Y}_{m'} & \mathbf{Y}_{m',n} \\ \mathbf{x}_{m',n}^T & \mathbf{Y}_{n,m'} & \mathbf{Y}_{n,n} \end{bmatrix} \begin{bmatrix} \mathbf{0}_{d\times 1} \\ 1 \\ -1 \end{bmatrix} \\ &= \mathrm{tr}\left\{ \begin{bmatrix} \mathbf{0}_{d\times 1} \\ 1 \\ -1 \end{bmatrix} \begin{bmatrix} \mathbf{0}_{d\times 1} \\ 1 \\ -1 \end{bmatrix}^T \begin{bmatrix} \mathbf{I}_d & \mathbf{x}_{m'} & \mathbf{x}_{m',n} \\ \mathbf{x}_{m'}^T & \mathbf{Y}_{m'} & \mathbf{Y}_{m',n} \\ \mathbf{x}_{m',n}^T & \mathbf{Y}_{n,m'} & \mathbf{Y}_{n,n} \end{bmatrix} \right\} \\ &= \mathbf{Y}_{m'} - \mathbf{Y}_{m',n} - \mathbf{Y}_{n,m'} + \mathbf{Y}_{n,n} \end{aligned} \tag{7}$$

where $\mathbf{Y}_{m'} = \mathbf{x}_{m'}^T\mathbf{x}_{m'}$, $\mathbf{Y}_{n,n} = \mathbf{x}_{m',n}^T\mathbf{x}_{m',n}$, $\mathbf{Y}_{m',n} = \mathbf{x}_{m'}^T\mathbf{x}_{m',n}$.

The form of (6) are convex, but the equality constraints of $\mathbf{Y} = \mathbf{y}^T\mathbf{y}$ are nonconvex. Using semidefinite relaxation, these equalities can be relaxed to inequality constraints of $\mathbf{Y} \succeq \mathbf{y}\mathbf{y}^T$. The matrix forms can be written as

$$\begin{bmatrix} \mathbf{Y} & \mathbf{y} \\ \mathbf{y}^T & 1 \end{bmatrix} \succeq 0 \tag{8}$$

where $\succeq$ means a positive definite (semidefinite) matrix, which is different from $\geq$.

For the constraint of (7), equality constraints of $\mathbf{Y}_{m'} = \mathbf{x}_{m'}^T\mathbf{x}_{m'}$, $\mathbf{Y}_{n,n} = \mathbf{x}_{m',n}^T\mathbf{x}_{m',n}$, $\mathbf{Y}_{m',n} = \mathbf{x}_{m'}^T\mathbf{x}_{m',n}$ are nonconvex. In (7), $\mathbf{Y}_{m'}$, $\mathbf{Y}_{n,n}$ and $\mathbf{Y}_{m',n}$ are coupled together. Thus, the matrix form of the SDP relaxation for the constraint ξ_2 are

$$\begin{bmatrix} \mathbf{I}_d & \mathbf{x}_{m'} & \mathbf{x}_{m',n} \\ \mathbf{x}_{m'}^T & \mathbf{Y}_{m'} & \mathbf{Y}_{m',n} \\ \mathbf{x}_{m',n}^T & \mathbf{Y}_{n,m'} & \mathbf{Y}_{n,n} \end{bmatrix} \succeq 0 \tag{9}$$

Using the form of (6), (7), (8), and (9), the initial problem of (5) can be can be formulated to a semidefinite programming form. The unknown parameter vector could be summarized as $\theta = [\mathbf{y}, \mathbf{x}_{m'}, \mathbf{Y}_{m'}, \mathbf{Y}_{n,n}, \mathbf{Y}_{m',n}]$. (5) can be equivalently reformulated as

