Improving GPS Service via Social Collaboration

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***Abstract*—The popularity of GPS-enabled smartphones enables a wide variety of new location-based or location-aware services and applications. However, the GPS module in a smartphone produces inaccurate position estimates and incurs high energy consumption, which inhibits the wide use of location-aware applications. To address this, we propose a social-aided cooperative location optimization (*Coloc*) scheme, which is capable of improving positioning accuracy and achieving low energy consumption. Specifically, our scheme enhances positioning accuracy by fusing the GPS positions of multiple co-located smartphones in a social network, or by neighborhood-based weighted least-squares estimation when relative distances between smartphones are available. The energy efficiency is achieved by sharing location information among co-located users and lower the update rate of the GPS module without sacrificing the accuracy. To validate our proposed approach, we conduct experiments in stationary and moving scenarios. Experimental results show that our proposed cooperative localization scheme can achieve sufficient performance gains in both indoor and outdoor environments.**

I. Introduction

Most new models of smartphones have built-in Global Positioning System (GPS) receivers. The GPS onboard enables a host of location-aware applications. According to a study published by the Pew Internet and American Life Project [1], more than 55% of smartphone owners use their phones to find directions, recommendations, or other information related to their present locations. In addition, geo-social "check in" services such as Foursquare or Gowalla are very popular among young adults [1]. New digital cameras or smartphones are equipped with geo-tagging features [2], making it easy to group photos by location or track the user's footprint.

Obtaining the GPS position information incurs a high cost; the whole process includes many complex calculations, e.g., correlation, demodulation, tracking, ranging and positioning. Moreover, satellite signals are hard to access especially in indoor and harsh environments due to the strong attenuation of the radio caused by building materials. The process of constantly searching and capturing the very weak beacon signal consumes a lot of power, and the estimated position is often inaccurate or even unavailable.

The rapid growth in people-centric mobile computing applications and location-based services has called for improved localization techniques. Energy-efficiency and accuracy are the two main objectives of such improvements. Authors in [3] [4] [5] have paid attention to tradeoff between energy and location accuracy. They try to use low power WiFi/GSM based schemes to lower the frequency of GPS startups, but at the expense of lower accuracy and update rates. Other approaches utilize dedicated devices for localization when GPS signal is unavailable. However, a lot of anchor nodes need to be placed at a very high density with known coordinates.

One compelling technique for improving the performance of localization is cooperative localization [6]. Cooperation among peer nodes at the physical layer can improve the communication capacity and coverage of wireless networks [7]. Recently, such a cooperation paradigm has been introduced for localization and navigation to improve the accuracy and reliability of positioning and circumvent the need for high-power infrastructure [8]. In this paradigm, it is assumed that devices can take intra- and inter-node ranging measurements in addition to measurements with respect to anchor nodes, since measurements with respect to anchor nodes only are insufficient for (accurate) positioning in harsh indoor/outdoor environments [9]. By exchanging the anchor node information and performing relative ranging between nodes, the position estimation for each node becomes possible and more accurate [10], [11].

However, existing cooperative localization techniques [7], [10], [11] require access to raw GPS ranging measurements. The GPS/WiFi position is the only information accessible by a user/application in a commercial smartpone. Therefore, the existing cooperative localization techniques [7], [10], [11] are not directly applicable to GPS-enabled smartphones. To deal with this inconvenience, authors [12], [13] propose practical approaches for optimizing the smartphone location results by leveraging the inter-node distance estimation. H. Liu et al. [12] maps users' locations jointly against WiFi signature map subjecting to ranging constraints, but show significant delay ($> 7s$) caused by ranging and WiFi scanning. Nandakumar et al. [13] utilizes the acoustic signal transmitted by desktop to assist the WiFi localization, however, the unconsideration of the mobile situation would limit their application in a smartphone.

In this paper, we propose cooperative location optimization (*Coloc*) scheme in a social network setting. Unlike conventional cooperative localization that utilizes physical-layer information fusion, our proposed social-aided location optimization performs data fusion at the application layer when coarse positions of smartphones are already known. Application-layer fusion can achieve practical performance improvement at a lower cost with minimum added complexity. The rationale is that when a group of people in a common location all carry smartphones with GPS capability,

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the accuracy of localization can be significantly improved by fusing the GPS positions of the smartphones in this group. Theoretically, this performance gain is ascribed to the law of large numbers and location diversity. Adjacent samples of GPS results have high correlation with limited new information, while the location from peers contributes to diversity gains. Thus, GPS update rate could be lowered as well as the power consumption without sacrificing the accuracy if peer-assisted information is available. For utilizing the ranging information, we derived the *necessary condition* and eliminate unnecessary ranging measurements. Two algorithms, i.e., sparse steepest descent optimization and polar optimization, are proposed to improve the overall location accuracy in a mobile environment. We want to emphasize that the driving force of cooperative localization is the fast-improving smartphone technology and people-centric pervasive social computing.

The rest of this paper is organized as follows. Section II summarizes our previous work on smartphone-based ranging, and related work on cooperative localization. Section III discusses our system design. Section IV describes mathematical models and the necessary condition for inter-node ranging. Section V presents the *Coloc* scheme for the case that relative distances between smartphones in a neighborhood are known. Section VI and Section VII present numerical results and experimental results, respectively. Section VIII concludes the paper.

II. Preliminary

A. Relative Ranging

In cooperative localization, the relative distances between peers are the additional information input to optimize the overall location accuracy. Realize relative ranging on a smartphone is crucial for *Coloc* scheme. Using acoustic time-of-arrival (TOA) based ranging has been demonstrated to have better accuracy than received-signal-strength (RSS) based ranging using WiFi/GSM/Bluetooth signals [12]–[15].

Transmitting simple acoustic beep and measure its flight delay is a practical way to implement the accurate ranging on a smartphone [12], [13]. However, using simple acoustic signal may cause the problem that there is no way to tell which smartphone emitted which signal, i.e., cause ambiguity due to using un-modulated signal. Resolving the problem by performing time-division multiple access and using radio signal for assistance would increase the overall delay, which is especially serious for the acoustic signal (low transmission speed), e.g., for N peers, total $N(N-1)/2$ relative distances need to be measured. For tracking users when they are walking around, sufficient ranging rate is required.

