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Multi-hop Localization Using Mobility (MLM) in Mixed LOS/NLOS Environments

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***Abstract*—This paper presents a novel technique for multi-hop localization by using mobility (MLM) in mixed line-of-sight/non-line-of-sight (LOS/NLOS) environments. In MLM, nodes equipped with ultra-wideband (UWB) radio first move randomly for collecting time-of-arrival (TOA) measurements and then apply a modified biased Kalman filter (MBKF) designed for mitigating NLOS errors. NLOS bias in the measurements is further mitigated by using the shortest path distance (SPD) selection. Node positions are initialized by using multidimensional scaling (MDS) and then estimated by using iterative trilateration accompanied by an error accumulation management. Our simulation results demonstrate that the positioning accuracy of MLM outperforms previous methods in obstructed building environments with a limited anchor heard (AH).**

I. INTRODUCTION

Due to the recent advances in micro electro mechanical system (MEMS) technologies, wireless sensor networks are getting closer to being a reality and are currently attracting significant attention from researchers. In sensor networks, determining the position of each sensor node is important for meaningful handling of sensing events or in applications such as tracking and navigation. Global positioning system (GPS) can not feasibly be used in many situations such as deployment inside buildings. Many research efforts, therefore, have been made for estimating the node positions in large-scale multi-hop networks.

In [1], an iterative multilateration algorithm is proposed that uses time-of-arrival (TOA) measurements to localize a large numbers of nodes while starting with a small number of anchor nodes, the nodes whose positions are known in advance. A robust trilateration algorithm using the rigidity of graph theory for flipping avoidance has been proposed in [2]. Although trilateration using TOA measurements can accurately estimate node positions, the accuracy of iterative trilateration depends not only on the initial positions but also on successfully controlling error propagation. Multi-dimensional scaling (MDS) has also been applied for localization of sensor networks, and it appears to provide accurate initial location estimation based on connectivity [3], [4]. However, that approach has not been applied to networks with non-line-of-sight (NLOS) links. To deal with NLOS conditions, linear programming (LP) based approach for mitigating NLOS errors has been proposed [5]. The LP based approach, however, is only valid when the number of anchors that a node has in its one-hop neighborhood, called anchor heard or AH, is at least three. Hence, the LP approach can not be applied to large-scale multi-hop networks with AH<3 in NLOS environments.

In this paper, we propose a multi-hop localization scheme that uses mobility for estimating node positions with AH<3 for large-scale multi-hop networks in mixed line-of-sight (LOS) /NLOS environments. In the proposed MLM, nodes equipped with ultra-wideband (UWB) radio randomly move for collecting TOA measurements and apply a modified biased Kalman filter (MBKF) to mitigate NLOS errors. Shortest path distance (SPD) selection method is then used to further mitigate the NLOS errors. The node positions in our MLM are initialized by using MDS and estimated by using iterative trilateration with an effective error accumulation management. Simulation results indicate that the positioning accuracy of MLM mostly outperforms the conventional MDS-MAP(P) [3] and primitive iterative trilateration (PIT) methods in rectangular and L-shaped node deployments with AH<3, a case which is left unhandled in the previously reported works in [5], [6].

The contribution of this paper is as follows. As opposed to traditional single-hop localization, we use multi-hop connectivity while localizing nodes under NLOS environments. It proposes to use mobility and SPD selection to mitigate NLOS errors, and to use multi-hop neighborhood for accurate location estimation. Novel aspect of SPD selection to mitigate NLOS errors , which is applicable to both static and mobile networks, is analyzed. Finally, the performance improvement by using the proposed NLOS error mitigation method is evaluated via simulations.

The rest of the paper is organized as follows. The MLM is described in Section II. An evaluation of MLM performance is presented in Section III. Finally, Section IV indicates the direction of our future work and concludes the paper.

¶The author was with Shizuoka University when the manuscript was submitted.