$$\begin{aligned} &\min\nolimits_\theta \epsilon \\ \text{s.t.} \quad &-\epsilon < \mathrm{tr}\left\{ \begin{bmatrix} \mathbf{Y} & \mathbf{y} \\ \mathbf{y}^T & 1 \end{bmatrix} \begin{bmatrix} \mathbf{I}_d & -\mathbf{x}_m \\ -\mathbf{x}_m^T & \mathbf{x}_m^T\mathbf{x}_m \end{bmatrix} \right\} - \hat{\mathrm{r}}_m^2 < \epsilon, \\ &-\epsilon < \mathrm{tr}\left\{ \begin{bmatrix} \mathbf{Y} & \mathbf{y} \\ \mathbf{y}^T & 1 \end{bmatrix} \begin{bmatrix} \mathbf{I}_d & -\mathbf{x}_{m'} \\ -\mathbf{x}_{m'}^T & \mathbf{x}_{m'}^T\mathbf{x}_{m'} \end{bmatrix} \right\} - \hat{\mathrm{r}}_{m'}^2 < \epsilon, \\ &-\epsilon < \mathbf{Y}_{m'} - \mathbf{Y}_{m',n} - \mathbf{Y}_{n,m'} + \mathbf{Y}_{n,n} - \hat{\mathrm{r}}_{m',n}^2 < \epsilon \\ &\begin{bmatrix} \mathbf{Y} & \mathbf{y} \\ \mathbf{y}^T & 1 \end{bmatrix} \succeq 0, \quad \begin{bmatrix} \mathbf{I}_d & \mathbf{x}_{m'} & \mathbf{x}_{m',n} \\ \mathbf{x}_{m'}^T & \mathbf{Y}_{m'} & \mathbf{Y}_{m',n} \\ \mathbf{x}_{m',n}^T & \mathbf{Y}_{n,m'} & \mathbf{Y}_{n,n} \end{bmatrix} \succeq 0 \end{aligned} \tag{10}$$

where $m \in \mathbb{R}_a^d$, $m' \in \mathbb{R}^d \cap \bar{\mathbb{R}}_a^d$ and $n \in \mathbb{R}_{a,m'}^d$. The location of the BLE tag $\mathbf{y}$ can be extracted from the optimal solution of $\theta = [\mathbf{y}, \mathbf{x}_{m'}, \mathbf{Y}_{m'}, \mathbf{Y}_{n,n}, \mathbf{Y}_{m',n}]$. The SDP problem can be solved by some standard convex optimization packages, e.g., SeDuMi and CVX package [13].

IV. Further Refinement via Virtual Anchor

Most of the existing literature on SDP-based location optimization focus on cases where the ranging measurements are sufficient for trilateration ($M_a \geq 3$), but with some slight perturbations, i.e., using zero-mean Gaussian noise to represent the ranging error. For crowd sensing based applications, significant portions of measurements are missing and cannot meet the minimum requirement of trilateration.

A. Cases of Insufficient Measurements

For one extreme case, if the participators with GPS location near the lost child is zero, then it is unable to obtain the location $\mathbf{y}$ via conventional approaches. This case can be denoted as $\mathbb{R}_a^d = \emptyset$, and the first constraint in (10) cannot be used. If there are no participator $a_{m'}$ in $\mathbb{R}^d$ that accessed GPS-enabled participators, i.e., $\mathbb{R}_{a,m'}^d = \emptyset$, $\mathbf{y}$ via (10) is unsolvable. Only when $M_a + N_a \geq 1$, $\mathbf{y}$ could be located. Here we focus on the case of $M_a + N_a \geq 1$, and improve the location accuracy.

Different value of M_a. If $M_a = 0$, the BLE Tag is only localizable via participator $a_{m'}$, that has $N_a \geq 1$. In (10), only the measurements $\hat{r}_{m',n}$ and $\hat{r}_{m'}$ are actually utilized.

The lowest resolution case is $N_a = 1$, assume x_{m',n_1} has location available with accuracy as σ_{m',n_1}^{GPS}. Then the achievable accuracy of $\mathbf{y}$ is in the order of

$$\sigma^{\mathbf{y}} = \sigma_{m',n_1}^{GPS} + \hat{r}_{m',n_1} + \sigma_{m',n_1}^{r} + \hat{r}_{m'} + \sigma_{m'}^{r} \tag{11}$$

where σ_{m',n_1}^{r},$\sigma_{m'}^{r}$ is the ranging accuracy between $a_{m'}$ and a_{m',n_1}, y and $a_{m'}$, respectively. Through this one-hop cooperation via $a_{m'}$, we could locate $\mathbf{y}$. However, the accuracy of (11) is very high, and not sufficient for finding the lost child in crowds.

Increasing the number M_a, the accuracy of $\mathbf{y}$ could be significantly improved. When $M_a = 1$, the $\sigma^{\mathbf{y}}$ could be reduced to $\sigma^{\mathbf{y}} = \sigma_m^{GPS} + \hat{r}_m + \sigma_m^r$. When $M_a = 2$, the possible position of $\mathbf{y}$ are reduced to two spots, with the accuracy in each spot depends on $\sigma_m^{GPS} + \sigma_m^r$. When $M_a \geq 3$, $\mathbf{y}$ could be localized even without the one-hop assistance, where the accuracy depends on σ_m^{GPS} and σ_m^r.