Based on our prior work [14], [15], we perform 2-PAM modulation for the acoustic signal and combine ranging and information bit transmission at the same time. With the information bits directly available in the ranging signal, we could identify the smartphone after signal demodulation. When one smartphone broadcasts its ranging beacon, other peers could all identify this beacon. Instead of performing transmit and reply for each ranging pair, we could achieve pair-wise ranging through one transmit and multiple replies. Thus, significant amount of time used in round-robin ranging could be reduced. Moreover, we apply cluster-based ranging approach to only estimate the user clusters with sufficient distance, i.e., the *necessary condition* for ranging presented in Section IV. Through this way, only several ranging measurements need to be performed, and the ranging delay could be minimized for tracking moving targets.

B. Related Work

Optimizing the GPS localization has a long way back to more than one decade; from improving the RF component design, signal processing, ranging and localization algorithm, to differential GPS system, and assisted-GPS [11], [16]. The recent exploration of the GPS-enabled smartphone and location-based services demonstrate the effectiveness and contribution of these approaches.

When smartphone becomes an important personal companions, researchers propose to use other auxiliary sensors embedded in a smartphone to improve the accuracy of GPS. Hybrid approaches have been proposed to balance the power and accuracy of GPS, e.g., using WiFi fingerprinting, or accelerometer [3], [5]. Authors in [17], [18] propose rate-adaptive approaches to balance the energy consumption and accuracy. Due to the inaccuracy of these auxiliary information, the performance improvement is not significant.

Recent approaches that using the microphone sensor in a smartphone for accurate ranging demonstrates a practical way for achieving accurate auxiliary measurements [12], [13]. H. Liu et al. [12] improved the accuracy of WiFi-based localization subjecting to ranging constraints. The problem is that the error of WiFi is even larger than the maximum ranging distance of the acoustic signal; the performance gains contributed by peer-wise ranging would be limited. The CDF results demonstrated in [12] only show improvement in overall error (most contributed by reduced bias), but the slope (determines the resolution) remains the same after their peer-assisted localization approach. Nandakumar et al. [13] utilized the acoustic signal transmitted by desktop to assist the WiFi localization, however, they do not consider the mobile situation, which would limit their application in real scenarios. These two approaches also suffer slow update time for the localization ($> 7s$) due to the time-divided multiple pair-wise ranging and the inherent low transmission speed of the acoustic signal. For N peers, total $N(N-1)/2$ ranging pairs need to be measured, and resulting at least $N(N-1)$ times acoustic signal transmission for two-way ranging mode. Reducing the ranging complexity and improve the performance gains of location optimization algorithm are the two key challenges.

III. System Design

Fig. 1 illustrates the *Coloc* system architecture and major functional components. In this section, we sketch an overview of the design consideration, then elaborate on some important components in the system.

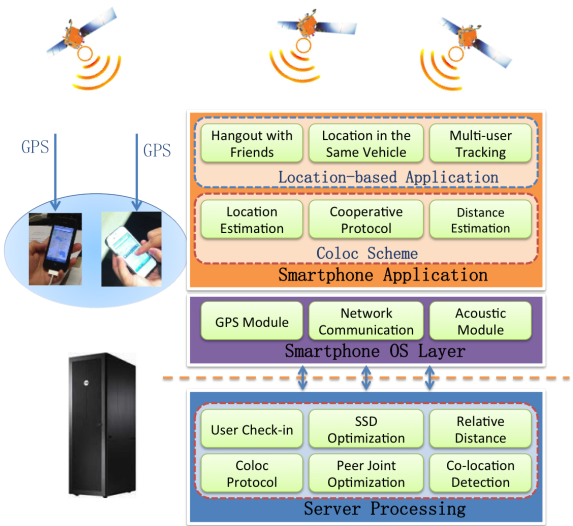


Fig. 1. System Architecture.

A. *Design Consideration*

In terms of accuracy, GPS is preferred over its alternatives, e.g., GSM/WiFi based approaches. However, GPS is extremely power hungry due to the inevitable complex computations. One possible way to provide accurate position information while spending minimal energy is to reduce the location update rate when the location information is less demanded. As the basic way to save energy, we also use reduced update rate for the GPS module, but we focus on balancing the GPS consumption to the network cost by applying the constraint that sufficient update rate is needed for tracking a moving target.

Using relative ranging information to improve the overall localization accuracy is the basic idea of our proposed *Coloc* scheme and [12], [13], the problem lies on how and when to utilize the ranging information. If the localization error surface of two peers is larger than their relative distance, the performance improvement contributed by this ranging measurement would be limited. Utilizing the ranging information when needed is essential in designing cooperative scheme for location optimization.

B. *Overview of the* Coloc *Scheme*

To realize *Coloc* scheme, we propose approaches for the smartphone to collect GPS data, report to the server and use the refined results calculated by the server. The *Coloc* scheme consists of the following three key components:

1) ***Coloc* Software Middleware in a Smartphone**:
Each smartphone obtains position by its own GPS receiver during the start-up period. Three basic modules in a smartphone are utilized: the GPS module for coarse location estimation; the network module for communicating with server; the acoustic module for peer detection and ranging. These three functionalities are realized by the software middleware in a smartphone. The cooperative process with peers is controlled by the pre-defined protocol. On top of the smartphone software middleware, cooperative location-based application are supported, e.g., recording or tagging GPS trajectories when hangout with friends; obtaining optimized location when multiple smartphones are in the same vehicle; tracking multi-users with high accuracy and reliability requirement.
2) **Server Processing for Position Optimization**:
The server receives all the GPS location information from all the users that checked-in our services. According to their coarse locations, users could be divided into groups, i.e., partition all the smartphones into groups. Only the users in the same group could cooperate with each other for location optimization, where the size of the group is by constrained by the maximum ranging distance. In each group we apply our *Coloc* scheme with relative ranging. Users in one group could also clustered into small clusters, where the size of the clusters could be determined by the GPS accuracy. Widely-used clustering algorithms include K-means, unnormalized spectral clustering, the G-cut algorithm, and the normalized cuts algorithm [19]. The reason that we perform clustering is that peer-to-peer ranging could be eliminated within one cluster to minimize the overall ranging cost and delay.
The server will send ranging coordination beacon to users for relative distance estimation. With all the information available, the server invokes the position optimization algorithm (i.e., neighborhood-based weighted least-squares estimation algorithm) to refine the position of each user by utilizing users' (coarse) GPS position information and the relative distances obtained in an iterative mode.
3) ***Coloc* Protocol**: *Coloc* protocol controls the ranging coordination in a round-robin manner for all the users in the current cluster. Not all the pairs of peers are need relative distance, only the peers meet the *necessary condition* should perform ranging, which reduces the overall cost and delay. The server also sends the refined position back to each smartphone by following the *Coloc* protocol; and each smartphone updates its position with the received value and controls the individual GPS update rate according to the desired accuracy.