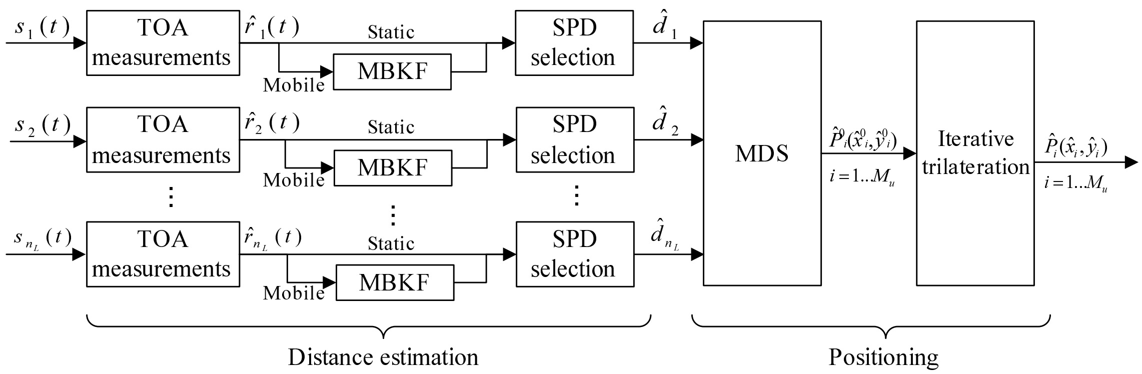


Fig. 1. Block diagrams of MLM.

II. Multi-hop Localization Using Mobility (MLM)

A. *Problem statement*

Let us first introduce some notations and formulate the problem. Consider that $M = M_A + M_u$ nodes are deployed on a two-dimensional field, where M_A is the number of anchor nodes whose positions are known a-priori and M_u is the number of nodes to be localized. All nodes have wireless networking capabilities to construct an ad-hoc network. The ad-hoc network is considered as a graph, $G = (V, E)$, where V is a set of nodes, and E is a set of wireless links between $\{k, l\}$, and where $k, l \in V$. We assume that a node is connected to other nodes within its transmission range R, and also assume that the set E has both LOS and NLOS links.

The objective of localization in this paper is to estimate the positions of unlocalized nodes by using TOA measurements. We assume that the TOA measurements are obtained by using UWB radio signals [7]. In a TOA measurement, the first arrival of the transmitted signal for a LOS link can accurately be obtained by detecting the strongest amplitude at the receiving node. However, if the direct path of the signal is blocked or highly attenuated due to obstructions, reflections of the transmitted signal from scatterers may reach the receiving node and introduce large errors in TOA measurement. We refer to such links as NLOS links. The E is therefore indexed by LOS links, $L_i, i = 1, \ldots, m_L$, and NLOS links, $L_i, i = m_L + 1, \ldots, n_L$.

Generally, TOA measurement between two nodes can be formulated as

$$\hat{r}_i = d_i + \begin{cases} n_i, & i = 1, \ldots, m_L \\ n_i + b_i, & i = m_L + 1, \ldots, n_L \end{cases} \tag{1}$$

where d_i is the actual distance between the nodes and $n_i \sim \mathcal{N}(0, \sigma_v)$ and $b_i \sim \mathcal{E}(\lambda)$. TOA measurements $\hat{r}_i$ are assumed to be taken independently and identically distributed (iid). The noise in TOA measurement for LOS link is modeled as zero-mean Gaussian distribution $\mathcal{N}(0, \sigma_v)$ with variance σ_v. Due to the fact that the time of arrival of UWB multi-path signal is modeled as Poisson distribution [8], we model the term b_i, called NLOS error, as an exponentially distributed random variable $\mathcal{E}(\lambda)$ with mean λ_i. NLOS bias b_i is assumed to be positive since multi-path signals travel longer than direct signal path.

Additionally, we put an assumption that NLOS bias b_i is spatial varying. This radio phenomenon can be explained as follows. Received multipath signals due to scatterers may overlap constructively or deconstructively [9]. Since the interference is different depending on the radio propagation paths, the phase shifts of the amplitudes are varied specific to the location. Consequently, the TOA measurement in the absence of direct LOS signal through mobile nodes become a dynamic (spatial varying).

