Self-Localizing On-Demand Portable Wireless Beacons for Coverage Enhancement of RF Beacon-Based Indoor Localization Systems

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***Abstract*—Localization using relative ranging from radio frequency (RF) wireless beacons installed in an indoor infrastructure is becoming the hallmark of indoor localization systems for asset tracking. However, the coverage of these beacons is not always complete. Moreover, installing the beacons in underutilized spaces is not cost-effective. Deploying portable on-demand beacons to extend the coverage is a cost-effective solution for a robust and reliable RF beacon-based localization system. The challenge though is how to localize these deployed beacons. This article presents a decentralized algorithm to allow deployed beacons to self-localize themselves. This solution removes the rigid requirement of the beacon connectivity, and thus, the need to deploy the beacons in a priori known and surveyed locations. The deployed beacons localize themselves in a collaborative and decentralized manner without the necessity of each of them being connected to three preinstalled infrastructure beacons. The proposed solution is a robust deployment method in the sense that if a portable beacon is moved for any reason, it can automatically relocalize itself in the decentralized manner. Simulation studies of the ultrawideband beacon deployment and localization demonstrates the effectiveness and robustness of the proposed solution in terms of the accurate autonomous position estimation for multiple beacons with 1-m positioning accuracy, and an average error reduction being 79.21% and 34.41% with respect to the conventional methods in literature.**

***Index Terms*—Decentralized cooperative localization, deployment, portable wireless beacon, positioning.**

I. Introduction

RADIO frequency (RF)-based wireless sensors, such as Wi-Fi, ultra-wideband (UWB), and long-term evolution are gradually fostering their adoption in indoor localization systems because of their accuracy and reliability [1], [2], [3], [4]. Localization systems using RF signals typically utilize preinstalled devices (beacons) with known locations [5]. That is, they use time-of-arrival (TOA) or received-signal strength measurements to obtain relative distances of an RF-tagged target/asset they want to track from the preinstalled beacons and use these relative range measurements and the known location of the beacons to localize the target. Robust solution requires access to at least three beacons at all times for continuous and high-accuracy localization. Despite the promise of the RF beacon-based indoor localization, the deployment of these wireless beacons still faces the coverage problem. Full coverage, i.e., making sure the targets will have access to at least three infrastructure beacons, requires installing a large number of beacons. Covering an indoor area may involve hundreds of nodes since wireless beacons have effective ranges and coverage degrades due to the signal attenuation. Moreover, knowing the accurate positions of the deployed beacons is vital for the indoor localization algorithms. Therefore, fast and accurate beacon deployment and positioning are key to the implementation of these indoor techniques [6].

Installing the beacons in underutilized spaces is not conducive. Moreover, in a dynamic environment, it is always possible to have blockage in line-of-sight access to beacons because of indoor obstructions. Deploying on-demand portable beacons to extend the coverage is a cost-effective solution for a robust and reliable RF beacon-based localization system. The challenge though is how to localize these deployed beacons. This article presents a decentralized algorithm to allow deployed beacons to self-localize themselves. This solution removes the need to deploy the beacons in a priori known and surveyed localizations.

In a typical scenario, the infrastructure beacon installment and the survey of their position coordinates are performed manually via specialized equipment (e.g., motion capture cameras and laser distance measurers) after the installation [7], [8], which is human-error prone and effort-demanding, especially for large-scale networks. Furthermore, in a large-scale deployment, measurement station must be moved frequently in the target area to ensure the line of sight toward all beacons, which requires multiple recalibration of the ground truth along with converting all measured positions to a common global coordinate frame [9]. Such a method cannot be applied for portable beacons.

The demand for automatic computing of the beacon positions via senor measurements and providing flexibility in beacon deployment has led to the development of an alternative approach, self-localization, which can be formulated as a parameter or state estimation problem. In literature, most of the work focus on trilateration method to localize beacons using at least two linear measurements or three nonlinear measurements from the

Manuscript received 6 October 2023; revised 21 November 2023; accepted 27 November 2023. Date of publication 1 December 2023; date of current version 12 December 2023. *(Corresponding author: Solmaz Kia.)*

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Digital Object Identifier 10.1109/JISPIN.2023.3338186

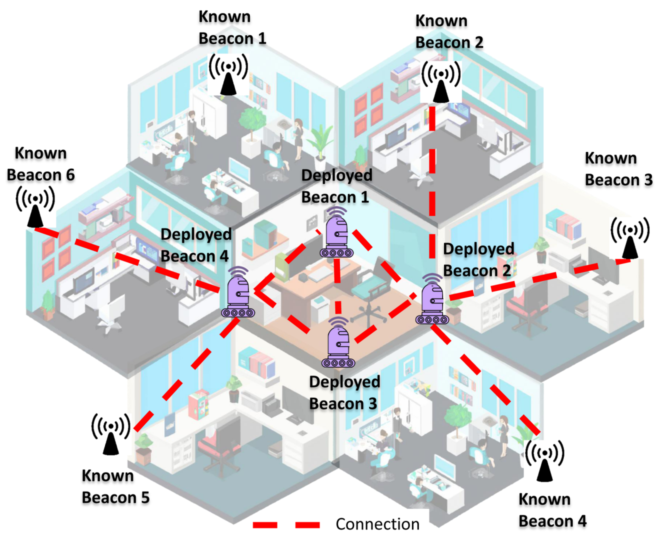


Fig. 1. Schematic depiction of portable wireless beacon deployment for coverage enhancement of indoor localization systems.