IV. System Modeling and Necessary Condition

A. *Geo-Coordinate*

We consider a social network consisting of m collaborators in $\mathcal{R}^d$, where d is the coordinate dimension, i.e., $d = 3$ for ellipsoidal space; $d = 2$ for the cartesian space. Let $\mathcal{N}_g = 1, 2, \ldots, m$ denote the set of collaborators.

Assume the ground truth position of each collaborator is $\mathbf{p}_i$, $i \in \mathcal{N}_g$. With ellipsoidal coordinates, $\mathbf{p}_i$ can be written as a form of Ecliptic latitudes (radians), longitudes (radians) and heights (m), i.e., $\mathbf{p}_i = (lat_i, lon_i, h_i)^T$. To simplify the process, we can change the ellipsoidal coordinates to the cartesian coordinate under the standard of Geodetic Reference System 1980 (GRS80) by function $\mathbf{p}_i(x,y,z) = f_{ell}(\mathbf{p}_i(lat, lon, h))$ as

$$\begin{aligned} v &= a/\sqrt{(1-e(\sin(lat))^2)} \\ x &= (v+h)\cos(lat)\cos(lon) \\ y &= (v+h)\cos(lat)\sin(lon) \\ z &= (v(1-e)+h)\sin(lat) \end{aligned} \tag{1}$$

where a and e are the reference of ellipsoid major semi-axis and eccentricity squared parameters defined in GRS80.

For small-scale geographic space, we can focus on the 2D cartesian coordinate without the heights (h) information. By subtracting a pre-defined reference point $\mathbf{p}_{ref} = (x_f, y_f)^T$, a local coordinate obtained by the GPS module in smartphone is $\hat{\mathbf{p}}_i = \hat{\mathbf{p}}_i - \hat{\mathbf{p}}_{ref} = (\hat{x}_i, \hat{y}_i)^T, i \in \mathcal{N}_g$ for plane-coordinate. Without further justification, the locations of the smartphone used in the following analysis are the plane-coordinate that converted from the geo-coordinate.

B. Mathematical Modeling

The estimation error of the location can be written as $\mathbf{e}_i = |\hat{\mathbf{p}}_i - \mathbf{p}_i|$. Assuming that the position estimated is unbiased, $\mathbf{e}_i$ follows a zero-mean Gaussian distribution as $\mathbf{e}_i \sim \mathcal{N}(0, \mathbf{\Sigma}_i)$. So, the probability density function of $\hat{\mathbf{p}}_i$ can be written as

$$f(\hat{\mathbf{p}}_i) = \frac{1}{\sqrt{2\pi \det(\mathbf{\Sigma}_i)}} \exp\left(-\frac{\mathbf{D}^T\mathbf{\Sigma}_i^{-1}\mathbf{D}}{2}\right) \tag{2}$$

where $\mathbf{D} = (\hat{\mathbf{p}}_i - \mathbf{p}_i)$, and $\det(\mathbf{\Sigma}_i)$ calculates the determinant of $\mathbf{\Sigma}_i$. $\mathbf{\Sigma}_i$ is the error covariance matrix and is assumed to be a diagonal matrix with diagonal entries of $(\sigma_i^x)^2$ and $(\sigma_i^y)^2$. Then, the position matrix of each collaborator can be written as $\hat{\mathbf{P}} = [\hat{\mathbf{p}}_1 \quad \hat{\mathbf{p}}_2 \quad \ldots \quad \hat{\mathbf{p}}_m] \in \mathcal{R}^{d\times m}$.

The problem of social-aided cooperative localization can be modeled as to refine the estimated positions ($\hat{\mathbf{p}}_i$) obtained by GPS. The additional information that we utilize to optimize the accuracy of GPS position are the co-location or relative distances ($\mathbf{D}$) between collaborators.

For a pair of collaborators $\mathbf{p}_i$ and $\mathbf{p}_j$, their Euclidean distance can be denoted as $d_{ij} = ||\mathbf{p}_i - \mathbf{p}_j|| = \sqrt{(x_i-x_j)^2 + (y_i-y_j)^2}$, where $||\cdot||$ is the 2-norm of the vector. Considering the measurement error, the estimated distance between collaborators is the noised version of d_{ij} as $\hat{d}_{ij} = d_{ij} + n_{ij}$, where n_{ij} is a Gaussian noise component with $n_{ij} \sim \mathcal{N}(b_{ij}, \sigma_{ij}^2)$. The term of b_{ij} is a range bias induced by non-line-of-sight (NLOS) propagation, and $b_{ij} = 0$ when the measurement is in line-of-sight (LOS) condition. In real situations, the inter-node distance information is not fully available, i.e., some of the measurements are missing or unavailable. To deal with such condition, we define distance measurement matrix as $\mathbf{D} = \{d_{ij} : (i,j) \in \mathcal{N}_g\}$ with $d_{ij} = 0$ represents the unavailable measurements. The matrix $\mathbf{D}$ is a sparse matrix with sparse rate γ defined as the number of $d_{ij} = 0$ terms divided by the total number of $m(m-1)/2$.

Fisher information J (the reciprocal of CRLB) is often used as a metric to assess the accuracy of a particular position estimation. Hence, parameters to be estimated are the collaborator's refined position $\hat{\mathbf{p}}_k = (\hat{x}_k, \hat{y}_k)^T, k \in \mathcal{N}_g$ by using their initial position and relative distance. For notational convenience, we denote the unknown parameter as $\theta = [\hat{p}_k]$, where $1 \leq k \leq N_g$. Let $\hat{\theta}$ denotes an estimation of the parameter θ. The error covariance matrix of $\hat{\theta}$ satisfies Information Inequality as

$$\mathbb{E}_r\{(\hat{\theta}-\theta)(\hat{\theta}-\theta)^T\} \geq \mathbf{J}_\theta^{-1} \tag{3}$$

where $\mathbf{J}_\theta$ is the Fisher information matrix (FIM) of non-random parameter θ.