B. *Block diagrams*

Figure 1 presents the block diagrams for estimating unlocalized node positions $P_i(x_i, y_i)$, $i = 1, \ldots, M_u$. First, TOA measurements $\hat{r}_j(t)$ from received signals $s_j(t)$ through wireless links L_j, $j = 1, \ldots, n_L$ are collected for a certain period t . When the TOA measurements between two nodes are mobile, MBKF is then used to obtain the distance with NLOS error mitigation. Next, SPD selection is conducted to obtain the multi-hop node distance including the one-hop node distance $\hat{d}_j$ with NLOS error mitigation. The initial node positions $\hat{P}_i^0(\hat{x}_i^0, \hat{y}_i^0)$ are determined by using MDS. Finally, node positions $\hat{P}_i(\hat{x}_i, \hat{y}_i)$ are obtained by using the iterative trilateration with the error accumulation management.

In MLM, nodes utilize the mobility for collecting the TOA measurements. This situation is valid when nodes have the mobile capabilities. Recently, *cooperative* mobile ad-hoc networks and robotic sensor networks have receive much attention [10], [11]. The MLM uses such mobile or robotic ad-hoc networks where each node *cooperatively* moves randomly for the TOA measurements in ad-hoc manner and stops for the positioning. It is noted that our work differs from the previous work [10], [11] since the MLM introduces a novel advantage of the mobility in localization.

C. *MBKF*

Biased Kalman filtering (BKF) for NLOS error mitigation is originally developed in [12] and the extension is found in [13]. We have developed the following formulae (2–9) of MBKF that is adopted to the UWB channel model with two major modifications from the one in [13]; first we use LOS/NLOS identification [14] to accurately identify LOS/NLOS conditions; second, we add constraint (9) to mitigate the false estimation of BKF.

The Kalman filter is the optimal state estimation of the dynamic system. The discrete-time linear dynamic state and measurement equations are described by

$$\mathbf{x_{k+1}} = \mathbf{\Phi x_k} + \mathbf{w_k}, \tag{2}$$

$$\mathbf{z_k} = \mathbf{H x}_k + \mathbf{v_k}, \tag{3}$$

where $\mathbf{x_k} = [x_k \ \dot{x}_k]^T$ is the state equation, where x_k is the relative distance between two nodes and $\dot{x}_k$ is node velocity, and $\mathbf{z_k}$ is the measurement equation, and $\mathbf{w_k}$ and $\mathbf{v_k}$ are the process noise and measurement noise with covariance matrices $\mathbf{Q} = \sigma_u^2$, $\mathbf{R}_k = \sigma_x^2$ with $\mathbf{\Phi} = \begin{bmatrix} 1 & \triangle t \\ 0 & 1 \end{bmatrix}$, $\mathbf{H} = [1 \ 0]$. As we discussed in Section II-A, NLOS bias b_i for TOA measurement is dynamic (spatial varying). Then, we can apply TOA measurement $\hat{r}_i(t_i)$ to (3).

The measurement update for the state estimate and estimation error covariance is calculated as follows:

$$\mathbf{M_k} = \mathbf{\Phi P_{k-1} \Phi^T} + \mathbf{Q}, \tag{4}$$

$$\mathbf{K_k} = \mathbf{M_k H^T}(\mathbf{H M_k^T H^T} + \mathbf{R_k})^{-1}, \tag{5}$$

$$\mathbf{P}_k = \mathbf{M_k} - \mathbf{K_k H M_k}, \tag{6}$$

$$\mathbf{\hat{x}_{k+1}} = \mathbf{\hat{x}_k} + \mathbf{K_k}(\mathbf{z_k} - \mathbf{H \Phi \hat{x}_k}). \tag{7}$$

Next, in order to mitigate NLOS error, the weight in (8) for diagonal elements of measurement covariance matrix is applied,

$$\sigma_x = \begin{cases} \beta \sigma_v, & \text{NLOS link,} \\ \sigma_v, & \text{LOS link.} \end{cases} \tag{8}$$

Since the Kalman filter puts more reliability on the state equation when σ_x is increased (biased), thus NLOS error in the TOA measurement is mitigated. However, increasing σ_x also increases the possibility to have false estimation. β is chosen experimentally to have a stable estimation in advance.

A hypothesis test based on sampled standard deviations of TOA measurements can be used to identify the LOS/NLOS link [13]. However, we have found that using sampled standard deviations does not work well, since the LOS/NLOS links shortly change in obstructed building environments. Therefore, we use the LOS/NLOS identification using UWB channel profiles [14], which nodes can accurately identify the LOS/NLOS condition by using individual TOA measurement.