preinstalled beacons with accurate known positions nearby [10], [11], [12], [13], which is the strict requirement of the trilateration method even though the workload of manually positioning has been significantly reduced. If the beacon to be deployed has been placed in the area lacking sufficient connections to known beacons, the trilateration method fails. To relax the connectivity, mobile beacons are adopted to provide extended coverage of sensor networks [14], [15], [16]. The mobile beacons can be any portable mobile robot or vehicle carrying the wireless sensors. Then the mobile beacons can be controlled and assigned to the area with enough measurements for self-localization. However, there still exist the scenarios that the areas of interest are not covered yet by the sensor networks. As depicted in Fig. 1, the beacons are deployed at some target locations but only beacon 2 has three connections to known beacons, which constrains the self-localization process. Moreover, recent works conduct beacon self-localization in a centralized manner, where the correlation between the deployed beacons are completely ignored or mishandled [9], [16], [17], [18]. And due to the mobility of the deployed beacons, centralized self-localization cannot suitably capture the dynamical changes of the network.

In this article, we propose a novel decentralized cooperative self-localization method to localize portable wireless beacons that are deployed to tackle the limited connectivity/coverage of the infrastructure beacons, see Fig 1. Our method is able to localize the deployed beacons in the condition that some of them have no access to the infrastructure beacons, but they are able to self-localize by cooperating with nearby deployed beacons which have connectivity to the infrastructure beacons. Besides, the correlation among deployed beacons are treated carefully and implicitly to ensure the consistency of the positioning. Finally, since this method can be computed in a distributed way, it is also suitable for the large-scale beacon deployment. We describe next the self-localization problem and the techniques we propose to solve it.

II. Problem Statement

Consider a network deployment of N ($N > 3$) beacons with communication and computation capabilities in an M-dimensional space, $M \in \{2, 3\}$, whose positions are denoted as $\mathbf{X} = [\mathbf{x}^1, \mathbf{x}^2, \ldots, \mathbf{x}^N] \in \mathbb{R}^{M\times N}$. Within the network, assume there are at least three infrastructure beacons installed at known positions $\mathbf{X}_k$, which have been measured elaborately, and the rest of the beacons are deployed, to enhance the beacon coverage and signal strength of certain areas, at unknown positions $\mathbf{X}_u$, which are required to be determined such that $\mathbf{X} = [\mathbf{X}_k, \mathbf{X}_u]$. Let the relative measurement (e.g., relative range, relative bearing, relative pose, or a combination of them) $\mathbf{z}_j^i \in \mathbb{R}^{n_z}, n_z \in \{1, 2, 3\}$ taken by beacon i from beacon j be described as

$$\mathbf{z}_j^i = \mathbf{h}(\mathbf{x}^i, \mathbf{x}^j) + \boldsymbol{\nu}^i \tag{1}$$

where $\mathbf{h}$ is the relative measurement model and $\boldsymbol{\nu}^i \sim \mathcal{N}(\mathbf{0}, \mathbf{R}^i)$ is the zero mean Gaussian measurement noise with covariance matrix $\mathbf{R}^i \in \mathbb{R}^{n_z\times n_z}$.

Given the available relative measurements $\{\mathbf{z}_j^i\}$ and the known beacon positions $\mathbf{X}_k$, our objective is to determine the unknown beacon positions $\mathbf{X}_u$ subject to limited connectivity between beacons, i.e., beacons are only connected to their neighbors whose positions may also belong to $\mathbf{X}_u$, and thus, need to be estimated. In other words, due to the effective range of wireless beacons, some deployed beacons may not be able to obtain direct measurements from the beacons at known positions. Another issue is the correlation among unknown beacons. Once the estimates of any two beacons, $\hat{\mathbf{x}}_u^i$ and $\hat{\mathbf{x}}_u^j$, are correlated; to keep an explicit track of the correlations requires a high communication and computation capability [19]. Moreover, given that the beacon network can be dynamical, i.e., beacons can be added or removed from the network as desired, centralized localization method are less suitable in terms of autonomous self-localization.

In general, the position of each beacon i in the set of beacons with unknown positions (hereafter we call them unknown beacons) denoted as U is estimated by solving the following optimization problem:

$$\hat{\mathbf{x}}_u^i = \underset{\mathbf{x}_u^i}{\operatorname{argmin}} \sum_{j\in N_G(i)} \left\|\mathbf{z}_j^i - \hat{\mathbf{z}}_j^i\right\|^2 \tag{2}$$

with the uncertainty $\mathbf{P}^i = \mathbb{E}[(\hat{\mathbf{x}}_u^i - \mathbb{E}[\hat{\mathbf{x}}_u^i])(\hat{\mathbf{x}}_u^i - \mathbb{E}[\hat{\mathbf{x}}_u^i])^\top]$, where $N_G(i)$ represents the set of neighbors of beacon i and $\hat{\mathbf{z}}_j^i = \mathbf{h}(\hat{\mathbf{x}}_u^i, \hat{\mathbf{x}}_u^j)$ is the estimated measurement.