The joint likelihood ratio of the discrete random vector $\mathbf{r}$ of the received signal and random parameter θ can be shown as $f(\mathbf{r}, \theta) = f(\mathbf{r}|\theta) \cdot g(\theta)$, where $f(\mathbf{r}|\theta)$ is the conditional pdf, $g(\theta)$ is the a priori probability density function of θ. The generalized Fisher Information Matrix (FIM) for θ is given by

$$\mathbf{J}_\theta \triangleq \mathbb{E}_{\mathbf{r},\theta}\{[\frac{\partial}{\partial\theta} lnf(\mathbf{r},\theta)] \cdot [\frac{\partial}{\partial\theta} lnf(\mathbf{r},\theta)]^T\} \tag{4}$$

(4) can be further decomposed,

$$\mathbf{J}_\theta = \underbrace{\mathbf{J}_{f(\mathbf{r},\theta)|j=i}}_{\text{GPS position info}} + \underbrace{\mathbf{J}_{f(\mathbf{r},\theta)|j\neq i}}_{\text{Info. from cooperation}} + \underbrace{\mathbf{J}_{g(\theta)}}_{\text{Prior Infor.}} \tag{5}$$

where the first term indicates the position information from a collaborator using GPS; the second term indicates the inter-ranging information between collaborator i and j; and the third term denotes a priori information on θ.

From (5), we know that the cooperative localization contributes to the second term; the resulting FIM can be much better than conventional localization methods that just use a prior information and $j = i$ term. By using the initial GPS position result and inter-note information as prerequisite, perform post-decision optimization can obtain a more accurate position result $\hat{p}_k = (\hat{x}_k, \hat{y}_k)^T, k \in \mathcal{N}_g$.

C. Necessary Condition for Relative Ranging

Performing pair-wise ranging for large amount of peers may cause substantial energy consumption and delay. In reality, some of these ranging pairs are unnecessary or only contribute to limited performance improvement. Selecting the ranging pairs that are necessary could be an effective solution to balance the performance improvement and ranging cost. In this Subsection, we derive the necessary condition for ranging based on the error probability distribution. The rational is that we analyze the performance gains contributed by direct fusing the location of co-location users, while this performance gains would be decreasing for larger relative distance. By analyzing the maximum allowable distance for performance gains of location fusion without using distance information, we can set this maximum allowable distance as the necessary condition of ranging. If the pair-wise distance is within the maximum allowable distance, direct fusing the co-located users could also improve the location accuracy, and no need for costly ranging process.

Consider the extreme case first, if all the collaborators are co-located in the same place, this co-location information of collaborators can be utilized to improve the overall localization accuracy due to the correlation between different estimated positions. For the co-location clusters $C_1, \ldots, C_K$, the mixture of the position information of cluster C_k can be written as

$$\hat{\mathbf{p}}_k = \frac{1}{N_k} \sum_{i \in C_k} \gamma_i \hat{\mathbf{p}}_i \tag{6}$$

where γ_i is the weighting coefficient of initial location for users in cluster C_k, and can be calculated by the historical position variance of user i.

To illustrate the performance gains with regard to the maximum allowable distance, we focus on the location fusion of two users case with $\hat{\mathbf{p}}_{i,j} = \gamma_i \hat{\mathbf{p}}_i + \gamma_j \hat{\mathbf{p}}_j$. The probability density function of the mixed random variable $\hat{\mathbf{p}}_{i,j}$ is $f(\hat{\mathbf{p}}_{i,j}) = \gamma_i f(\hat{\mathbf{p}}_i) + \gamma_j f(\hat{\mathbf{p}}_j)$. If equal weighting method is used for information fusion, the coefficients are $\gamma_i = \gamma_j = \frac{1}{2}$. The location estimation result $\hat{\mathbf{p}}_{i,j}$ still follows a Gaussian distribution as $(\hat{\mathbf{p}}_i + \hat{\mathbf{p}}_j)/2 \sim \mathcal{N}\left((\mathbf{p}_i + \mathbf{p}_j)/2, \mathbf{\Sigma}_{i,j}\right)$, where $\mathbf{\Sigma}_{i,j}$ is a diagonal matrix with diagonal entries of $((\sigma_i^x)^2 + (\sigma_j^x)^2)/4$ and $((\sigma_i^y)^2 + (\sigma_j^y)^2)/4$.

The mean square error (MSE) is often used as a characteristic metric to illustrate the accuracy of the estimation result. The MSE of the estimation of $\hat{\mathbf{p}}_i$ is $MSE_i = (\sigma_i^x)^2 + (\sigma_i^y)^2$. Define $(\sigma_i^p)^2 = (\sigma_i^x)^2 + (\sigma_i^y)^2$. The MSE of $\hat{\mathbf{p}}_{i,j}$ is given by

$$\begin{aligned} M\hat{S}E_i &= \mathrm{E}[||\mathbf{p}_i - \hat{\mathbf{p}}_{i,j}||^2] \\ &= \mathrm{E}[||\mathbf{p}_i - (\hat{\mathbf{p}}_i + \hat{\mathbf{p}}_j)/2||^2] \\ &= \frac{1}{4}||\mathbf{p}_j - \mathbf{p}_i||^2 + \frac{1}{4}(\sigma_i^p)^2 + \frac{1}{4}(\sigma_j^p)^2 \end{aligned} \tag{7}$$

where $||\mathbf{p}_j - \mathbf{p}_i||^2$ is the 2-norm of the distance difference, i.e., the biased value of the estimator. The MSE for the initial position estimation result is $MSE_i = (\sigma_i^p)^2$. The $\hat{\mathbf{p}}_{i,j}$ can be defined as the difference of the MSE value as

