Mobility Improves LMI-based Cooperative Indoor Localization

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***Abstract*—With the proliferation of mobile devices such as smartphones, an interesting problem is how to make use them to improve the accuracy of localization in indoor environments. In this paper, we develop a novel cooperative localization scheme exploiting mobility in the indoor environment. The problem is formulated as a semidefinite program (SDP) using Linear Matrix Inequality (LMI). With the proposed approach, mobile users utilize their top RSS measurements for distance estimation and to mitigate the the shadowing effect found in indoor environments. In addition, we utilize the estimated position for a user from the last time slot as a virtual access point (AP) to obtain the next position estimation, by utilizing the inertial measurement unit (IMU) data from smartphones. To better take advantage of the moving direction and velocity information provided by the smartphones, we next apply Kalman filter to further mitigate the errors in estimated positions. Simulation results confirm that both the mean error and variance can be effectively reduced by exploiting IMU data and Kalman filter.**

***Index Terms*—Gaussian-Newton algorithm; indoor localization; Kalman filter; linear matrix inequality; mobility; received signal strength.**

I. Introduction

Location awareness nowadays is an essential feature of many wireless networks and a plethora of consumer applications. It is expected to spawn many new applications in various areas. Indoor positioning is the key component for location awareness and has become a hot, challenging research topic due to the lack of global positioning system (GPS) service in the indoor environment. Since wireless access is now widely available, the problem of accurate indoor localization using wireless signals has been extensively studied.

The process of localization using wireless technologies is called location sensing, geolocation, position location or radiolocation [1]–[3]. Among the many localization techniques, Received Signal Strength (RSS)-based localization systems have attracted much attention in recent years. It is considered as a promising, inexpensive, and scalable solution for indoor positioning, because it does not require any specialized hardware at the mobile device or at the access points (AP) (e.g., an antenna array) [4], [5]. However, due to the nature of electromagnetic wave propagation in complex indoor environments, the accuracy of RSS-based localization systems is affected significantly by environment settings. Considerable research efforts are needed to improve the precision of RSS-based indoor localization.

Cooperative localization, in which nodes help each other to determine their locations, has been extensively studied in the context of wireless sensor networks [6]. Nowadays, there is new interest on cooperative localization in wireless indoor networks [7]. Collaborative localization under the presence of non-LOS (NLOS) propagations was studied and solved by using the iterative parallel projection method (IPPM) [8]. Authors in [9] reviewed various cooperative localization approaches and applied them to position nodes in an ultra-wideband (UWB) wireless network. On the other hand, Linear Matrix Inequality (LMI) in cooperative localization has been proposed to position a node with proximity constraints imposed by known connections [10]. LMI was utilized to improve the accuracy of GPS localization in vehicular networks [11] and in heterogeneous wireless systems [12]. These papers only consider using APs to obtain user's position, but user mobility is not considered to improve cooperative localization.

Nowadays, more and more powerful smartphones are equipped with inertial measurement units (IMU) including accelerometer and gyroscope. These inertial sensors measure force and angular velocity, which is free information that can be exploited to improve localization accuracy. Fan, et al., in [13] developed a practical indoor localization system that relies on inertial sensors in mobile phones only and demonstrated both reliability and localization accuracy. Moreover, Li, et al., in [14] proposed a navigation algorithm that combines received signal strength indicator (RSSI) and inertial sensor measurements to improve indoor localization. But these papers do not consider cooperation among users. Thus, the potential of IMU-based navigation can be fully harvested if it is integrated with RSS-based cooperative localization when mobile users are moving around in an indoor environment.

In this paper, we propose a novel cooperative localization scheme based on user mobility in the indoor environment. We first formulate cooperative localization for mobile users as a semidefinite program (SDP) based on LMI. With the proposed scheme, mobile users use their top RSS measurements to cooperatively estimate their distances and mitigate the the shadowing effect in indoor environments. Moreover, when users are moving, we propose to utilize the smartphone IMU data to further improve the localization performance. In essence, we utilize the estimated position from the last time slot as a virtual AP, which will also be used to estimate the next position combined with the IMU data. To better take advantage of user's moving direction and velocity information, we propose to apply Kalman filter to improve the estimated positions obtained from the LMI method. Simulation results are presented to confirm that integrating smartphone IMU data and Kalman filter can effectively reduce both the mean error and variance for indoor localization.