In MBKF, to mitigate the false estimation error the constraint in (9) is added.

$$\text{if } \hat{r}_i(t_i) < \hat{x}_{t_i}, \text{then } \hat{x}_{t_i} = \hat{r}_i(t_i). \tag{9}$$

D. SPD selection

Next, SPD selection is applied to obtain the multi-hop distance and to mitigate NLOS error. SPD selection is usually used for calculating the multi-hop distance in routing or localization [3] and it can be implemented by Warshall-Floyd algorithm [15]. However, we have found that SPD selection has a novel property to mitigate the NLOS bias. The property of SPD selection to mitigate NLOS distance is derived from a triangle inequality as follows. Assume that node v_{src} has i multiple routes to v_{dst} through nodes $v_{2,1}, v_{2,2}, \ldots, v_{p,q_i-1}$

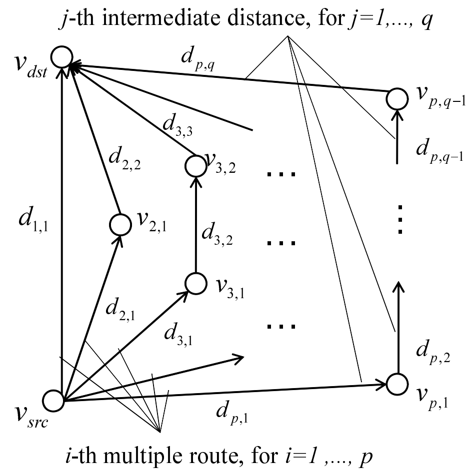


Fig. 2. Example multiple routes and notations of SPD selection.

as shown in Fig. 2. The actual intermediate distance corresponds to $d_{1,1} = d(v_{src}, v_{dst}), d_{2,1} = d(v_{src}, v_{2,1}), d_{2,2} = d(v_{2,1}, v_{dst}), \ldots, d_{p,q} = d(v_{p,q_i-1}, v_{dst})$. Let us first consider the case $p = 2, q_2 = 2$, i.e., only three nodes $v_{src}, v_{dst}, v_{2,1}$ are deployed and v_{src} estimates the distance $d_{1,1}$ to v_{dst}. Also, we have the inequality constraint in (10).

$$d_{2,1} + d_{2,2} \geq d_{1,1}. \tag{10}$$

(10) is known as the triangle inequality. When NLOS bias $b_{i,j} > 0$ with iid is added to each distance with the assumption that NLOS bias is much larger than Gaussian noise $n_{i,j} \ll b_{i,j}$, we can obtain the following two cases for (10) depending on b_i,

$$\begin{cases} \sum_{j=1}^{q_2} (d_{2,j} + b_{2,j}) \geq d_{1,1} + b_{1,1} > d_{1,1}, \\ d_{1,1} + b_{1,1} > \sum_{j=1}^{q_2} (d_{2,j} + b_{2,j}) > d_{1,1}. \end{cases} \tag{11}$$

From (11), we can derive (12).

$$d_{1,1} + b_{1,1} \geq \min(\sum_{j=1}^{q_2} (d_{2,j} + b_{2,j}), d_{1,1} + b_{1,1}) > d_{1,1}. \tag{12}$$

Therefore, node v_{src} can mitigate the NLOS error for $d_{1,1}$ by using SPD selection. (10) can be extended to the $\sum_{j=1}^{q_i} d_{p,j} \geq d_{1,1}$, for arbitrary p. (12) then produces the general case that the number of nodes is more than three as in (13).

$$d_{1,1} + b_{1,1} \geq \min(\sum_{j=1}^{q_1} (d_{1,j} + b_{1,j}), \sum_{j=1}^{q_2} (d_{2,j} + b_{2,j}), \ldots, \sum_{j=1}^{q_p} (d_{p,j} + b_{p,j})) > d_{1,1}. \tag{13}$$

It is worth noting that (13) means that SPD selection can mitigate the NLOS error for $d_{1,1}$ without the false NLOS mitigation and anchor nodes. The distance estimated by using the SPD selection is used for MDS and iterative trilateration in MLM. Since the SPD selection is independent of variance of NLOS bias, it can be applied both static and mobile networks.