III. Beacon Self-Localization

To solve (2), depending on whether the neighbor beacon j has a known position $\mathbf{x}_k^j$ or an unknown position $\mathbf{x}_u^j$, the solutions differ in two cases.

A. Recursive Least Squares Method

For the first case, if $j \notin U$, which indicates the beacon i is connected to the known neighbor j, (2) is solved for all $j \in N_{G(i)}$ at time t by the recursive least squares (RLS) algorithm [20] with uncertainty $\mathbf{P}^i[t]$ using sequential updating to process multiple concurrent measurements $\{\mathbf{z}_j^i[t]\}$ (see [20]) as follows:

$$\hat{\mathbf{x}}_u^i[t] = \hat{\mathbf{x}}_u^i[t-1] + \mathbf{K}^i[t](\mathbf{z}_j^i[t] - \hat{\mathbf{z}}_j^i[t]) \tag{3a}$$

$$\mathbf{P}^i[t] = \left(\mathbf{I} - \mathbf{K}^i[t]\mathbf{H}^i[t]\right)\mathbf{P}^i[t-1] \tag{3b}$$

where $\mathbf{K}^i[t] = \mathbf{P}^i[t-1]\mathbf{H}^{i^\top}[t](\mathbf{H}^i[t]\mathbf{P}^i[t-1]\mathbf{H}^{i^\top}[t] + \mathbf{R})^{-1}$ is known as the Kalman gain and $\mathbf{H}^i[t] = \partial\mathbf{h}(\hat{\mathbf{x}}_u^i[t-1], \hat{\mathbf{x}}_k^j[t-1])/\partial\mathbf{x}_u^i$.

If beacon i is connected to an unknown neighbor j, i.e., $j \in U$, solving the optimization problem in (2) requires careful handling of the correlation between unknown beacons. In short, once a relative measurement is proceeded to update the estimate of two unknown beacons, they are correlated. If the correlation is not properly taken care of or is completely ignored, the estimator will be likely to diverge [19]. Therefore, in the following subsection, we introduce a decentralized cooperative localization algorithm, namely, discorrelated minimum variance (DMV), proposed in [19] to solve the self-localization problem (2) with elaborate design to deal with the correlation issue instead of the RLS. For more information, see [19].

B. Decentralized Cooperative Self-Localizing Method

To simplify the notation and avoid confusion, hereafter we only include the subscripts u and k for position estimates when clarification is needed. For $i, j \in U$, let the joint position estimate mean and covariance of the beacons i and j at time $t-1$ be $\hat{\mathbf{x}}_J[t-1]$ and $\mathbf{P}_J[t-1]$, respectively, where

$$\hat{\mathbf{x}}_J[t-1] = \begin{bmatrix} \hat{\mathbf{x}}^i[t-1] \\ \hat{\mathbf{x}}^j[t-1] \end{bmatrix} \tag{4a}$$

$$\mathbf{P}_J[t-1] = \begin{bmatrix} \mathbf{P}^i[t-1] & \mathbf{P}^{ij}[t-1] \\ \mathbf{P}^{ij}[t-1]^\top & \mathbf{P}^j[t-1] \end{bmatrix}. \tag{4b}$$

When beacon i takes a relative measurement $\mathbf{z}_j^i[t]$ from beacon j at time t, beacon i can correct its local estimate using the measurement feedback $\mathbf{z}_j^i[t] - \hat{\mathbf{z}}_j^i[t]$. When the cross-covariance term $\mathbf{P}^{ij}[t-1]$ is known, the feedback gain can be computed from a Kalman like update procedure. When $\mathbf{P}^{ij}[t-1]$ is not available or computationally too expensive to be tracked, the DMV algorithm is able to process the relative measurement $\mathbf{z}_j^i[t]$ to correct the local estimates in the absence of explicit knowledge of the cross-covariance $\mathbf{P}^{ij}[t-1]$. It is important to note that correlation terms $\mathbf{P}^{ij}[t-1]$ due to prior relative measurement updates cannot be ignored trivially. Ignoring the correlations leads to overconfident estimates and even filter divergence [21].

The DMV algorithm is inspired by the covariance intersection method in sensor fusion [22], which accounts for unknown cross-covariances in an implicit manner. In the DMV method, a discorrelated upper bound, which acts as a conservative joint covariance matrix, is used to account for any unknown cross-covariance term $\mathbf{P}^{ij}[t-1]$ as

$$\begin{bmatrix} \mathbf{P}^i[t-1] & \mathbf{P}^{ij}[t-1] \\ \mathbf{P}^{ij}[t-1]^\top & \mathbf{P}^j[t-1] \end{bmatrix} \preceq \begin{bmatrix} \frac{1}{\omega}\mathbf{P}^i[t-1] & \mathbf{0} \\ \mathbf{0} & \frac{1}{1-\omega}\mathbf{P}^j[t-1] \end{bmatrix} \tag{5}$$

for $\omega \in [0, 1]$.[1]