The remainder of this paper is organized as follows. The system model and problem statement are presented in Section II. The proposed scheme is described in Section III and validated in Section IV. Section V concludes this paper.

II. System Model and Problem Statement

A. Propagation Model

When an AP communicates with mobile users, it can also collect RSS measurements. An effective means for users to communicate with each other is through Wi-Fi Direct if they are equipped with devices supporting this standard. Wi-Fi Direct, initially called Wi-Fi P2P, is a Wi-Fi standard that enables devices to connect easily with each other and to communicate at typical Wi-Fi data rates [15]. With Wi-Fi Direct, one mobile user can easily collect RSS values from another user. With these shared RSS values between pairs of mobile users, localization accuracy can be improved, especially in areas where APs are not densely deployed.

The proposed localization methods in this paper are based on measured RSS values. We consider the log-normal path loss model for indoor environments, which is given by

$$\mathrm{PL}(d) = \mathrm{PL}(d_0) + 10\alpha \log\left(\frac{d}{d_0}\right) + X_\sigma, \tag{1}$$

where α is the path loss exponent for the environment and X_σ represents a normal random variable (in dB) having a zero mean and a standard deviation of σ dB. $\mathrm{PL}(d)$ in dB represents the total path loss experienced between the receiver and sender, which are separated with a distance d. $\mathrm{PL}(d_0)$ represents the reference path loss in dB for the desired frequency and d_0 is the reference distance.

We can set a predefined RSS threshold to rule out those received RSS powers that are not useful for localization estimation, since a weak RSS sample may not contribute to distance estimation but may even introduce extra errors. We can also rule out NLOS parts of the RSS values by studying the variance errors of many records or by studying the difference between empirical measurements and estimated positions. After filtering those received RSS measurements and using fewer RSS records for distance estimation, cooperative localization between mobile users becomes more competitive.

B. Problem Statement

Consider an indoor system of mobile users equipped with devices that support Wi-Fi communications. When the mobile devices are in the coverage range of each other, they can exchange data on an opportunistic basis. Several Wi-Fi access points (AP) are placed around these users and the precise locations of the APs are known. In addition, we assume that the mobile users collaborate with each for localization by communicating with each other during a certain period of time, such as during the Active Scanning procedure of IEEE 802.11. Then two users can opportunistically exchange data if their scan phase overlap in time and they are in geological proximity.

Assume there are m access points with their positions A_k, for $k = 1, 2, \cdots, m$, and n mobile users with their positions $P_i(t)$ at the scan period t, for $i = 1, 2, \cdots, n$, for $t = 1, 2, \cdots, T$. Let R denote the maximum communication range. Define $N_p(t)$ as set of user pairs, where the distance between each pair of users i and j, denoted by $d_{ij}(t)$, does not exceed R at scan period t. Define $N_a(t)$ as set of user-AP pairs, where the distance between user i and AP k, denoted as $d_{ik}(t)$, does not exceed R at scan period t. That is,

$$N_p(t) = \{(i,j) : d_{ij}(t) = \|P_i(t) - P_j(t)\| \le R\} \tag{2}$$
$$N_a(t) = \{(i,k) : d_{ik}(t) = \|P_i(t) - A_k\| \le R\}. \tag{3}$$

For the indoor localization problem, we focus on how to obtain the positions of mobile users, i.e., $P_i(t)$, for $i = 1, 2, \cdots, n$, for $t = 1, 2, \cdots, T$, given the precise locations of the APs, i.e., A_k, for $k = 1, 2, \cdots, m$, and the above two connectivity constrain sets $N_p(t)$ and $N_a(t)$. Choosing a trivial objective function of zero, the indoor localization problem can be formulated as follows.