E. MDS

The position of each node is initialized by using a classical MDS. To cope with the large-scale multi-hop networks, we use the merging method proposed in [3]. First, all nodes construct the distance matrix by using the SPD selection $\hat{d}_{\{k,l\}}$ between the all pairs of nodes (k, l) within two-hops. Nodes estimate the node positions within two-hops by using the classical MDS and obtain the local coordinates. These local coordinates are iteratively merged into one set of coordinates.

The classical MDS is operated as follows. First, the squared distance matrix, $\mathbf{D}_i^{(2)} = \{\hat{d}^2_{\{k,l\}}\}$ is generated. The scalar product matrix, $\mathbf{B}_i$ is constructed by applying double centering as $\mathbf{B}_i = -\frac{1}{2}\mathbf{J}_i\mathbf{D}_i^{(2)}\mathbf{J}_i$, where $\mathbf{J}_i = \mathbf{I}_n - \frac{1}{n}\underline{1}\underline{1}^T$ and $\underline{1}$ is an n by 1 vector of ones and n is the length of $\mathbf{D}_i$. A singular value decomposition is conducted as $\mathbf{B}_i = \mathbf{U}_i\mathbf{V}_i\mathbf{U}_i^T$. A coordinate matrix is then given by $\mathbf{X}_i = \mathbf{U}_i\mathbf{\Lambda}_i^{1/2}$. $P_i^0(x_i^0, y_i^0)$ is obtained by extracting the first and second columns of $\mathbf{X}_i$.

F. Iterative trilateration

Finally, when there are at least three anchor nodes within one-hop, the node conducts the trilateration for the unlocalized node position based on the anchor nodes. Once an unlocalized node position is estimated, it is configured as a pseudo-anchor node, and it conducts the trilateration for other unlocalized nodes iteratively. The estimated position $(\hat{x}_i, \hat{y}_i)$ for unlocalized node i using trilateration is given by minimizing the cost function in (14),

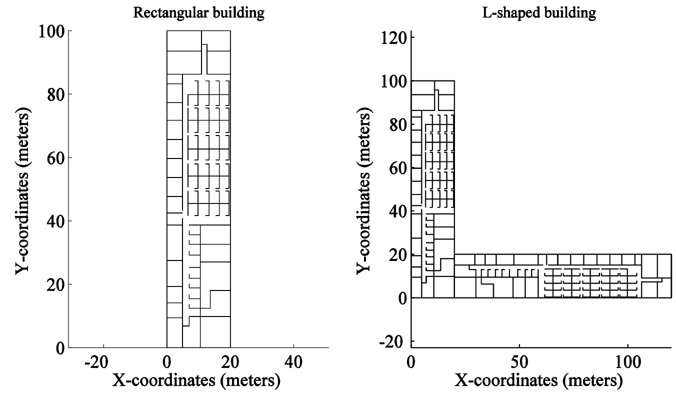
$$\sum_{j=1}^{M_A^1}\left\{\hat{d}_j - \sqrt{(\hat{x}_i - x_j)^2 + (\hat{y}_i - y_j)^2}\right\}^2, \tag{14}$$

where (x_j, y_j) are anchor node positions and $\hat{d}_j$ is the estimated distance from the unlocalized node i to anchor nodes j for $j = 1, \ldots, M_A^1$ within one-hop. Although trilateration can accurately estimate node positions based on anchor nodes, it suffers from error accumulation.

In order to avoid the error accumulation, we introduce the error accumulation management, which limits the iterative trilateration by only using the pseudo anchor nodes with a certain number of iterations γ. In the experiment, we experimentally determine $\gamma = 2$ to avoid large error accumulations. Let $N(v)$ denote the set of the one-hop nodes of $v \in V$ and S^A is the set of anchor nodes and U^N is the set of unlocalized nodes. The pseudo-code for iterative trilateration with the error accumulation management is described in Algorithm 1.