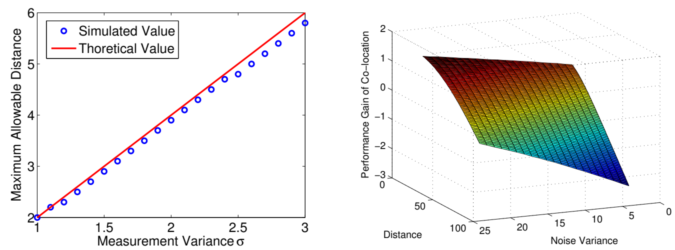
$$\begin{aligned} \Delta MSE_i &= \frac{1}{4}||\mathbf{p}_j - \mathbf{p}_i||^2 + \frac{1}{4}(\sigma_i^p)^2 + \frac{1}{4}(\sigma_j^p)^2 - (\sigma_i^p)^2 \\ &= \frac{1}{4}||\mathbf{p}_j - \mathbf{p}_i||^2 + \frac{1}{4}(\sigma_j^p)^2 - \frac{3}{4}(\sigma_i^p)^2 \end{aligned} \tag{8}$$

In order to achieve performance gains for user i when using the position of user j for information fusion, the condition $\Delta MSE_i < 0$ should be satisfied. Define the performance gain of user i using the position information from i and j as $G_i(i,j) = -\Delta MSE_i$. The maximum allowable distance constraint can be shown as

$$||\mathbf{p}_j - \mathbf{p}_i||^2 < 3(\sigma_i^p)^2 - (\sigma_j^p)^2 \tag{9}$$

(9) means the condition that the performance gains can be achieved by using co-location information fusion. Only if the condition (9) is satisfied, two users can be called as "co-location". If the initial measurement variance of user i and j are approximately the same, i.e., $\sigma_i^p = \sigma_j^p = \sigma^p$. Then (9) can be simplified as $d_{ij}^p < \sqrt{2}\sigma^p$, where $d_{ij}^p = ||\mathbf{p}_j - \mathbf{p}_i||$ is the calculated relative distance by using the measured GPS position. Since $\sigma^p = \sqrt{(\sigma^x)^2 + (\sigma^y)^2}$, if $\sigma^x = \sigma^y = \sigma$, then $d_{ij}^p < \sqrt{2}\sqrt{2\sigma^2} = 2\sigma$.

The relation between maximum allowable distance and measurement variance is shown in Fig. 2a; the performance



(a) Maximum Allowable Distance

(b) Performance Gains

Fig. 2. (a) The relation between maximum allowable distance and measurement variance and (b) the performance gains with regard to the relative distance and variance.

gains with regard to the relative distance and variance is shown in Fig. 2b. Note that d_{ij}^p is different from the ranging measurement $\hat{d}_{ij}$; d_{ij}^p is obtained by fusing GPS positions of smartphones, while $\hat{d}_{ij}$ is obtained by inter-user ranging. Using the initial measured coarse GPS location information, d_{ij}^p can be estimated. In addition, d_{ij} is the unknown true distance between Node i and Node j.

If d_{ij}^p does not meet the constraint of (9), then we can call it *necessary condition* for ranging, since the pair-wise ranging is needed for improving the location accuracy.

V. Cooperative Location Optimization

If the estimated d_{ij}^p violates (9), i.e., meets the *necessary condition* for ranging, then pair-wise ranging should be conducted. To improve the positioning accuracy in this condition, we develop a cooperative localization scheme that leverages relative distances among the smartphones.

A. Sparse Steepest Descent Optimization

With two independent measurements $\hat{\mathbf{p}}_i$ and $\hat{d}_{ij}$ available, the problem can be described as to refine the position $\hat{\mathbf{p}}_i$ by utilizing the relative ranging information $\hat{d}_{ij}$. Typically, the ranging accuracy of $\hat{d}_{ij}$ is more accurate than the GPS positioning accuracy due to the short distance between users. We use the following neighborhood-based weighted least-squares estimation to improve the positioning accuracy of $\hat{\mathbf{p}}_i, \forall i$, i.e., minimizing the squared error between the calculated distance and the measured distance:

$$\hat{\mathbf{P}} := \arg\min_{\hat{\mathbf{P}}} e(\hat{\mathbf{P}}) = \arg\min_{\hat{\mathbf{P}}} \sum_{(i,j) \in \mathcal{N}_g} \mu_{ij} (||\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j|| - \hat{d}_{ij})^2 \tag{10}$$

where $e(\hat{\mathbf{P}})$ is the total sum of distance errors between all the users, and μ_{ij} is a weight that is inversely proportional to the variance σ_{ij}^d. $\hat{\mathbf{P}}$ is a matrix whose columns are $\hat{\mathbf{p}}_i$, $i \in \mathcal{N}_g$, where $\mathcal{N}_g$ is the set of all the collaborators in a neighborhood.

The objective function of (10) achieves the minimum value when the total distance calculated by GPS position equals to the measured distance, i.e., more accurate results of position is achieved at the level of the ranging accuracy. To solve the optimization problem of (10), we apply steepest descent method to reduce the error function and calculate the updated version of user position.

Perform the gradient operation ∇ of the error function $e(\hat{\mathbf{P}}) = \sum_{(i,j)\in\mathcal{N}_g} \mu_{ij}(||\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j|| - \hat{d}_{ij})^2$ with respect to the user i has

$$\nabla_i e(\hat{\mathbf{P}}) = 2 \sum_{(i,j)\in\mathcal{N}_g} \mu_{ij}(||\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j|| - \hat{d}_{ij})\nabla_i(||\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j|| - \hat{d}_{ij}) \tag{11}$$

where $\hat{d}_{ij}$ is a measurement value, $\nabla_i \hat{d}_{ij} = 0$. $||\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j||$ represents the distance from $\hat{\mathbf{p}}_i$ to $\hat{\mathbf{p}}_j$, i.e., $||\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j|| = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$. The gradient of such distance can be written as $\nabla_i ||\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j|| = (\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j)/||\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j||$. Then (11) can be calculated as

$$\begin{aligned} \nabla_i e(\hat{\mathbf{P}}) &= 2 \sum_{(i,j)\in\mathcal{N}_g^+} \mu_{ij}(||\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j|| - \hat{d}_{ij}) \frac{\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j}{||\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j||} \\ &= 2 \sum_{(i,j)\in\mathcal{N}_g^+} \mu_{ij}(1 - \hat{\mathbf{d}}_{ij}^n)(\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j) \end{aligned} \tag{12}$$

where $\hat{\mathbf{d}}_{ij}^n = \hat{d}_{ij}/||\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j||$ is the normalized relative distance; it also characterizes the difference between measured distance and calculated distance from position. After optimization, $\hat{\mathbf{d}}_{ij}^n$ should approaching to 1. $\mathcal{N}_g^+$ represents the sparse set that $\hat{d}_{ij} \neq 0$. The relative ranging results between users are not fully available that some measurements of $\hat{d}_{ij}$ are missing, i.e., $\hat{d}_{ij} = 0$. The sparse property of the distance matrix $\mathbf{D} = \{d_{ij} : (i,j) \in \mathcal{N}_g\}$ causes the performance gains contributed by distance restraint not fully available especially when the sparse rate γ is high. However, such sparse feature can be utilized to speedup the processing by using sparse matrix operation.