$$\min: \quad 0 \tag{4}$$
$$\text{s. t.} \quad \|P_i(t) - P_j(t)\| \le R, \forall (i,j) \in N_p(t) \tag{5}$$
$$\|P_i(t) - A_k\| \le R, \forall (i,k) \in N_a(t). \tag{6}$$

Because the above two constraints are convex, this is a convex optimization problem. Applying Schur Complement, the two non-linear constraints can be transformed into two linear matrix inequalities (LMI). Thus this optimization problem becomes an SDP, which is given by

$$\min: \quad 0 \tag{7}$$
$$\text{s. t.} \quad \begin{bmatrix} \boldsymbol{I}R & P_i(t) - P_j(t) \\ (P_i(t) - P_j(t))^T & R \end{bmatrix} \ge 0 \tag{8}$$
$$\begin{bmatrix} \boldsymbol{I}R & P_i(t) - A_k \\ (P_i(t) - A_k)^T & R \end{bmatrix} \ge 0. \tag{9}$$

For this optimization problem, we consider the case that all constraints are limited with the same maximum range R. In fact, a tighter upper bound on each node can be estimated by the measured distance $\hat{d}_{ij}(t)$ for any node i and node j at the scan period t, if $\hat{d}_{ij}(t) < R$ [10]. Thus, the semidefinite program becomes

$$\min: \quad 0 \tag{10}$$
$$\text{s. t.} \quad \begin{bmatrix} \boldsymbol{I}\hat{d}_{ij}(t) & P_i(t) - P_j(t) \\ (P_i(t) - P_j(t))^T & \hat{d}_{ij}(t) \end{bmatrix} \ge 0 \tag{11}$$
$$\begin{bmatrix} \boldsymbol{I}\hat{d}_{ik}(t) & P_i(t) - A_k \\ (P_i(t) - A_k)^T & \hat{d}_{ik}(t) \end{bmatrix} \ge 0. \tag{12}$$

With these inequality constraints, this problem is to find a feasible solution. If such a feasible solution exists, the problem is called a feasible problem in the LMI system. The solution to this feasible problem provides an estimate of user locations in the network area. The LMI solver in the Robust Control Toolbox of MATLAB can be used to solve this problem.

In this paper, based on the LMI framework, we focus on how to improve localization accuracy with measured RSS values from mobile users, especially in the situation when the APs are sparsely deployed in the area. We allow opportunistic cooperation among the mobile users, and show that the opportunistic information exchanges among the devices can be very helpful. On the other hand, we also employ the IMU data to improve the accuracy of localization, as well as Kalman filter to further reduce the errors in the estimated results of the LMI solver. We aim to develop effective algorithms and study their performance in such an indoor localization environment.

III. Proposed Approach

Before introducing the proposed localization algorithms, we first obtain a distance estimation from measured RSS values by setting X_σ to a constant value, such as zero, in which case radio propagation is simplified to a unit-disk model, or an empirical value.

A. LMI-based Approach

In the proposed system, each mobile user collects RSS measurements from nearby APs as well as other mobile users within the range. The top three RSS measurements for each mobile user are selected as input to the proposed localization algorithm. Based on the propagation model, we can estimate the distance between an AP and a mobile user, and the distance between two mobile users at scan period t, respectively, as

$$\bar{d}_{ij}(t) = d_0 \cdot 10^{(\mathrm{PL}(\bar{d}_{ij}(t)) - \mathrm{PL}(d_0))/(10\alpha)} \quad (13)$$

$$\bar{d}_{ik}(t) = d_0 \cdot 10^{(\mathrm{PL}(\bar{d}_{ik}(t)) - \mathrm{PL}(d_0))/(10\alpha)}. \quad (14)$$

We relax the constraints by setting X_σ to a constant value. Recall that X_σ is a Gaussian random variable with an unknown standard deviation, which is usually between 3 dB and 7 dB for indoor environments [12]. In our estimation procedure, we add the distance difference introduced by the shadowing effect, i.e., $10^{X_\sigma/10\alpha}$, to the estimation derived from RSS measurements.