Different value of N_a. If $N_a = 0$, there will be no benefit from using this one-hop assistance. If $0 < N_a < 3$, the performance improvement from this one-hop assistance is significant when M_a is insufficient for trilateration. If $N_a \geq 3$, $a_{m'}$ could be localized by trilateration that is more reliable, which could in turn provide performance improvement, especially for cases when $M_a < 3$.

B. Virtual Anchor Assistance

During the SDP optimization of (10), the location of $a_{m'}$ is used as an unknown parameter in θ as $\mathbf{x}_{m'}$. To utilize the feature that $\mathbf{x}_{m'}$ is accurate and reliable when $N_a \geq 3$, the estimated result of $\hat{\mathbf{x}}_{m'}$ from (10) could be used as a *virtual anchor* that optimize the location result of $\hat{\mathbf{y}}$, and obtain an optimized value of $\hat{\mathbf{y}}_{op}$.

After the process of (10), the obtained $\hat{\mathbf{x}}_{m'}$ could be used to construct a new vector of nearby anchor points as $\mathbf{z}_{m_a} = [\mathbf{x}_m \quad \hat{\mathbf{x}}_{m'}]$, where $m_a = 1, \cdots, M_a + 1$. The ranging measurement vector could be reconstructed as $\mathbf{r}_{m_a} = [\hat{\mathbf{r}}_m \quad ||\hat{\mathbf{y}} - \hat{\mathbf{x}}_{m'}||_2]$. Another step of optimization via the new constructed anchor vector $\mathbf{z}_{m_a}$ could be executed by relying on the minimization of residual error ϵ with the unknown parameter as $\theta = [\mathbf{y}_{op} \quad \mathbf{Y}_{op}]$, where $\mathbf{Y}_{op} = \mathbf{y}_{op}^T \mathbf{y}_{op}$. The constraint of this refinement could be written as

$$-\epsilon < \mathrm{tr}\left\{ \begin{bmatrix} \mathbf{Y}_{op} & \mathbf{y}_{op} \\ \mathbf{y}_{op}^T & 1 \end{bmatrix} \begin{bmatrix} \mathbf{I}_d & -\mathbf{z}_{m_a} \\ -\mathbf{z}_{m_a}^T & \mathbf{z}_{m_a}^T \mathbf{z}_{m_a} \end{bmatrix} \right\} - \mathrm{r}_{m_a}^2 < \epsilon \tag{12}$$

For some cases, the refined result of $\mathbf{y}_{op}$ may suffer performance degradation than the initial result of $\hat{\mathbf{y}}$ due to the large error of the *virtual anchor*. Thus, threshold based detection process needs to be applied to mitigate *virtual anchor* with low-confidence.

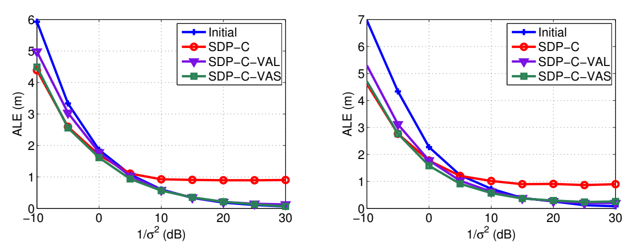
The whole process of using SDP optimization of (10) and *virtual anchor* for assistance is summarized in Algorithm 1, where σ_{th} and γ are the threshold for minimizing the side-effect of *virtual anchor*.

V. Evaluation

To illustrate the effectiveness of our proposed approach, we compare our proposed SDP-based Cooperative location optimization proposed in (10) ("SDP-C") with conventional LS-based approach ("Initial"). Approaches that using *virtual anchor* via LS and SDP are denoted as "SDP-C-VAL" and "SDP-C-VAS", respectively. We use average location error (ALE) as the performance metric. Simulation and experimental evaluation are conducted.

A. Simulation

Sufficient for trilateration. When the number of nearby participators with GPS location (anchors) is sufficient for trilateration, i.e., $M_a \geq 3$, we conduct simulation to evaluate the performance improvement contributed by the one-hop assistance. Fig. 2b shows the simulation results when the anchor error is added by $\sigma^2 = 2.25m$. In this case, the performance improvement contributed by the one-hop assistance is limited. Therefore, if $M_a \geq 3$, we could direct utilize the location of participators without leveraging multi-hops.