After obtaining the gradient function of the error function $e(\hat{\mathbf{P}})$, the new position can be updated by using

$$\hat{\mathbf{P}} := \hat{\mathbf{P}} + \alpha \nabla_i e(\hat{\mathbf{P}}) \tag{13}$$

where α is the iterative step size and $\alpha \in (0, 1]$. Eq. (13) should be interpreted column-wisely as $\hat{\mathbf{p}}_i := \hat{\mathbf{p}}_i + \alpha \nabla_i e(\hat{\mathbf{P}}), \forall i$ with $\hat{\mathbf{p}}_i = (\hat{x}_i, \hat{y}_i)^T$.

The steepest descent approach is a local optimization method with strong requirement of the initial value selection. However, for our application that GPS position results can be used as the initial value, the overall performance of steepest descent can be guaranteed to provide an optimized value of the position under the restraint of the relative distance measurement.

B. Weighting Center based Polar Optimization

In the previous subsection, the optimized position results are achieved by minimizing the error between $||\hat{\mathbf{p}}_i - \hat{\mathbf{p}}_j||$ and measured distance $\hat{d}_{ij}$. The optimization process is utilizing the gradient iteration. Another feasible approach is assume the measured distance accurate and replace the true relative distance with $\hat{d}_{ij}$. The weighting center between two users' position is more accurate than the individual results. Then update $\hat{\mathbf{p}}_i := f(\hat{\mathbf{p}}_i, \hat{d}_{ij})$ with the relative distance and weighting center.

The relation to the position of user i and j can be expressed as $d \equiv ||\mathbf{p}_i - \mathbf{p}_j||$. For the measured relative distance $\hat{d}_{ij}$, d can be replaced by $d \triangleq \hat{d}_{ij}$. The initial position measurement $\hat{\mathbf{p}}_i$ follows Gaussian distribution with mean value of $\mathbf{p}_i$. The weighting center of position $\hat{\mathbf{p}}_i$ and $\hat{\mathbf{p}}_j$ is theoretically more stable because random deviation can be canceled out with high probability. Denote the weighting center $\mathbf{p}_{ij}^w = (\hat{\mathbf{p}}_i + \hat{\mathbf{p}}_j)/2$, which can be viewed as more accurate than $\hat{\mathbf{p}}_i$ and $\hat{\mathbf{p}}_j$, where $\mathbf{p}_{ij}^w = (\hat{x}_{ij}^w, \hat{y}_{ij}^w)^T$, $\hat{\mathbf{p}}_i = (\hat{x}_i, \hat{y}_i)^T$, $\hat{\mathbf{p}}_j = (\hat{x}_j, \hat{y}_j)^T$. The angle from the position of node i to node j is estimated as

$$\hat{\theta} = \arctan(y_i - y_j)/(x_i - x_j) \tag{14}$$

With the weighting center and θ available, the node position i and j can be re-estimated in the Polar-coordinate domain. The position of user j can be calculated by transferring the Polar-coordinate to Cartesian coordinate by

$$\begin{aligned} \hat{x}_i &:= \hat{x}_{ij}^w + \mathbf{a}_x d/2 \cdot \cos(\hat{\theta}) \\ \hat{y}_i &:= \hat{y}_{ij}^w + \mathbf{a}_y d/2 \cdot \sin(\hat{\theta}) \\ \hat{x}_j &:= \hat{x}_{ij}^w - \mathbf{a}_x d/2 \cdot \cos(\hat{\theta}) \\ \hat{y}_j &:= \hat{y}_{ij}^w - \mathbf{a}_y d/2 \cdot \sin(\hat{\theta}) \end{aligned} \tag{15}$$

where $\mathbf{a}_x$ and $\mathbf{a}_y$ are the unit vector from the direction of node i to j, with equation as $\mathbf{a}_x = (x_i - x_j)/|x_i - x_j|$ and $\mathbf{a}_y = (y_i - y_j)/|y_i - y_j|$.

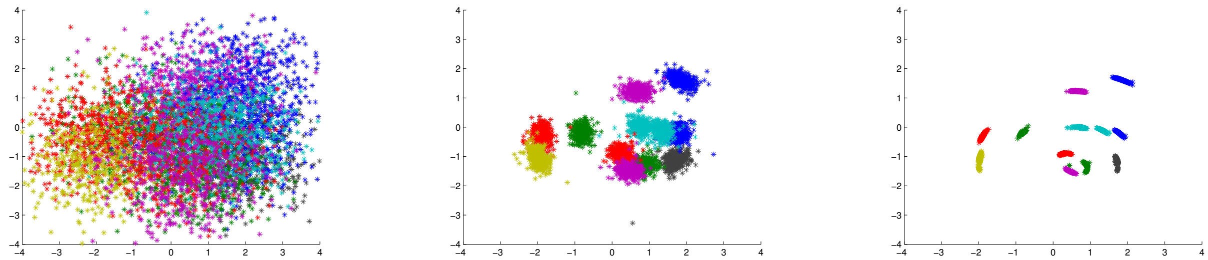
For every iteration process, we need to use the measured position results of $\hat{\mathbf{p}}_i$ and $\hat{\mathbf{p}}_j$ to update the weighting centering $\mathbf{p}_w$ and θ. The coefficient of updating is chosen as $(W_m + n - 1)/(W_m + n)$, where W_m is the window length, n is the iteration step. Then, substitute $\mathbf{p}_{ij}^w$ and θ in (15) with new estimated, the optimized position results for node i and j are obtained.

Different from the calculation of (11) that performs over all the available nodes of $\sum_{(i,j)\in\mathcal{N}_g^+}$, (15) only process for two users, i.e., user i and j. Through perform such pair-wise optimization over the whole sparse set $\mathcal{N}_g^+$, the positions for all the users can be optimized.