$$\hat{d}_{ij}(t) = \bar{d}_{ij}(t) \cdot 10^{X_\sigma/10\alpha} \quad (15)$$

$$\hat{d}_{ik}(t) = \bar{d}_{ik}(t) \cdot 10^{X_\sigma/10\alpha}. \quad (16)$$

Therefore $\hat{d}_{ij}(t)$ (or $\hat{d}_{ik}(t)$) is the maximum estimated range where the user can be located after taking into account of the shadowing effect. In our algorithm, we set X_σ to be an empirical value $\hat{X}_\sigma$ such that the probability with which X_σ falls below $\hat{X}_\sigma$ is above 90%.

$$\Pr\left\{X_\sigma \le \hat{X}_\sigma\right\} \ge 0.9. \quad (17)$$

The distribution of X_σ is Gaussian with an estimated standard deviation. After obtaining distance estimations from RSS measurements, we then use these distance estimations to construct LMI constraints for each user pair.

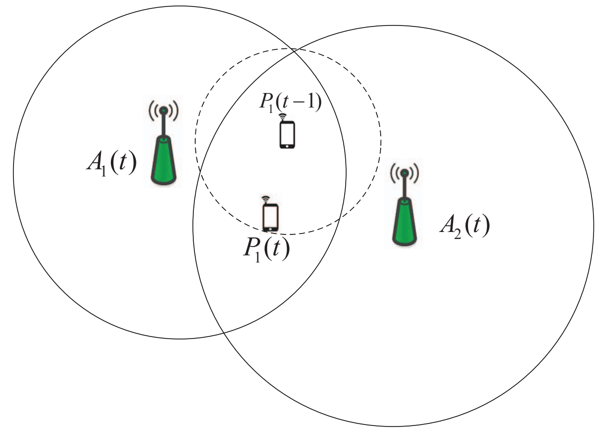

Fig. 1. Illustration of how mobility improves LMI based localization.

B. Exploiting Mobility and Historic Data

Since this paper focuses on the localization problem in an indoor environment, it is reasonable to assume that the users do not move arbitrarily or at a very high speed. Assuming time is slotted, we can simply apply LMI-based algorithms to estimate user locations in each time slot. The idea is to exploit mobility and historic data to further refine such estimations.

In particular, we can utilize the estimated position from the last time slot as a virtual AP, which will also be used to determine the next position estimation. For example, in Fig. 1, mobile user 1 obtains an estimated position $P_1(t-1)$ at time $(t-1)$ using the LMI solver. When this user moves to a new position $P_1(t)$ at time t, the distance between the last estimated position and this new position can be estimated using the accelerometer and magnetometer in the smartphone. We then use the last estimated position $P_1(t-1)$ as center and the estimated distance as radius to draw a disk. This new disk can reduce the overlapped areas estimated from the two APs (i.e., $A_1(t)$ and $A_2(t)$ in Fig. 1).

There are several advantages of using this method over the pure LMI method. First, the estimated distance by using the accelerometer and magnetometer in smartphones is usually more accurate than that estimated from RSSI. Furthermore, by adding virtual APs, the constraint area can be greatly reduced (as shown in Fig. 1). Since the estimated distance $\|P_i(t) - P_i(t-1)\|$ (i.e., how far a use can move in one time slot) is usually much smaller than the AP-user distances $\|P_i(t) - A_1(t)\|$ and $\|P_i(t) - A_2(t)\|$, the reduction in the constraint area could be considerable, thus leading to higher accuracy for indoor localization.

In particular, given the last know position or the last estimated position $P_i(t-1)$, the next position estimation $P_i(t)$ can be calculated, if the user's moving distance and direction in the time slot, denoted by a vector $\Delta\hat{d}$, are known (i.e., from the IMU data). Then we obtain a new estimation for the user's new location, as

$$P_i(t) = P_i(t-1) + \Delta\hat{d}. \quad (18)$$

Using $P_i(t-1)$ as a virtual AP and $\Delta\hat{d}$ as the measured distance, a connection between $P_i(t)$ and $P_i(t-1)$ can be represented by a 2-norm constraint as