Algorithm 1 Pseudo-code for iterative trilateration

```
for unlocalized node v ∈ U^N, L(v) = 0 do
    N^A(v) = N(v) ∩ S^A, κ = |N^A(v)|
    if (κ ≥ 3 && (Σ^κ L(N^A(v)))/κ ≤ γ) then
        Conduct trilateration for v using (14)
        ▷ Configure v as pseudo anchor node
        S^A ← S^A + {v}, U^N ← U^N − {v}
        L(v) ← (Σ^κ L(N^A(v)))/κ + 1
```



(a) Rectangular building (b) L-shaped building

Fig. 3. Obstruction deployments for (a) rectangular of 100 (height) × 20 (width) (m) and (b) L-shaped of 100 (height) × 120 (width) (m) buildings.

III. Performance evaluation

A. Simulation setting

The performance of MLM in mixed LOS/NLOS environments is evaluate by using Matlab simulator. We evaluated two obstruction deployments as shown in Fig. 3. Figure 3(a) is the rectangular building based on the floor map presented in the UWB channel measurements [16] and Fig. 3(b) is the L-shaped building that is made by patching the two rectangular buildings. Nodes are randomly deployed inside the buildings.

We use the UWB radio propagation models for both LOS and NLOS defined in IEEE 802.15.4a channel modeling subcommittee [8]. The radio coverage of each node is determined by using the path loss model of the office indoor environment [8]. The receiver sensitivity is set as -95 (dbm). We assume that the coverage of TOA measurement is identical to the radio coverage. LOS measurement variance σ_v is set to $\sigma_v = 0.25$ (m). For the NLOS measurement noise, we use the multi-path delay parameter specified in [17]. The interarrival times of the received impulse clusters are modeled by a Poisson distribution [17] and the multi-path cluster arrival rate is specified by $\Lambda(1/ns)$ [17]. Therefore, mean value of NLOS bias λ is computed as $(1/\Lambda) * c = 2.49$ (m), where c is the speed of the light.

The measurement update interval of MBKF is set to 0.1 (s). $\beta = 12$, and $\sigma_u^2 = 0.1$ are chosen. The nodes move along with random way point (RWP), which the velocity v_{mn} is randomly chosen from $0 < v_{mn} \leq 2$ (m/s). The observation time to collect the TOA measurements is 20 (s).

For the metric of localization performance, we use the root mean squared error (RMSE) defined as

$$RMSE = \sqrt{\frac{1}{M_u}\sum_{i=1}^{M_u}(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2}, \tag{15}$$

where (x_i, y_i) represents the actual position of node i, and $(\hat{x}_i, \hat{y}_i)$ is the estimated position. Simulation trials are conducted 40 times with random seeds and these are averaged.

We compared the MLM performance with the following methods:

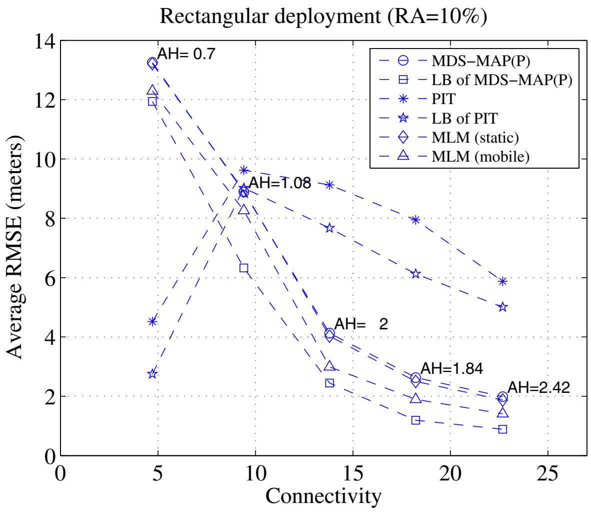


Fig. 4. Average RMSE in rectangular deployment for varying the number of nodes when the RA is 10%.