VI. Numerical Results

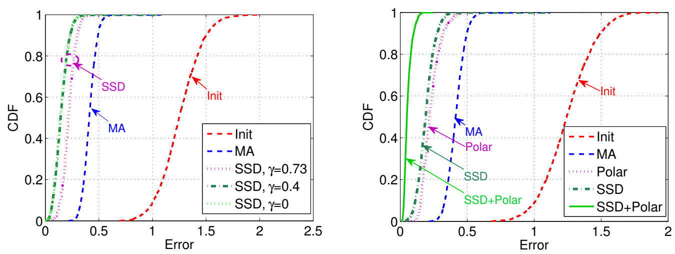
To illustrate the performance gains contributed by the *Coloc* scheme, we conduct monte-carlo simulation to calculate the error cumulative distribution funnction (CDF) by changing the noise variance of initial position results. The (x, y) coordinates of the positions of twelve users (smartphones) are shown as a scatter figure in Fig. 3a; the positions of each user follow the same two-dimensional Gaussian distribution and are shown by different colors.

The mean CDF curves for twelve users of various approaches and different sparse rates are shown in Fig. 4a with initial measurement variance of $\sigma = 0.3$. The "MA" represents the conventional moving average method used for the initial measurements, while "SSD" represents our proposed Sparse Steepest Descent Optimization approach. Even when



(a) Initial (b) SSD (c) SSD+Polar

Fig. 3. Numerical results with 12 users under $\sigma = 1$ and $R = 2$: (a) initial positions, (b) refined positions obtained by SSD, and (c) refined positions obtained by SSD+Polar.



(a) Different Sparse Rate (b) Joint Approach

Fig. 4. The CDF of location accuracy under various processing types: 1. Using SSD with different sparse rate of ranging; 2. Using joint optimization approaches of SSD and Poloar.

the ranging sparse rate is very high ($\gamma = 0.73$), i.e., only several ranging pair measurements are utilized, the performance superiority over "MA" is still sufficient. Another interesting point lies in the no apparent performance degradation when sparse rate is lower than $\gamma = 0.4$. Such property can help reduce the overall ranging costs and delay while maintaining desired performance gains.

The performance of the *Coloc* scheme using ranging information can be even improved when combine our proposed Sparse Steepest Descent Optimization and Weighting Center based Polar Optimization together. Since Polar based optimization is performed for two users, i.e., in a local way, we execute the Polar method after the the global SSD approach. The measurement results are shown in Fig. 3. "Initial" is the initial position measurement; "SSD" case is using our proposed Sparse Steepest Descent Optimization; "SSD+Polar" is using the Polar optimization after the SSD processing.

The CDF figure is shown in Fig. 4b. We can know that using Polar and SSD optimization, the performance gains are larger than using the conventional moving average method. When combine SSD and Polar together, the performance can be even improved as shown in Fig. 4b.

VII. Experimental Validation

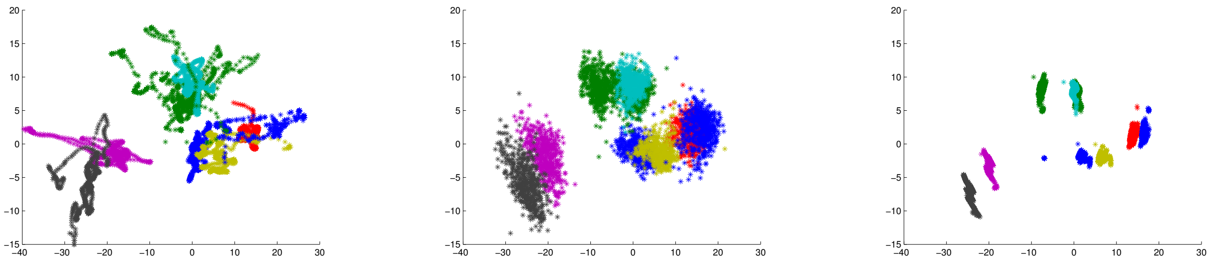
A. Experiment Setup

We conducted experiments by using smartphones to collect location data, and validate our proposed cooperative localization technique by using these real measured results. The data is collected by using Apple iOS smartphones (iPhone4, iPhone4S and iPhone5 are used in the experiment). Two cases of situations are tested: stationary situation for accuracy test; moving situation for tracking and dynamic performance test. To facilitate the data processing, we convert the longitude and latitude value to the cartesian coordinate (x,y) under the standard of GRS80.

B. Case Study I: Stationary Users

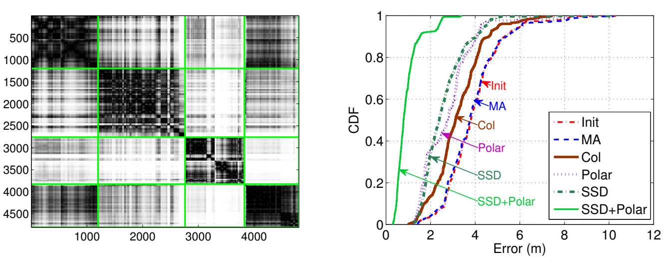
To evaluate the performance of our proposed cooperative location optimization approach for multi-users in real environments, we conduct measurements for nine users with random positions in a campus environment. The initial measurement results are shown in Fig. 5a. From Fig. 5a, we know that the initial GPS localization results are very noisy due to the blockage and interference of the satellite signal. Different from the simulation results, the obtained GPS results show strong correlation among adjacent measurements. That's also why lower the GPS update rate is possible to save energy without sacrificing the accuracy. To demonstrate the performance gains contributed by *Coloc* scheme, we perform social-aided cooperative processing under the co-location and relative distance constraint. For convenience, we denote "Init" as the initial position results; "Col" is the result obtained by only utilizing the co-location information without ranging; "Polar", "SSD" and "Polar+SSD" are our proposed schemes by using the ranging-based information for collaboration. We follow the same terms/notations used in Section VI.

We applied the normalized cuts algorithm [19] algorithm to the affinity matrix corresponding to Fig. 5a, and obtained the clustering results of four clusters as shown in Fig. 6a, i.e., the positions with large similarity measures are grouped together. By clustering nine users into four clusters with co-location, we can perform location fusion without relative ranging. This approach is labeled as "Col". The CDF results of using different algorithms are shown in Fig. 6b. We observe that the conventional moving average "MA" approach does not show performance improvement over the initial position results due to the dependency between adjacent measurements. By clustering nine users into four clusters with co-location, the



(a) Initial (b) SSD (c) SSD+Polar

Fig. 5. Experimental results with 9 users: (a) initial positions obtained by GPS, (b) refined positions obtained by SSD, and (c) refined positions obtained by SSD+Polar.