$$\|P_i(t) - P_i(t-1)\| \leq \left\|\Delta\hat{d}\right\| \tag{19}$$

Incorporating the above new constraint into the LMI framework, the enhanced optimization problem is given by

$$\min: \quad 0 \tag{20}$$

$$\text{s. t.} \begin{bmatrix} \boldsymbol{I}\hat{d}_{ij}(t) & P_i(t) - P_j(t) \\ (P_i(t) - P_j(t))^T & \hat{d}_{ij}(t) \end{bmatrix} \geq 0 \tag{21}$$

$$\begin{bmatrix} \boldsymbol{I}\hat{d}_{ik}(t) & P_i(t) - A_k \\ (P_i(t) - A_k)^T & \hat{d}_{ik}(t) \end{bmatrix} \geq 0 \tag{22}$$

$$\begin{bmatrix} \boldsymbol{I}\Delta\hat{d} & P_i(t) - P_i(t-1) \\ (P_i(t) - P_i(t-1))^T & \Delta\hat{d} \end{bmatrix} \geq 0. \tag{23}$$

Similarly, the LMI solver can be used to obtain a feasible solution to this new SDP. The user's location can be narrowed down by this approach, since the feasible region is reduced by adding the last constraint (23), as illustrated in Fig. 1. On the other hand, the IMU data based distance estimation is not error free. The estimation error in $\Delta\hat{d}$ will influence the final localization result, and will be addressed in the next subsection by incorporating a Kalman filter.

C. Kalman Filter

To better suppress the localization error, we incorporate a Kalman filter in the proposed scheme. The Kalman filter can enhance one measurement given a more accurate measurement from another source using a sequential recursive algorithm. In the following, we use a Kalman filter to refine the estimated location obtained with the IMU data enhanced approach discussed in the previous subsection.

In order to develop the state-space of the discrete time Kalman filter equations, the system dynamics and measurement models have to be defined first as follows.

$$\boldsymbol{P}_l = \boldsymbol{\Phi}\boldsymbol{P} + \boldsymbol{n_l} \tag{24}$$

$$\boldsymbol{P}_s = \boldsymbol{\Phi}\boldsymbol{P} + \boldsymbol{n_s}, \tag{25}$$

where $\boldsymbol{P}_l$ is the solution from the LMI system by exploiting mobility; $\boldsymbol{P}_s$ is the estimation result based on the IMU data from smartphone sensors; $\boldsymbol{\Phi}$ is an identity matrix since the actual positions do not change during the estimation iterations; $\boldsymbol{n_s}$ and $\boldsymbol{n_l}$ are Gaussian noises with covariance matrices $\boldsymbol{Q}$ and $\boldsymbol{R}$, respectively. $\boldsymbol{Q}$ and $\boldsymbol{R}$ are set to be $\frac{1}{2}\left\|\Delta\hat{d}\right\|^3\boldsymbol{I}$, where $\Delta\hat{d}$ is the estimated trajectory of the user movement in the time slot, and $\boldsymbol{I}$ is the identity matrix [16].

Let $\boldsymbol{H}$ denote the covariance of the state vector estimate. The initial state estimation input to the Kalman filter is the estimated positions from the LMI method $\boldsymbol{P}_l$, and the covariance matrix is initialized as $\boldsymbol{H} = \mathbb{E}\left[<\boldsymbol{P_l}\cdot\boldsymbol{P_l}^T>\right]$. Then $\boldsymbol{P}_s$, which is relatively more accurate, will be used as the observation in the Kalman filter to correct $\boldsymbol{P_l}$. The Kalman filter will then output the a priori covariance $\boldsymbol{H}_k(-)$, which can be used in the next time slot, as well as the Kalman gain matrices $\boldsymbol{K}_k$. Then we update the LMI estimated positions $\boldsymbol{P_l}$ and get the posterior covariance matrix $\boldsymbol{H}_k(+)$. The Kalman equations can be derived as

$$\boldsymbol{H}_k(-) = \boldsymbol{\Phi}\boldsymbol{H}_{k-1}(+)\boldsymbol{\Phi}^T + \boldsymbol{Q}_{k-1} \tag{26}$$