Using the matrix in the right-hand side of (5) as the conservative but discorrelated joint covariance matrix, the DMV algorithm updates the position estimate of agent i at time $t-1$, $(\hat{\mathbf{x}}^i[t-1], \mathbf{P}^i[t-1])$, according to

$$\hat{\mathbf{x}}^i[t] = \hat{\mathbf{x}}^i[t-1] + \bar{\mathbf{K}}^i(\omega_\star^i)\left(\mathbf{z}_j^i[t] - \hat{\mathbf{z}}_j^i[t]\right) \tag{6a}$$

$$\mathbf{P}^i[t] = \bar{\mathbf{P}}^i(\omega_\star^i) \tag{6b}$$

where the optimal gain is

$$\bar{\mathbf{K}}^i(\omega) = \frac{\mathbf{P}^i[k-1]}{\omega}\mathbf{H}_i^{i^\top}\left(\mathbf{H}_i^i\frac{\mathbf{P}^i[k-1]}{\omega}\mathbf{H}_i^{i^\top} + \mathbf{H}_j^i\frac{\mathbf{P}^j[k-1]}{1-\omega}\mathbf{H}_j^{i^\top} + \mathbf{R}^i\right)^{-1} \tag{7}$$

and the corresponding covariance

$$\bar{\mathbf{P}}^i(\omega) = \left(\omega(\mathbf{P}^i[t-1])^{-1} + (1-\omega)\mathbf{H}_i^{i^\top}(\mathbf{H}_j^i\mathbf{P}^j[t-1]\mathbf{H}_j^{i^\top} + (1-\omega)\mathbf{R}^i)^{-1}\mathbf{H}_i^i\right)^{-1} \tag{8}$$

with $\mathbf{H}_i^i = \partial\mathbf{h}(\hat{\mathbf{x}}^i[t-1], \hat{\mathbf{x}}^j[t-1])/\partial\mathbf{x}^i$ and $\mathbf{H}_j^i = \partial\mathbf{h}(\hat{\mathbf{x}}^i[t-1], \hat{\mathbf{x}}^j[t-1])/\partial\mathbf{x}^j$.

The optimal coefficient ω, denoted by $\omega_\star^i$, is obtained from the optimization problem

$$\omega_\star^i = \underset{0\le\omega\le1}{\operatorname{argmin}} \log\det\bar{\mathbf{P}}^i(\omega). \tag{9}$$

Similarly, the sequential updating technique is applied for DMV. According to [19, Th. 3.1], despite the unknown $\mathbf{P}^{ij}[t-1]$, the DMV update is guaranteed to be no worse than the local estimates of beacon i and j. The computation complexity in (9) can be reduced by applying machine learning tools as we have demonstrated in our prior work in [23]. The optimal coefficient ω can be predicted directly from a neural network as

$$\omega_\star^i = f_{\mathrm{DMV}}(\mathbf{P}^i, \mathbf{P}^j, \mathbf{H}^i, \mathbf{H}^j) \tag{10}$$

where the f_{DMV} is the function approximated by the neural network. See [23] for more information.

C. Full Algorithm

In summary, the entire beacon self-localization process consists of both RLS and DMV which is depicted in Algorithm 1.

IV. Simulation Study

In this section, we assess the effectiveness of our beacon self-localization algorithm through a simulated scenario. The scenario involved the deployment and self-localization of 25 UWB beacons in a 2-D space with an area of 60 m × 60 m, i.e., $M = 2$ and $N = 25$. UWB beacons can take the TOA ranging

[1] $\preceq$ is in the matrix inequality sense, that is, if we subtract the matrix on the left-hand side the result of the matrix on the left-hand side from the one on the right-hand side of the inequality, the results will be a negative semidefinite matrix.

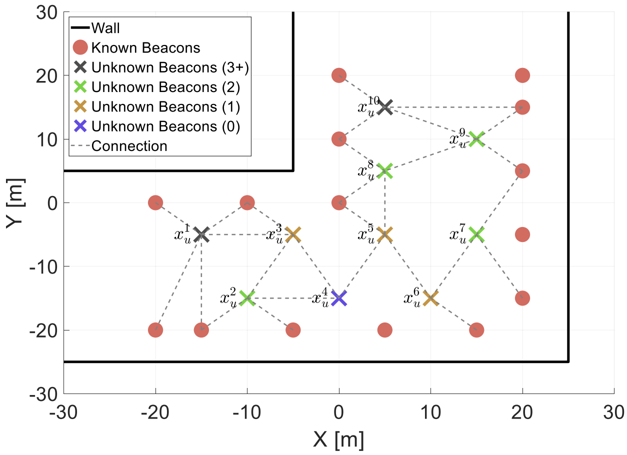


Fig. 2. Simulation configuration of beacon self-localization. The black, green, orange, and blue crosses represent the unknown beacons with more than three connections, two connections, only one connection, and no connection to known beacons, respectively.

Algorithm 1: Beacon Self-Localization.