(a) No Anchor Error (b) With Anchor Error

Figure 2. Localization Accuracy via one-hop when $M_a = 3$ and $N_a = 3$ for cases (a) without anchor error; (b) with anchor error ($\sigma^2 = 2.25m$).

Insufficient for trilateration.

When the number of anchors near BLE tag is sufficient for trilateration, i.e., $M_a < 3$, the location of the BLE tag cannot be determined without ambiguity as the case of "Initial" shown in Fig. 3 and Fig. 4. No matter how accurate the

Algorithm 1: Locating the lost child via SDP and virtual anchor assistance.

input : The nearby set of participators $\mathbb{R}^d$, and the subset of participators with GPS location $\hat{\mathbf{x}}_m$ as $\mathbb{R}^d_a$

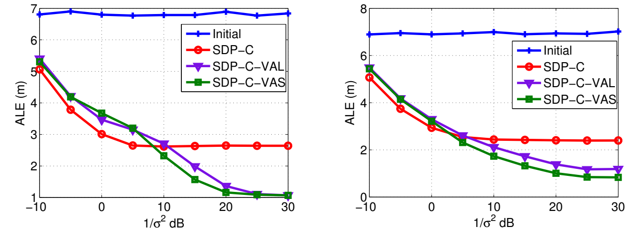
output: Estimated target location $\mathbf{y}$

while *The searching request is still effective* **do**
- **for** *every participator m that received the broadcast* **do**
  - calculate the ranging results $\hat{\mathbf{r}}_m$ from BLE RSS measurement ;
  - obtain the location $\hat{\mathbf{x}}_m$ for participators with GPS location as set $\mathbb{R}^d_a$ (total number is M_a) ;
  - **if** $M_a < 3$ **then**
    - **for** *every participators in $\mathbb{R}^d$* **do**
      - search $a_{m'}$, and obtain its nearby participators with GPS location ;
    - select $a_{m'}$ with largest N_a ;
    - obtain ranging measurements $\hat{\mathbf{r}}_m$, $\hat{\mathbf{r}}_{m'}$ and $\hat{\mathbf{r}}_{m',n}$ for all the participators in $\mathbb{R}^d$ and $\mathbb{R}^d_{a,m'}$;
    - perform SDP optimization via (10); obtain $\mathbf{y}$ and $\mathbf{x}_{m'}$;
    - **if** $N_a > 3$ **then**
      - using $\mathbf{x}_{m'}$ as a virtual anchor, construct new vector of anchors as $\mathbf{z}_{m_a}$;
      - estimate the new ranging vector as $\mathbf{r}_{m_a} = [\hat{\mathbf{r}}_m \quad ||\hat{\mathbf{y}} - \hat{\mathbf{x}}_{m'}||_2]$;
      - perform SDP optimization via the constraint of (12), and obtain $\mathbf{y}_{op}$;
      - leveraging historical information to estimate the variance of $\mathbf{y}_{op}$ and $\mathbf{x}_{m'}$ as $\sigma^{\mathbf{y}}$ and $\sigma_{m'}$;
      - **if** $\sigma^{\mathbf{y}} + \sigma_{m'} < \sigma_{th}$ & $||\mathbf{y}_{op} - \mathbf{y}||_2 < \gamma$ **then**
        - replace $\mathbf{y}$ with $\mathbf{y}_{op}$;
  - **else**
    - perform SDP optimization via (10) with constraints from $\hat{\mathbf{r}}_m$ only; obtain $\mathbf{y}$;

ranging result is, the accuracy shows no improvement due to the ambiguity in determining the location. After using one-hop assistance, the location of BLE tag could be determined and the accuracy improves with better ranging results.

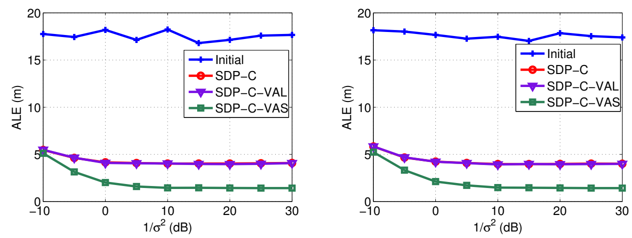
In Fig. 3, where $M_a = 2$ and $N_a = 3$, the performance improvement of our proposed SDP-based approaches over the "Initial" is significant. When $N_a = 3$, that the location estimation result for the assistant node is reliable, and it could be utilized as a *virtual anchor* for further performance improvement.