$$\boldsymbol{K}_k = \boldsymbol{H}_k(-)\boldsymbol{\Phi}^T(\boldsymbol{\Phi}\boldsymbol{H}_k(-)\boldsymbol{\Phi}^T + \boldsymbol{R}_k)^{-1} \tag{27}$$

$$\boldsymbol{P_l} = \boldsymbol{P_l} + \boldsymbol{K}_k(\boldsymbol{P_s} - \boldsymbol{P_l}) \tag{28}$$

$$\boldsymbol{H}_k(+) = (\boldsymbol{I} - \boldsymbol{K}_k\boldsymbol{\Phi})\boldsymbol{H}_k(-) \tag{29}$$

After obtaining the updated LMI estimations from the Kalman filter, we use a weighted sum to estimate the mobile users' positions to reduce the errors, as

$$\boldsymbol{P} = \frac{1}{2}\left(\boldsymbol{P}_s + \boldsymbol{P}_l\right). \tag{30}$$

In every time slot, we apply the Kalman filter to correct the estimations from the LMI method based on mobility and obtain the estimated positions as the weighted sum. We present our simulation results in the next section that validate the proposed approach.

IV. Simulation Validation

In this section, we evaluate the performance of the proposed algorithms with MATLAB simulations. The LMI solver provided in the Robust Control Toolbox of MATLAB is used to implement the LMI-based method in our simulations. For results proposed in this section, 100 individual experiments with different random seeds for each scheme are executed. The simulation setup is show in Fig. 2. We assume a network in a 100×100 square area. We place nine APs around twenty mobile users who are randomly placed in the network area and move according to the random walk model. A red circle in Fig. 2 represents an AP, while a black dot represents a mobile user. In every time slot, each mobile user randomly picks a direction and a speed between 0 and 5 m/s and moves. In addition, we set the parameter α to 2 and use the function norminv(0.9,0,3) in MATLAB to add the distance difference introduced by the shadowing effect.

The performance metric for the comparison of different localization schemes is the mean sum error $\mathcal{E}$. Assume the estimated location of an unknown user i is $(\hat{x}_i, \hat{y}_i)$ and the actual position of the user is (x_i, y_i). For n mobile users in the area, the mean sum error of distance estimation is computed as

$$\mathcal{E} = \frac{1}{n}\sum_{i=1}^{n}\sqrt{(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2}. \tag{31}$$

A. Localization of Stationary Users

We first study the performance of the three approaches (i.e., Gaussian-Newton Algorithm, LMI without Cooperation, and LMI with Cooperation) when the users are stationary, where cooperation means that users within the communication range help each other to determine their positions. We use the Gaussian-Newton algorithm as a benchmark scheme. The Gaussian-Newton algorithm is an effective method for solving

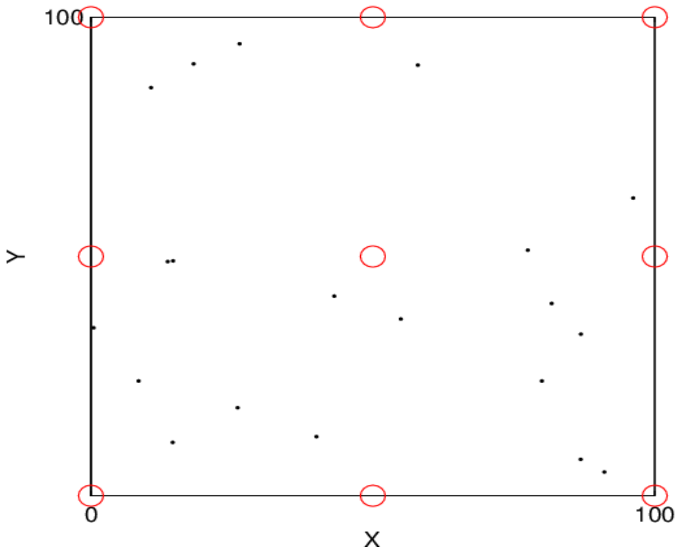

Fig. 2. The network topology used in the simulation (Red Circle: AP; Black Dot: Mobile user).