Input: $\{\hat{\mathbf{x}}^i[t=0], \mathbf{P}^i[t=0], \mathbf{z}^i_j\}$ for all $i \in U$ and $j \in N_{G(i)}$
repeat
  $t = t+1$
  for each $j \in N_{G(i)}$ **do**
    if $j \notin U$ **then**
      Calculate $\hat{\mathbf{x}}^i[t]$ and $\mathbf{P}^i[t]$ using (3)
    else
      Calculate $\hat{\mathbf{x}}^i[t]$ and $\mathbf{P}^i[t]$ using (6) and (9) or (10)
until Convergence
Output: $\hat{\mathbf{x}}^i[t]$, $\mathbf{P}^i[t]$

measurements, i.e., $\mathbf{h}(\mathbf{x}^i, \mathbf{x}^j) = \sqrt{(\mathbf{x}^i - \mathbf{x}^j)^2}$, to obtain the distance information between beacons. Moreover, the measurement noise covariance was chosen to be $R = 0.01$ with respect to the empirical ranging error of UWB sensor whose standard deviation is 0.1 m. The simulation time interval was $\Delta t = 0.1$, the total simulation time was $T = 50$ s, and the sampling rate of the UWB beacon was 10 Hz. The configuration of the simulation is illustrated in Fig. 2. As it is shown in Fig. 2, there are 15 beacons with known positions denoted by red circles being installed in the hallway environment while ten additional beacons denoted by the crosses are deployed at the locations as desired. The dashed lines represent the connectivity among the known and unknown beacons which is designed on purpose. We assumed the prior knowledge of the positions of the unknown beacons that we desired to deploy them inside the area surrounded by the known beacons. In fact, without such information, the problem has the potential to become underdetermined, which will be studied in our future work. The objective is to determine the positions of all unknown UWB beacons x^i_u ($i = 1, 2, \ldots, 10$, in this case) given the range measurements and constrained by the connectivity. Note that in this setting, beacon 2, 7, 8, and 9 (marked with green crosses in Fig. 2) connect to two known beacons; beacon 3, 5, and 6 (marked with orange crosses) only connect to one known beacon; and beacon 4 (marked with a blue cross) connects to no known beacons by design to simulate the limited connectivity condition while all unknown beacons connect to at least three beacons.

TABLE I
Localization Accuracy Regarding Average RMSE and Maximum Error in Three Groups Over 1000 Simulations

Method	RMSE [m]	Maximum Error [m]
RLS	5.1599	12.0692
NaiveCL	1.6355	4.0473
Proposed	1.0727	2.3298

Three groups of simulations were conducted to estimate the unknown beacon positions separately and the simulations were repeated 1000 times in each group to mitigate the random error that occasionally caused by the bad initialization of unknown beacons. In the first group of simulations, we only proceed the measurements between the known and unknown beacons using an RLS estimator to make it serve as a control group. The second one was what we called "NaiveCL" group referring to the naive way of processing the correlation between correlated beacons, where the correlations are completely ignored. It is equivalent to using the RLS solely to estimate all unknown beacon positions with all available measurements. We implemented the proposed self-localization method in the last group of simulations. Besides, without loss of generosity, we intentionally moved beacon 6 to a new assigned location at timestamp 300 when the algorithm converged for the first time to demonstrate the robustness of our method in terms of the autonomous relocalization capability. The simulation results are illustrated in Figs. 3–5 and Table I, where the average root mean square error (RMSE) and maximum error were used as the performance metric of the self-localization. Absolute error and the $3-\sigma$ bound were drawn to compare the consistency and robustness of the methods. And we drew gray semitransparent boxes in the figures to highlight the beacons of interest and their corresponding ground truth locations.

As it is visualized in Fig. 3(a), beacons 3–6 cannot self-localize themselves well with measurements from only one known beacon as expected, because at least measurements from three beacons (noncollinear with the beacon to be estimated) are needed to estimate precisely the positions in the 2-D space. Therefore, the relative measurements between unknown beacons should also be taken into account to estimate the beacon positions. However, if we naively update the local estimates and ignore the correlation between the unknown beacons, the localization performance will be deteriorated. Fig. 3(b) shows the corresponding evidence and in Table I, the average RMSE and maximum error of the NaiveCL are significantly larger than those of our proposed method due to the inconsistency of the estimator when correlations are neglected although the NaiveCL outperforms the RLS method in the first group. In contrast, our proposed method significantly improves the localization performance, as shown in Fig. 3(c), with the lowest average RMSE and maximum error in Table I. With a particular care