No virtual anchor available. When the number of accessed anchors of the assistant m' is $N_a < 3$, i.e., insufficient for trilateration. The performance improvement is only contributed by leveraging all the measurements in SDP optimization. Fig. 5 shows the localization accuracy under different cases via one-hop assistance with anchor location errors. The achieved improvement over "Initial" case is huge, and in turn demonstrates the effectiveness of SDP optimization even without *virtual anchor* assistance.



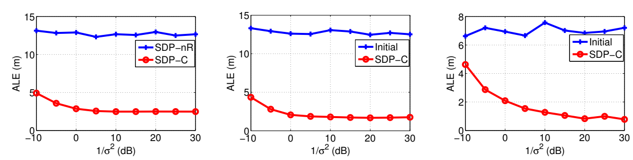
(a) No Anchor Error (b) With Anchor Error

Figure 3. Localization Accuracy via one-hop when $M_a = 2$ and $N_a = 3$ for cases (a) without anchor error; (b) with anchor error ($\sigma^2 = 2.25m$).



(a) No Anchor Error (b) With Anchor Error

Figure 4. Localization Accuracy via one-hop when $M_a = 1$ and $N_a = 3$ for cases (a) without anchor error; (b) with anchor error ($\sigma^2 = 2.25m$).



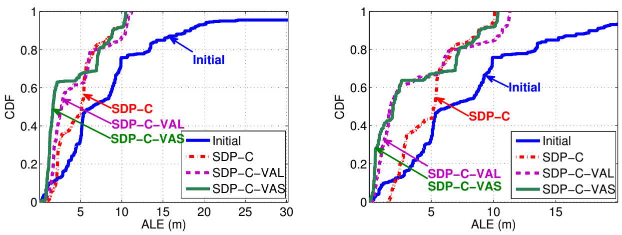
(a) $M_a = 1$, $N_a = 1$ (b) $M_a = 1$, $N_a = 2$ (c) $M_a = 2$, $N_a = 2$

Figure 5. Localization Accuracy via one-hop with anchor location error ($\sigma^2 = 2.25m$) for three cases.

B. Experiment

Similar to the configurations in simulation evaluation, we conduct experiment to evaluate the system performance with different connectivity of nearby participators. The BLE RSS ranging is performed similar to [6], where the accuracy is in the meter-level. The key problem of our proposed "FindingNemo" is relying on these inaccurate ranging results to localize the "unlocalizable" target, or solving the location ambiguity problem. Our goal is to achieve large accuracy improvement rather than struggling on slightly improve the ranging accuracy, since several meters of ranging difference does not matter too much when searching the child.

Sufficient for trilateration. When the number of nearby anchors is sufficient for trilateration, i.e., $M_a \geq 3$, the experimental results under different cases are shown in Fig. 6. Similar to the conclusion obtained in simulation, performance improvement under this case is minimal. But, it is still beneficial to utilize the one-hop assistance when $M_a \geq 3$. When the number of N_a is reduced from 6 to 3, the performance difference is not apparent when $N_a \geq 3$.

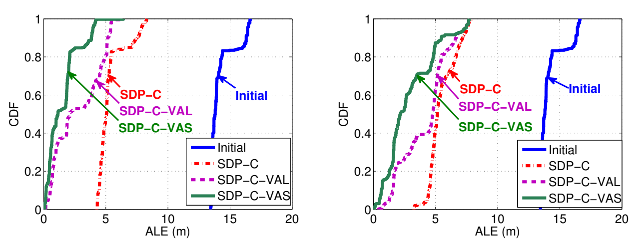


(a) $M_a = 3$, $N_a = 6$ (b) $M_a = 3$, $N_a = 3$

Figure 6. Experimental localization accuracy via one-hop for two cases.

Insufficient for trilateration. When $M_a < 3$, we cannot localize the BLE tag without ambiguity via conventional methods. In real applications of locating the lost child, M_a is actually small for most of the cases. Leveraging the multi-hop and SDP-based optimization, we could make the target localizable and dramatically reduce the location error.

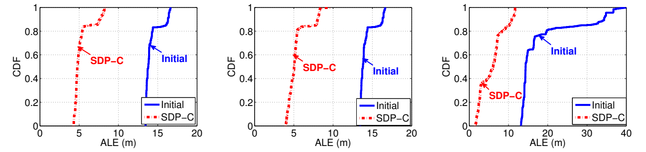
Fig. 7 shows the CDF of the ALE results when $M_a = 2$, $N_a = 3$ for different cases when the *virtual anchor* is utilized. The proposed "SDP-C-VAS" achieves best performance over most cases. Fig. 8 shows the CDF of the ALE results when $M_a = 2$, $N_a = 2$ for different cases, where the *virtual anchor* cannot be utilized. Even without *virtual anchor*, the performance improvement of using SDP optimization is still apparent.