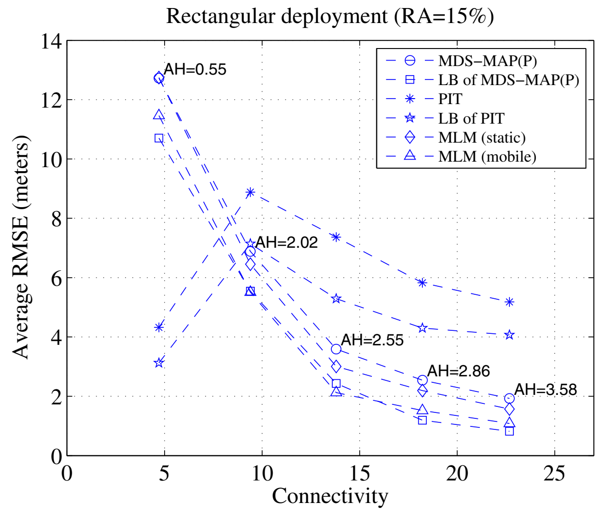


Fig. 5. Average RMSE in rectangular deployment for varying the number of nodes when the RA is 15%.

1) MDS-MAP(P) [3]: two-hop local maps generated by applying classical MDS are iteratively merged to estimate all node positions.
2) Lower bound (LB) of MDS-MAP(P): two-hop local maps constructed by using the distance information with the assumption that all links are LOS regardless of the obstructions is applied to MDS-MAP(P). This assumption is impossible for NLOS environments, however, we use the case as the best achievable performance benchmark of the method.
3) Primitive iterative trilateration (PIT): Trilaterations are iteratively applied to estimate node positions. For PIT, initial positions are randomly determined by using a uniform distribution over the deployment field.
4) LB of PIT: PIT is conducted by using the distance information with the assumption that all links are LOS. Initial positions are randomly determined by using a uniform distribution over the deployment field.

We do not compare the performance with the local and global refinement steps described in [3] since the refinement steps can be applied to MLM and other localization techniques after determining the initial positions.

B. Simulation results

1) Rectangular node deployment: Figure 4 shows the average RMSE when the number of nodes is varied and ratio of anchor nodes (RA) is 10%. The number of nodes is increased from 20 to 100. AH is plotted against each connectivity that shows the average number of one-hop nodes. MLM (mobile) corresponds to the case when all nodes are mobile for TOA measurements such that MBKF and SPD selection are applied to mitigate NLOS errors. MLM (static), on the other hand, corresponds to the case when all nodes are stationary and only SPD selection is used to mitigate NLOS error. The RMSE of MLM (mobile) outperforms MDS-MAP(P). On the other hand, the performance of MLM (static) is similar to that of MDS-MAP(P). For example, MLM (static) and MLM (mobile) have 4% and 27.8% better accuracy than MDS-MAP(P), respectively when the connectivity is 18.2. Although PIT and LB of PIT show fine accuracy for the connectivity of 4.7 and 9.4, the percentage of localized nodes is quite low. For instance, the percentage of localized nodes for PIT is 11.8, 64, and 99.2% for the connectivity of 4.7, 9.4 and 13.7, respectively, while that of MLM is 100% for the connectivity of 4.7.

It is worth mentioning that the value of AH is less than three in Fig 4, which can not be handled by the approach reported in previous work [5], [6]. The results demonstrate that using mobility for localization is beneficial and, as a result, the MLM is a more robust solution for the mixed LOS/NLOS environments.

Due to space limitation, we do not show the detailed results of MBKF in this paper. We, however, have found that MBKF sufficiently mitigates the NLOS error even in the situations where nodes have the LOS/NLOS radio coverage inside the obstructed buildings. Such an operational environment introduces LOS/NLOS transitions for short periods and disconnections of ad-hoc networks with the random motion.

Figures 5 shows the average RMSE when the number of nodes varies and RA is 15%. The RMSE of MLM (static) is improved as compared to the results of Fig. 4 and it outperforms the MDS-MAP(P). That is so, because the MLM conducts the iterative trilateration using SPD selection based on the anchor nodes. The RMSE of MLM (mobile) sufficiently outperformed MDS-MAP(P) and it is much closer to the LB of MDS-MAP(P). For example, MLM (static) and MLM (mobile) have 13.8% and 40.2% better accuracy than MDS-MAP(P), respectively, when the connectivity is 16.9.