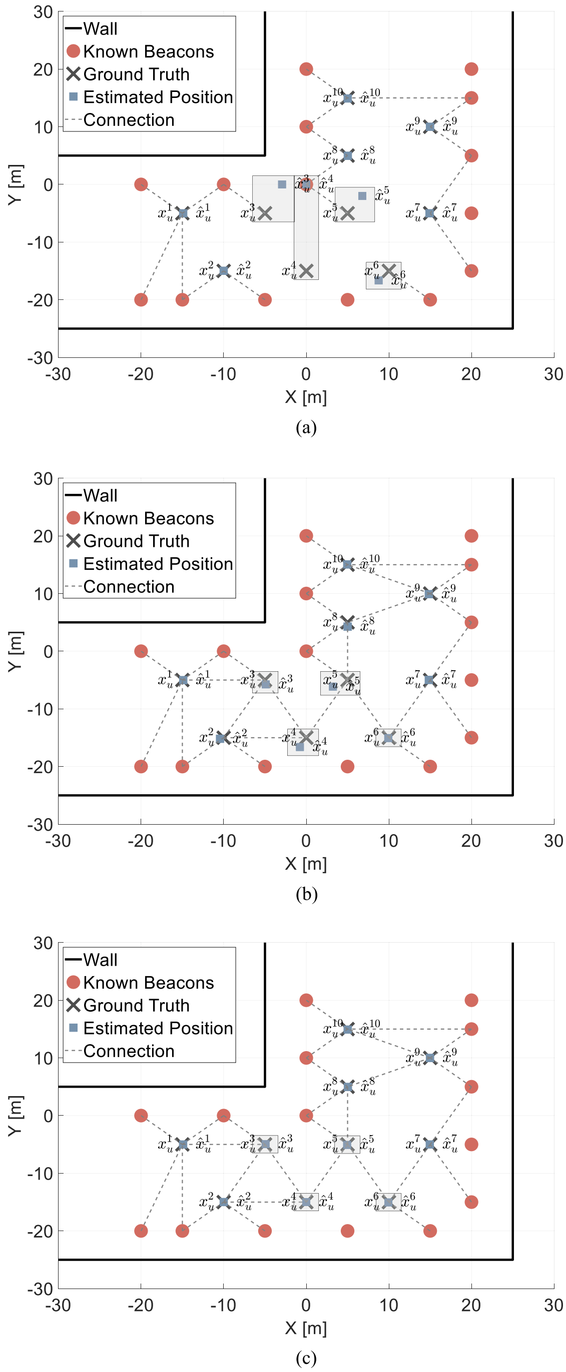


Fig. 3. Self-localization results in three groups of simulations. The gray semitransparent boxes in the figures bound the highlighted beacons of interest and their ground truth locations. The means of localization RMSE for RLS, NaiveCL, and Proposed are 5.1599 , 1.6355 , and 1.0727 m while the corresponding variances are 0.7214 , 0.5087, and 0.4331 m^2, respectively. (a) RLS. (b) NaiveCL. (c) Proposed.

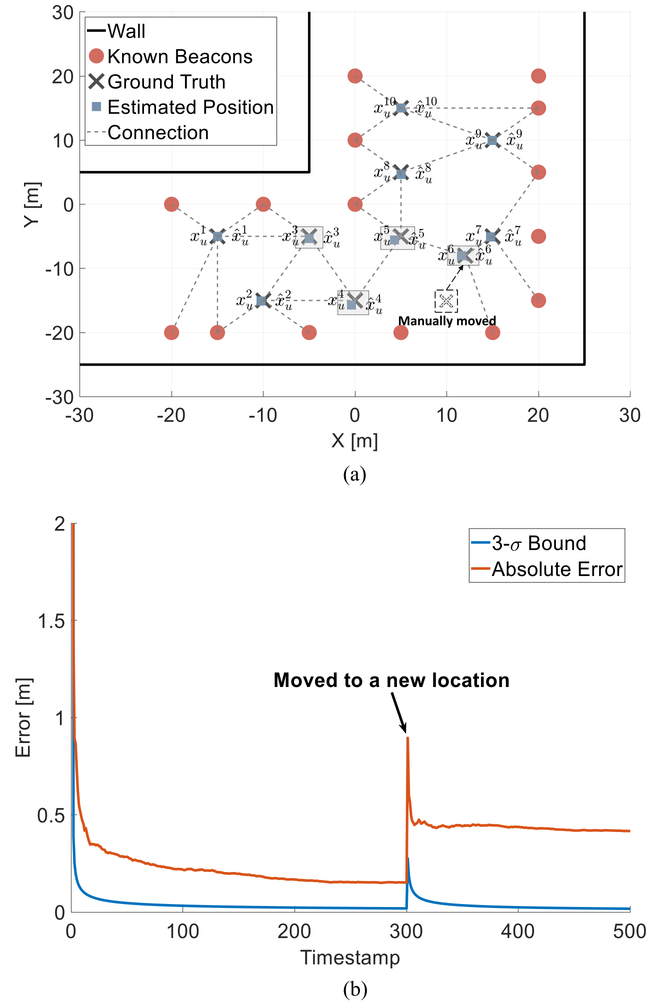
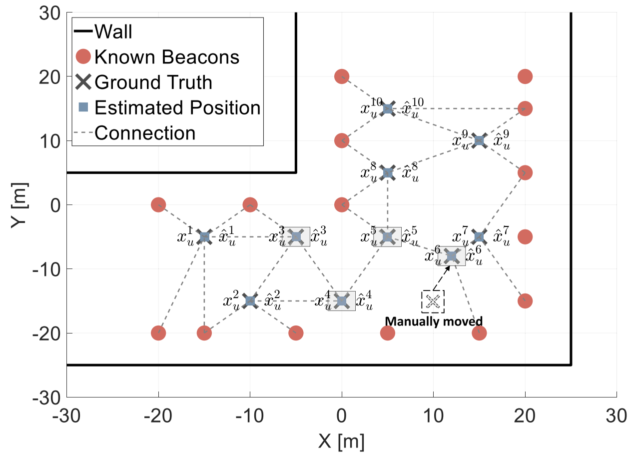


