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NomLoc: Calibration-free Indoor Localization With Nomadic Access Points

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Abstract*—Newly popular indoor location-based services (ILBS), when integrated with commerce and public safety, offer a promising land for wireless indoor localization technologies. WLAN is suggested to be one of the most potential candidates owing to its prevalent infrastructure (i.e., access points (APs)) and low cost. However, the overall performance can be greatly degraded by the spatial localizability variance problem, i.e., the localization accuracy across various locations may have significant differences given any fixed AP deployment. As a result, it brings in user experience inconsistency which is unfavorable for ILBS. In this paper, we propose NomLoc - an indoor localization system using nomadic APs to address the performance variance problem. The key insight of NomLoc is to leverage the mobility of nomadic APs to dynamically adjust the WLAN network topology. A space partition (SP)-based localization algorithm is tailored for NomLoc to perform calibration-free positioning. Moreover, fine-grained channel state information (CSI) is employed to mitigate the performance degradation of the SP-based method due to multipath and none-line-of-sight (NLOS) effects. We have implemented the NomLoc system with off-the-shelf devices and evaluated the performance in two typical indoor environments. The results show that NomLoc can greatly mitigate spatial localizability variance and improve localization accuracy with the assistance of nomadic APs as compared with the corresponding static AP deployment. Moreover, it is robust to the position error of nomadic APs.

I. Introduction

Modern indoor location-based services (ILBS) have rapidly expanded into people's daily life for convenience, utility, and entertainment. Predicted by MarketandMarkets [1], indoor location market will worth $2.6 Billion$ US dollars by 2018. To meet the breath of the golden opportunity, several major coop-erations have initiated their researches on indoor localization, such as Apple, Google, Microsoft, Nokia, etc. Meanwhile, the research community has gained increasing interests in developing positioning systems to deliver ILBS. With the proliferation of wireless communication and mobile computing, WLAN advances indoor localization with its prevalent infrastructure and low cost, as compared with multiple short range communication technologies like infrared, ultrasonic, RFID, and Zigbee sensors. In WLAN, positioning systems consist of several fixed access points (APs) and an object with a WiFi-enabled device (e.g., laptop or smartphone). Relying on the fixed AP deployment, the location of an object can be estimated via either range-based [17] or fingerprint-based [24] mechanisms.

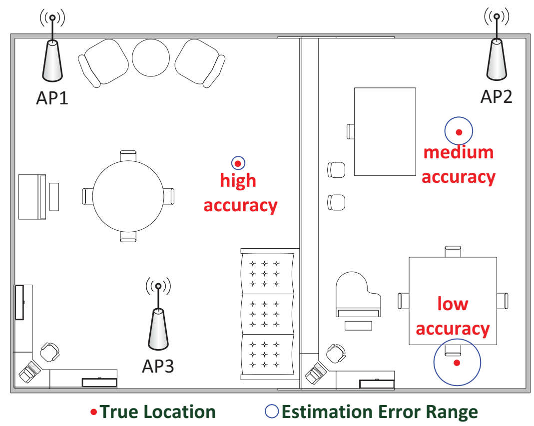

Fig. 1: Spatial Localizability Variance.

Even though existing WLAN-based indoor positioning systems have made considerable progress, they still suffer from a serious problem named "spatial localizability variance" in complex indoor environments. That is, the localization accuracy will be in high resolution at the locations in certain open areas while low resolution at the cluttered places. Fig. 1 gives an example of three locations with different resolutions. Each red dot represents the true position of the object and the blue circle stands for the estimation error range. Given the AP deployment, the object can be accurately located when there are strong links (i.e., line-of-sight (LOS) paths) between the object and APs. Conversely, the ambient obstacles can block such LOS paths and bring in rich multipath effects. Both none-line-of-sight (NLOS) and multipath can lead to erroneous location estimation due to weak and fluctuating radio signals. In this way, it creates unfavorable "user experience inconsistency" (UEI). One typical example of UEI can be found in indoor location-based advertising. In a large marketplace, merchants seek for the best locations to advertise their products in the most cost-effective way. The usual practice is to acquire the frequent locations for each customer as to target the point of sale. But the statistic data can be misleading or even crash profits due to spatial localizability variance. Security patrol serves as another common scenario. Secure inspectors need

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to monitor every place of the region with the assistance of localization systems. Unfortunately, the spatial localizability variance will result in miss detection at a blind area where the suspect can slip in. This spatial localizability variance problem has its roots in the AP deployment. The AP deployment cannot be optimized for all indoor positions due to physical constraints like power supply, cable length, and wall material, etc. In addition, even if the AP deployment is optimized, once being fixed, it still cannot be further adaptive to the dynamically changing indoor environment. And worse still, in most cases the APs are deployed for the purpose of wireless network coverage rather than dedicated for localization functionality. Fortunately, we have the observation that most of the mobile devices are capable of serving as WLAN APs, and moving people who carry these devices can act as nomadic APs, such as the shop greeters with smartphone circling around the customers, or the public securities with intercom patrolling around the crowds. The network topology can be dynamically changed with these nomadic APs such that it provides the potential to reduce the spatial localizability variance.