(a) Clustering Results (b) CDF Results

Fig. 6. 1. The clustering results for the 9 users; 2. The CDF of location accuracy under various processing types.

location accuracy of "Col" is much better than "MA" as shown in Fig. 6b.

If the relative distance information can be obtained, the accuracy can be even improved by using "Polar" and "SSD" approaches. The scatter figure of using "SSD" is shown in Fig. 5b. After perform joint optimization of "SSD+Polar", the more accurate results are shown in Fig. 5c. By comparing the results to the initial measurement results Fig. 5a, the performance improvement of using "SSD+Polar" is significant.

From the statistical results of Fig. 6b, and using 80% probability as an example, the initial GPS accuracy is around 5 m. After fusing the co-located users without ranging, the achieved accuracy is about 4 m. When using our proposed ranging-based optimization approach "SSD+Polar", the positioning accuracy is approximately 1.2 m, which is a significant improvement.

C. Case Study II: Moving Users

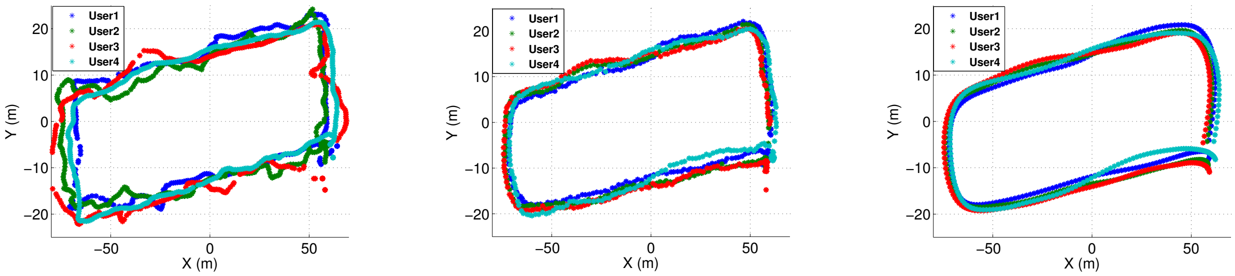
To evaluate the performance improvement of *Coloc* scheme in moving scenarios, we conduct experiments for the second case study with moving users. Users carry GPS-enabled smartphones and perform cooperative localization with peers when walking in a campus parking lot. The GPS update time interval is t_G; we use lower t_G when applying *Coloc* scheme to save the energy.

Fig. 7a shows the initial measurement of GPS trajectory of 4 users when walking around a parking lot, where $t_G = 0.997s$. Using low update GPS data ($t_G = 1.994s$), and after perform our proposed "SSD" approach, the devision of the GPS trajectory has been greatly suppressed as shown in Fig. 7b. After apply the "Polar" approach in addition to "SSD", the trajectory is more smooth as shown in Fig. 7c, which is much better than the initial high update rate data.

To test the effectiveness of *Coloc* scheme when users walking in two separate groups with certain amount of distance, we conduct experiment by letting three users form a group and walking in parallel with another user. The walking traces of these four users are shown in Fig. 7a. After "SSD" and joint "SSD" and "Polar" optimization, the accuracy of walking traces improved significantly as shown in Fig. 7b and Fig. 7c. These results demonstrate the energy efficiency (lower update rate) and accuracy (better trajectory) of our proposed *Coloc* scheme.

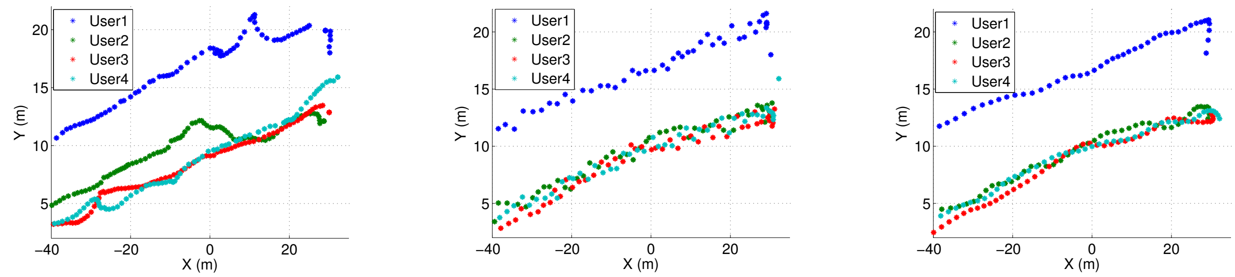
VIII. Conclusions

The GPS receiver of a smartphone does not produce accurate position and does not work in harsh environments such as indoor environment. In addition, the GPS receiver onboard is inefficient in power consumption. To address positioning inaccuracy and power inefficiency, in this paper, we proposed social-aided *Coloc* scheme. Specifically, we use neighborhood-based weighted least-squares estimation when relative distances between smartphones are available. The energy efficiency is achieved by sharing location information among co-located users and lower the GPS update rate. Numerical and experimental results conclusively demonstrate that our proposed cooperative localization schemes can achieve considerable performance gain in both indoor and outdoor environments. For example, in the experiments of nine users with random positions, when relative distances are available, the positioning accuracy of our scheme is 1.2 m with a confidence level of 80%. In contrast, a regular GPS receiver has an accuracy of 4.7 meters with a confidence level of 80%. The optimized GPS trajectory also demonstrates the effectiveness of *Coloc* scheme for tracking moving targets. Our future work will further enhance the accuracy of *Coloc* scheme and make our smartphone app available for more location-based or location-aware services and applications.



(a) Initial, $t_G = 0.997s$ (b) SSD, $t_G = 1.994s$ (c) SSD+Polar, $t_G = 1.994s$

Fig. 7. Experiment results of 4 users GPS trajectory when walking around a parking lot.



(a) Initial, $t_G = 0.997s$ (b) SSD, $t_G = 1.994s$ (c) SSD+Polar, $t_G = 1.994s$

Fig. 8. Experiment results of 4 users GPS trajectory when walking along a line.

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