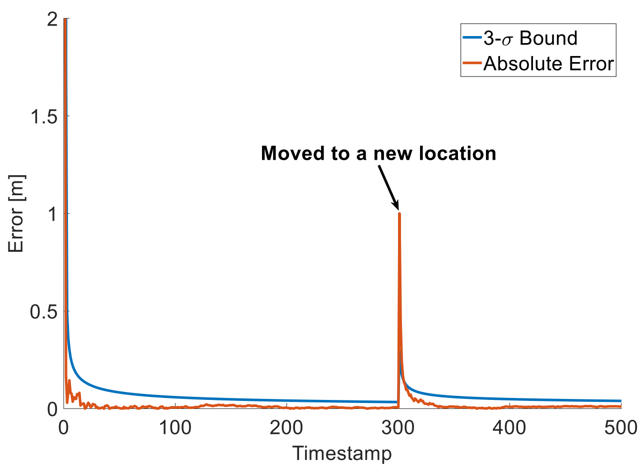
Fig. 4. Relocalization performance of the NaiveCL method. Before the beacon was moved to a new location, the NaiveCL has worse performance of self-localization in terms of consistency. After the relocalization, it generates larger error and cannot converge to the new ground truth. The mean of the relocalization error of all beacons over 1000 simulations is 2.0925 m and the corresponding variance is 0.6923 m^2. (a) Relocalization result. (b) Absolute error.

of the correlation between the unknown beacons, our proposed method enables the accurate beacon self-localization without the necessity of each beacon being connected to three preinstalled infrastructure beacons compared with the other two methods.

Another comparison regarding to the robustness is that after being moved for certain reasons to a new positions, beacon 6 cannot accurately acquire its new position and even ends up with affecting the neighbor beacons and resulting in a higher localization error using the NaiveCL, as shown in Fig. 4. However, by implementing our proposed method, beacon 6 still relocalizes itself in the decentralized manner without effecting the neighbor beacons demonstrated in Fig. 5. Note that in this simulation, we set the beacon to reinitialize the covariance to a large value if it detects the motion or receives the command to relocate to a new location, which prevents the vanishing of the Kalman gain. Adding process noise can have the same effect. The localization error falls into the $3-\sigma$ bound throughout the entire simulation, which exemplifies the robustness of our solution and the capability to deploy the beacons on demand to extend the coverage of the beacon networks. As long as each beacon has at least three connections to neighbors, preknowledge or manual measurement of only a handful of beacon position is sufficient to estimate other unknown ones accurately,



(a)



(b)

Fig. 5. Relocalization performance of our proposed method. After the beacon was moved to a new location, our method made the estimate converged to the new ground truth and stayed consistency as before. The mean of the relocalization error of all beacons over 1000 simulations is 1.2476 m and the corresponding variance is 0.5031 m^2. (a) Relocalization result. (b) Absolute error.

which perfectly facilitates the coverage enhancement for the beacon-based localization systems. Future work will focus on the initialization of the unknown beacons to avoid the estimated beacon positions being stuck in a statistical local minimum and further enhance the robustness of the proposed algorithm.

V. Conclusion

This article considers beacon self-localization under limited connectivity for deploying the portable wireless beacons. Specifically, we propose a decentralized beacon self-localization algorithm which relaxes the essential requirement of sufficient connections to the beacons with known positions and avoids the labor-intensive and error-prone manual measurement of the beacon positions. The simulation results demonstrated the efficacy of our proposed method in terms of the accurate autonomous position estimation for multiple beacons and its robust relocalization capability which enables a more flexible deployment of the on-demand portable beacons. The achievable positioning accuracy with the proposed method is around 1 m given that the empirical ranging error of UWB sensor is roughly 0.1 m. Comparing to the RLS and NaiveCL method, the localization accuracy of our proposed algorithm is increased by 79.21% and 34.41%, respectively. In addition, the distributed computation pattern reduces the computational burden on each single device. After applying the learning tools in our prior work [23], the computational complexity of our proposed method can be further reduced by 53.85%. When the position estimates of beacons are accurate sufficiently, they can serve as the new known beacon to consequently extend the network coverage. Last but not least, in large-scale settings, the significant reduction in human labor fulfilled by our method is substantial.

References

[1] M. Abbas, M. Elhamshary, H. Rizk, M. Torki, and M. Youssef, "WiDeep: WiFi-based accurate and robust indoor localization system using deep learning," in *Proc. IEEE Int. Conf. Pervasive Comput. Commun.*, 2019, pp. 1–10.

[2] C. Chen, C.-S. Jao, A. M. Shkel, and S. S. Kia, "UWB sensor placement for foot-to-foot ranging in dual-foot-mounted ZUPT-aided INS," *IEEE Sens. Lett.*, vol. 6, no. 2, Feb. 2022, Art. no. 5500104.

[3] C.-S. Jao et al., "PINDOC: Pedestrian indoor navigation system integrating deterministic, opportunistic, and cooperative functionalities," *IEEE Sensors J.*, vol. 22, no. 14, pp. 14424–14435, Jul. 2022.