In this paper we present NomLoc, a novel calibration-free indoor localization system with nomadic APs to address the aforementioned challenge - spatial localizability variance. The key intuition behind NomLoc is that nomadic APs with instinctive mobility are more agile to dynamic deployment whereas static APs are unlikely to accomplish. We are thus motivated to explore the potential of aggregating nomadic APs with static ones to dynamically change the network topology for performance improvement. To provide a calibration-free approach, we leverage space partition (SP)-based method which is previously adopted in wireless sensor networks [2] and RFIDs [3], rather than the commonly used range-based or fingerprint-based method so that neither calibration nor training is required. Moreover, we use fine-grained channel state information (CSI) rather than coarse received signal strength (RSS) measurement [18]. This is because CSI has the potential to overcome the disadvantages of multipath and NLOS in indoor environment [23], which is crucial for the SP-based method. Therefore, the NomLoc design involves two main modules: power of direct path (PDP)-based proximity determination and space partitioning (SP)-based location estimation. The primary task of PDP-based proximity determination is to eliminate the environmental disturbances, i.e., multipath and NLOS in complex indoor scenarios. One approach could be to extract the dominant PDP among the reflection paths as an indicator of distance between the object and APs. In particular, we unleash the power of PHY layer CSI for PDP-based proximity determination due to its favorable temporal stability and frequency diversity properties. It is then followed by the second SP-based location estimation that harnesses nomadic APs for accurately locating the object. The space partition problem is transferred to a multi-variable linear programming problem, which also takes into consideration the possibility of erroneous PDP estimation, as well as the position estimation of the nomadic APs.

To summarize, we make the following contributions:

- We are the first to identify the spatial localizability problem for existing WLAN-based positioning systems and NomLoc is the first attempt to resolve this problem by leveraging nomadic APs.
- We propose a novel SP-based algorithm which is suitable for nomadic AP scenario without calibration efforts. The location estimation problem is formulated as linear programming which can be solved within polynomial time.
- We utilize PDP mechanism to address the multipath and NLOS effects based on CSI from the PHY layer. To enable the calibration-free SP-based approach, we harness CSI for mitigating the underlying environmental interference.
- We implement NomLoc and present thorough field experiments to objectively assess its performance. In our evaluation, we observe that NomLoc can achieve great spatial localizability variance reduction, and significant accuracy gain over the corresponding static AP deployment.

The remainder of the paper is structured as follows. The next Section II outlines the related work. We introduce our our novel design of NomLoc along with challenging issues in Section III. Section IV presents our methodology in detail. We present our implementation and evaluation results in Section V. Finally, Section VI renders the concluding remarks.

II. Related Work

Our work is closely related to the following two research areas: (i) infrastructure deployment and (ii) CSI-based indoor localization.

Infrastructure Deployment. A range of localization schemes require the availability of anchors or landmarks, whose positions are known in advance. Consequently, the geometric layout of anchors significantly affects localization performance [4]. Chen *et al.* [5] analyze the geometry of landmark deployment and propose a maxL-minE algorithm to achieve landmark layout that minimizes the maximum localization error. Dulman *et al.* [6] investigate the stability of anchor topologies, and propose an iterative algorithm to place three anchors given a set of stationary target nodes. Dong *et al.* [12] formulate an optimal AP deployment problem aiming to accomplish double-utilization including full coverage and area localization by a least number of APs. Ying *et al.* [7] quantify the geometric impact of anchor placement on localization accuracy for a given traversal area. Besides stationary infrastructure deployment for positioning, mobile anchors are also exploited to assist sensor network localization [8], [9]. And numerous efforts have designed path plans for wireless sensor network localization [10], [11]. Note that all these approaches rely on the coarse measured RSS which is unreliable for localization. In this paper, we also harness mobility to boost WLAN localization performance, yet this is the first attempt to implement a practical indoor localization system with nomadic APs and fine-grained CSI.

CSI-based Indoor Localization. Multipath effects fundamentally limit the accuracy of RSS-based indoor positioning systems [13], [14]. As a promising substitute, CSI can resolve multipath via frequency diversity [15], and has been employed in numerous novel localization systems [16]. FILA [17] leverages CSI to extract LOS path only for accurate ranging, and boosts localization performance even by simple trilateration. Authors in [20], [23] also exploit CSI to separate LOS path, yet assist angle-of-arrival (AOA) estimation by body blocking effect [20] or antenna arrays [23]. Other pioneer efforts harness the rich multipath information in CSI to build finer-grained and more temporally stable location fingerprints [19], and report sub-meter level accuracy. In the context of device-free systems, where targets need not carry on any wireless devices, CSI is introduced for fine-grained motion detection [21], [22] and single entity localization [24]. This is because CSI can better capture the impact of humans while resists other environmental interference. Although these systems have dramatically improved localization accuracy, they are static in nature and it is unknown whether the deployment would stay optimal over time. In contrast, we explore how AP mobility would dynamically assist localization and guarantee optimal performance in time.