(a) $M_a = 2$, $N_a = 3$ (b) $M_a = 2$, $N_a = 3$

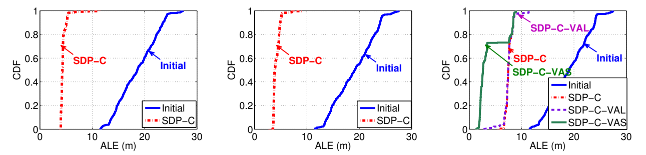
Figure 7. Experimental localization accuracy via one-hop for two cases.

When the number of accessed anchors M_a is reduced to 1, the error of "Initial" is very large as shown in Fig. 9. When the number of N_a increases from 1 to 3, we can clearly see the performance improvement of using one-hop assistance, especially when the *virtual anchor* can be utilized.



(a) $M_a = 2$, $N_a = 2$ (b) $M_a = 2$, $N_a = 2$ (c) $M_a = 2$, $N_a = 2$

Figure 8. Experimental localization accuracy via one-hop for three cases.



(a) $M_a = 1$, $N_a = 1$ (b) $M_a = 1$, $N_a = 2$ (c) $M_a = 1$, $N_a = 3$

Figure 9. Experimental localization accuracy via one-hop for three cases.

Table I
EXPERIMENTAL LOCALIZATION ACCURACY VIA ONE-HOP WHEN $M_a = 0$

	Initial	SDP-C (m)	SDP-C-VAL (m)	SDP-C-VAS (m)
$N_a = 6$	NaN	6.9105	6.9105	4.9471
$N_a = 3$	NaN	7.0643	7.0643	4.9710
$N_a = 2$	NaN	9.7185	9.7185	9.7185
$N_a = 1$	NaN	15.0772	15.0772	15.0772

When $M_a = 0$, the location of the target cannot be determined via "Initial", i.e., "NaN" for the ALE as shown in Table. I. When leveraging one-hop assistance, the target could be localized. Table. I shows the ALE results when change the number N_a from 6 to 1. Due to very limited measurements, the achieved accuracy around 15m to 4.9m is sufficient, and really helps when searching the child.

VI. Related Work

Crowd sensing is suitable for tasks that are hard, costly or infeasible to finish without collaboration [14], [15]. When extended to mobile areas, the sensor-rich personal smartphone becomes the central of future MCS applications. Unleashing the potential of large scale sensing, researchers propose solutions in terms system architecture, algorithm to enable various specific applications. For example, mCrowd [16] is a system architecture for continuously sensing with high energy efficiency; Authors in [17] balances the performance needs of the application and the resource demands of continuous sensing on the phone. Crowd sensing based applications are also emerging, e.g., authors in [18] developed an application to predict the bus arrival time with mobile phone based participatory sensing. Sensing the user's activity or surroundings via accelerometer, microphone and GPS sensors becomes a hot topic [19]–[21]. However, all these proposed sensing tasks are individual-based monitoring and loosely coupled between different participators.

Locating the lost child via MCS requires high coupling and collaboration between participators, in which the peer-to-peer measurements are key to the success and high accuracy of localization. Moreover, continuous sensing applications on smartphone is challenging because of the high resource demands and limited battery capacity. Our proposed approach leverages high efficient BLE notification for starting the sensing task, and lasts only a few seconds for demand-based transparent participation with low cost.

VII. Conclusion

The sensor-rich smartphones have become the most important personal computing companions, which bridge the virtual and physical world via sensing at scale. The ubiquitous availability and mobility, efficient computing and communication capacities, makes Mobile Crowd Sensing (MCS) a much more flexible and cost-effective solution than conventional static sensor/anchor networks. We design "FindingNemo" for family members via MCS. The application requirements, incentive schemes, and design considerations are elaborated. We propose SDP-based cooperative location optimization via one-hop or multi-hop assistance to cover more participators. The proposed solution could locate the "unlocalizable" target with location ambiguous, and significantly improve the location accuracy over conventional approaches. Further optimization via *virtual anchors* are proposed to leverage assistants with sufficient measurements for trilateration. The different configuration and accessibility of participators are analyzed via simulations and experiments, along with the comparison of performance improvement. The flexibility and accuracy of proposed approaches may boost the rapid emergence of a consumer-centric participatory MCS.

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