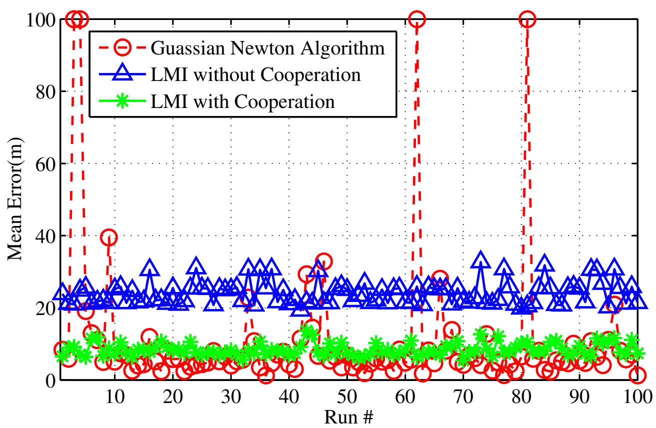

Fig. 3. Comparison of the mean errors of the three schemes when users are stationary.

non-linear least squares problems. The algorithm starts with an initial guess, and then updates the initial solution iteratively to minimize the mean sum square error. The number of iterations is set to 5 for the Gaussian-Newton Algorithm.

Fig. 3 shows the comparison of the mean errors of the three schemes when the users are stationary. The curves of the Gaussian-Newton Algorithm and the LMI with Cooperation scheme are very close to each other. Furthermore, the mean error of the LMI without Cooperation scheme is about 24 m, which is much higher than the other two approaches. In fact, the LMI without Cooperation scheme cannot achieve a good performance because most of the nodes in the network are out of range of each other.

Fig. 4 plots the cumulative distribution function (CDF) of the three schemes when the users are stationary. It can bee seen that the CDFs for the Gaussian-Newton Algorithm and the LMI with Cooperation scheme approaches 0.9 when the

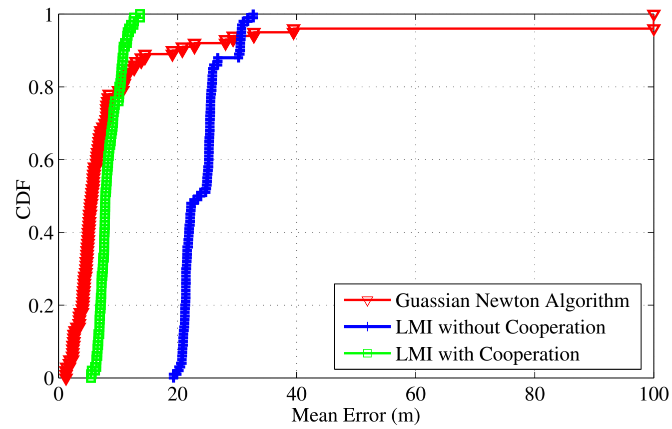

Fig. 4. Comparison of the CDFs of the three schemes when users are stationary.

TABLE I
MEAN ERROR AND STANDARD DEVIATION WHEN USERS ARE STATIONARY

Algorithm	*Mean error (m)*	*Std. dev. (m)*
Gaussian-Newton algorithm	11.1611	19.3247
LMI without Cooperation	24.0731	3.2180
LMI with Cooperation	8.4815	1.7333

mean error is over 10m, while the CDF for the LMI without Cooperation reaches 0.9 when the mean error is over 30 m. In addition, although the Gaussian-Newton Algorithm has a faster convergence speed than the LMI without Cooperation scheme, its solution exhibits very larger variations. This is because the performance of the Gaussian-Newton Algorithm is heavily dependent on the first guess of the user location. The mean sum errors and standard deviations for this simulation are presented in Table I. The LMI with Cooperation scheme achieves the minimum mean error, which is 8.4815 m, and the minimum standard deviation, which is 1.7333 m.