2) L-shaped node deployment: Figure 6 shows the average RMSE when the number of nodes varies and RA is fixed at 10%. The number of nodes is increased from 50 to 170. Both MLM (static) and MLM (mobile) outperforms the MDS-MAP(P) in terms of RMSE. For example, MLM (static) and MLM (mobile) have 17.9% and 26.5% better accuracy than MDS-MAP(P) respectively when the connectivity is 16.9. Notably, the RMSE of MLM (mobile) is much closer or

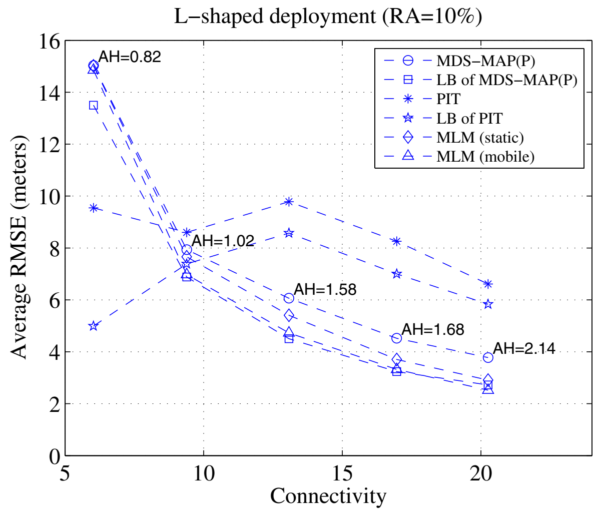


Fig. 6. Average RMSE in L-shaped deployment for varying the number of nodes when the RA is 10%.

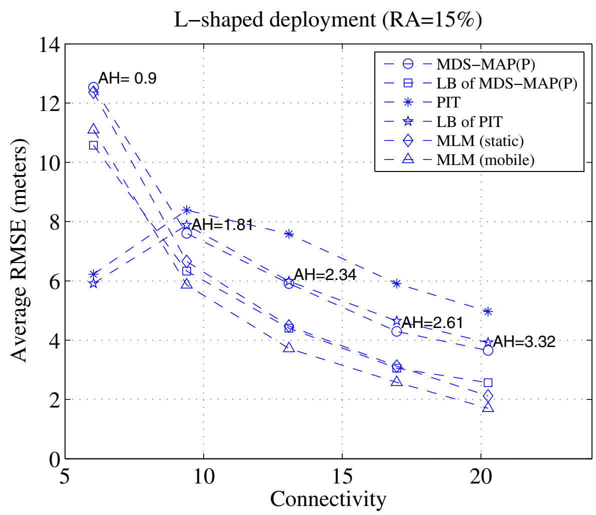


Fig. 7. Average RMSE in L-shaped deployment for varying the number of nodes when the RA is 15%.

at some cases better than that of the LB of MDS-MAP(P). This is because MDS-MAP(P) has poor performance in the non-convex networks than convex networks [3]. MLM uses iterative trilateration with the error accumulation management based on anchor nodes after initialization by using MDS, hence, it is more robust for the non-convex networks. Again, it should be noted that MLM is still with AH<3, which previous related work [5], [6] does not cope with this case.

Figure 7 shows the average RMSE when the number of nodes is varied and RA is 15%. Remarkably, the RMSE of MLM (mobile) is better than that of the LB of MDS-MAP(P) in most cases. The RMSE of MLM (static) is also approaching the LB of MDS-MAP(P). MLM (static) and MLM (mobile) have 27.3% and 39.9% better accuracy than MDS-MAP(P), respectively when the connectivity is 16.9.

IV. Conclusion

The key aspect of the MLM is to exploit mobility to make the TOA measurement dynamic during the localization in a multi-hop ad-hoc network. We have shown that TOA measurements with mobility enhance localization performance in NLOS environments. We have also shown that SPD selection has the useful property of mitigating NLOS errors. Our simulation results demonstrate that the proposed combined positioning approach with MDS initialization and iterative trilateration with the error accumulation management mostly provides the superior performance than the previous methods when AH<3.

Due to the hardware limitations, TOA measurement capability may not be available for all nodes. Our future work focuses on extending our current research to also use received signal strength (RSS) for localization in combination with mobility while using a suitable filtering technique such as a particle filter. An experiment for validation with real sensor nodes is also future work.

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