[4] H. Obeidat, W. Shuaieb, O. Obeidat, and R. Abd-Alhameed, "A review of indoor localization techniques and wireless technologies," *Wireless Pers. Commun.*, vol. 119, pp. 289–327, 2021.

[5] A. Haeberlen, E. Flannery, A. M. Ladd, A. Rudys, D. S. Wallach, and L. E. Kavraki, "Practical robust localization over large-scale 802.11 wireless networks," in *Proc. 10th Annu. Int. Conf. Mobile Comput. Netw.*, 2004, pp. 70–84.

[6] P. S. Farahsari, A. Farahzadi, J. Rezazadeh, and A. Bagheri, "A survey on indoor positioning systems for IoT-based applications," *IEEE Internet Things J.*, vol. 9, no. 10, pp. 7680–7699, May 2022.

[7] Y. Zhuang, J. Yang, Y. Li, L. Qi, and N. El-Sheimy, "Smartphone-based indoor localization with bluetooth low energy beacons," *Sensors*, vol. 16, no. 5, 2016, Art. no. 596.

[8] D. Gualda, J. Ureña, J. Alcalá, and C. Santos, "Calibration of beacons for indoor environments based on a digital map and heuristic information," *Sensors*, vol. 19, no. 3, 2019, Art. no. 670.

[9] P. Corbalán, G. P. Picco, M. Coors, and V. Jain, "Self-localization of ultra-wideband anchors: From theory to practice," *IEEE Access*, vol. 11, pp. 29711–29725, 2023.

[10] C. S. Mouhammad, A. Allam, M. Abdel-Raouf, E. Shenouda, and M. Elsabrouty, "BLE indoor localization based on improved RSSI and trilateration," in *Proc. 7th Int. Jpn.-Afr. Conf. Electron. Commun. Comput.*, 2019, pp. 17–21.

[11] B. Yang, L. Guo, R. Guo, M. Zhao, and T. Zhao, "A novel trilateration algorithm for RSSI-based indoor localization," *IEEE Sensors J.*, vol. 20, no. 14, pp. 8164–8172, Jul. 2020.

[12] T. Yang, A. Cabani, and H. Chafouk, "A survey of recent indoor localization scenarios and methodologies," *Sensors*, vol. 21, no. 23, 2021, Art. no. 8086.

[13] D. Csík, P. Sarcevic, R. Pesti, and Á Odry, "Comparison of different radio communication-based technologies for indoor localization using trilateration," in *Proc. IEEE 17th Int. Symp. Appl. Comput. Intell. Inform.*, 2023, pp. 487–492.

[14] Y. Su, L. Guo, Z. Jin, and X. Fu, "A mobile-beacon-based iterative localization mechanism in large-scale underwater acoustic sensor networks," *IEEE Internet Things J.*, vol. 8, no. 5, pp. 3653–3664, Mar. 2021.

[15] A.-T. Popovici, C.-C. Dosoftei, and C. Budaciu, "Kinematics calibration and validation approach using indoor positioning system for an omnidirectional mobile robot," *Sensors*, vol. 22, no. 22, 2022, Art. no. 8590.

[16] V. R. Kulkarni, "Comparative analysis of static and mobile anchors in sensor localization," in *Proc. Int. Conf. Device Intell. Comput. Commun. Technol.*, 2023, pp. 115–120.

[17] Q. Luo, K. Yang, X. Yan, J. Li, C. Wang, and Z. Zhou, "An improved trilateration positioning algorithm with anchor node combination and k-means clustering," *Sensors*, vol. 22, no. 16, 2022, Art. no. 6085.

[18] A. Mahmoud, P. Coser, H. Sadruddin, and M. Atia, "Ultra-wideband automatic anchor's localization for indoor path tracking," in *Proc. IEEE Sensors*, 2022, pp. 1–4.

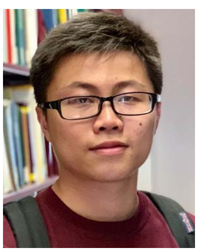
[19] J. Zhu and S. S. Kia, "Cooperative localization under limited connectivity," *IEEE Trans. Robot.*, vol. 35, no. 6, pp. 1523–1530, Dec. 2019.

[20] Y. Bar-Shalom, X. R. Li, and T. Kirubarajan, *Estimation With Applications to Tracking and Navigation: Theory Algorithms and Software*. Hoboken, NJ, USA: Wiley, 2001.

[21] S. S. Kia, S. Rounds, and S. Martínez, "Cooperative localization for mobile agents: A recursive decentralized algorithm based on Kalman filter decoupling," *IEEE Control Syst. Mag.*, vol. 36, no. 2, pp. 86–101, Apr. 2016.

[22] M. Zarei-Jalalabadi, S. M. Malaek, and S. S. Kia, "A track-to-track fusion method for tracks with unknown correlations," *IEEE Control Syst. Lett.*, vol. 2, no. 2, pp. 189–194, Apr. 2018.

[23] C. Chen and S. S. Kia, "Cooperative localization using learning-based constrained optimization," *IEEE Robot. Automat. Lett.*, vol. 7, no. 3, pp. 7052–7058, Jul. 2022.



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