B. Enhanced Performance by Exploiting User Mobility

In the second experiment, we exploit user mobility to improve indoor localization. Since now the user position changes over time, we compute the average result of the estimated positions for different slots in every individual experiment. Moreover, given the last known position or the last estimated position, we can directly calculate the next moving distance when the moving speed and direction are known. Then we can use this estimated distance to enhance the LMI system output, thus obtaining a more accurate estimate for the next position. To further enhance localization accuracy, we apply Kalman filter in the mobile user localization process to reduce estimation noise. We call this scheme Smartphone LMI with Kalman Filter and compare it with the other two approaches (i.e., Gaussian-Newton Algorithm and LMI with Cooperation) under the presence of user mobility.

In Fig. 5, the Smartphone LMI with Kalman filter scheme achieves the smallest mean error and the most stable performance. We find that the mean error of the Gaussian-Newton

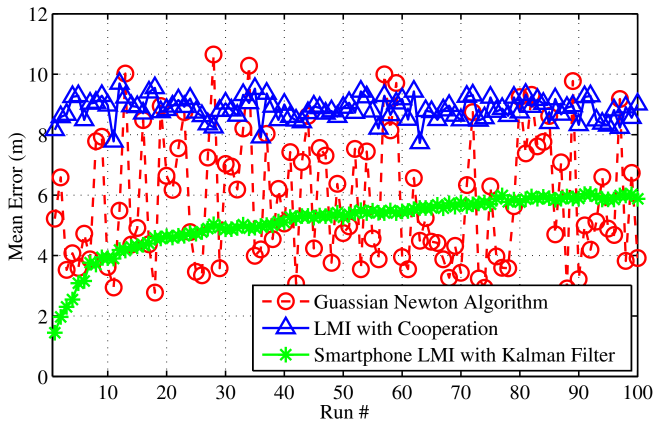

Fig. 5. Comparison of the mean errors of the three schemes with user mobility.

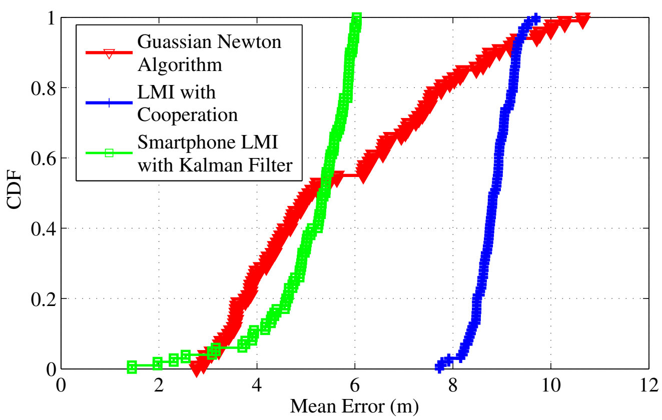

Fig. 6. Comparison of the CDFs of the three schemes with user mobility.

TABLE II
MEAN ERROR AND STANDARD DEVIATION WITH USER MOBILITY

Algorithm	*Mean error (m)*	*Std. dev. (m)*
Gaussian-Newton Algorithm	5.7967	2.1244
LMI with Cooperation	8.8390	0.3834
Smartphone LMI with Kalman Filter	5.1059	0.9102

Algorithm has much larger fluctuations than the other two algorithms. In Fig. 6, it can be seen that the CDF for the Smartphone LMI with Kalman Filter scheme reaches 0.9 when the mean error is over 6 m, while the CDFs of the other two methods reaches 0.9 when the mean error is over 9 m. The simulated mean sum errors and standard deviations are presented in Table II for the three proposed schemes. The results confirm that the Smartphone LMI with Kalman Filter scheme achieves the minimum mean error of 5.1059 m. Clearly mobility can improve the performance of cooperative indoor localization.

V. CONCLUSION

In this paper, we presented a new cooperative localization scheme exploiting user mobility in the indoor environment. The traditional RSS-based LMI approach was considered. The main idea is to exploit user mobility information as given by the IMU data from smartphones, to further narrow down the constraint area of the LMI based scheme, thus increasing the localization accuracy. We also incorporate Kalman filter to further suppress the estimation error. Simulation results confirm the effectiveness of exploiting the IMU data and Kalman filter.

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