III. An Overview of NomLoc

At present, most WLAN-based indoor positioning systems depend on static AP deployment. Such static AP deployment can inevitably bring in the spatial localizability variance. In this way, the ILBS experience of users at different locations can exhibit large diversity, known as user experience inconsistence. To complement such inconsistence deficiency, adding one or more APs at the "blind" locations (i.e., sites with low localizability) comes into a common solution [25]. But exploring the low resolution sites can be very labor-intensive and time-consuming. Because it brings in undesirable manual efforts for collecting the calibration data at the sample sites. In addition, it is restricted to deploy new APs at some of those sites. Moreover, the positions of these blind sites may change as the environment changes, i.e., the move of furniture or equipment. Alternatively, we come up with an idea to leverage the mobility of nomadic APs for the potential of improving the AP deployment. Before presenting the design details, we will start off by clarifying the challenges and then introduce the framework of the proposed NomLoc system.

A. Challenges

With the presence of bursty ILBS demands, the objectives of the proposed indoor positioning system NomLoc are twofold: (1) to minimize the spatial localizability variance for performance improvement, and (2) to minimize the calibration efforts without additional war-driving assistance. To balance such performance-time consumption tradeoff, we need to settle two challenging problems:

1) **How to leverage the mobility of nomadic APs for localization resolution enhancement?** The main motivation of using nomadic APs is that these APs with inherent mobility can establish a dynamic topology instead of a static one. A key question in this proposal is how to harness such mobility. Being aware that the past advances in WLAN-based localization broadly involve two classes: fingperprinting and ranging, we tend to explore the possibility of direct utilization of these methods. However, the former location fingerprinting is a poor fit for our goals. That is, the establishment of location fingerprint database relies on WiFi signal collection from static APs. Intrinsically, it is impossible to construct this database with nomadic APs on account of the nature of mobility. It is obvious that the widely applied fingerprint-based techniques become no longer suitable for these dynamic scenarios. For the latter class, we cannot expect these range-based techniques to achieve high localization resolution at every location. This is because the location uncertainty of nomadic APs will greatly degrade the system performance. Moreover, calibration is still needed to obtain the environment parameters [17], [23]. For those range-based systems, the performance heavily relies on the radio propagation model, whereas its parameters are closely correlated to the indoor environment. Such that calibration - estimating the environment parameters - serves as a prerequisite for such modelling approaches due to the varying physical characteristics and layout structure of different indoor venues. Therefore, inapplicability of the above conventional methods underscores the difficulty of seeking a well-suited solution to overcome this challenge.
2) **How to resolve the extensive existence of multipath and NLOS effects in indoor venues?** In complex indoor scenarios, the radio propagation between a pair of transmitter (TX) and receiver (RX) can easily be disturbed by the severe multipath effects. The source of multipath effects includes everything in the surrounding area, i.e., both natural and artificial objects along the multiple reflection paths. It serves as the major concern for deploying a radio-based localization system and leads to erroneous ranging outcome or non-unique fingerprints. Furthermore, most of these radio-based indoor positioning techniques suffer from NLOS propagation. In general, radio-based approaches depend on the LOS propagation path between the TXs and RXs. However, the ambient obstacles like ceilings, furniture as well as human beings indoors are prone to obstruct LOS signals, known as NLOS effects. Without LOS signal, the time-based or angle-based localization methods may perform very poorly owing to the misleading of NLOS signals. Thus it is challenging to achieve precise localization by compensating multipath and NLOS, even if there are nomadic APs in those regions of interest.

B. NomLoc Framework

In response to the above challenges, we propose our NomLoc approach by leveraging the mobility nature of nomadic APs. The underlying idea is to apply space partition method to

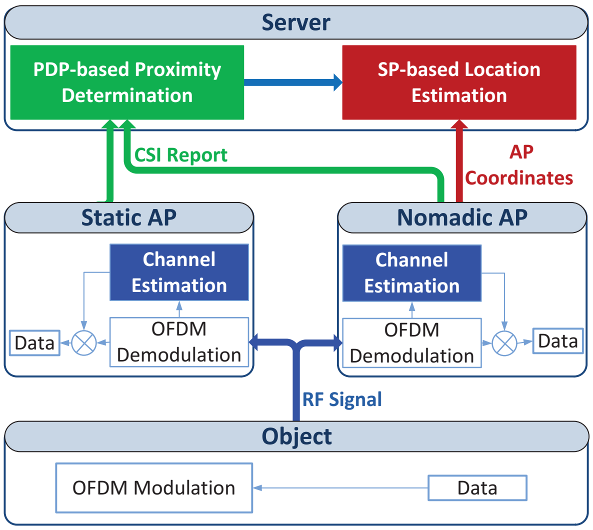


Fig. 2: An architectural overview of NomLoc.

subdivide the area of interest into certain segmentations. In this way, it does not involve the non-trivial radio map construction process nor the distance calculation relying on the specified propagation model. As such NomLoc circumvents the limitations of either fingerprint-based or range-based methods. Furthermore, fine granularity segmentation results can stem from the nomadic APs' assistance, resulting in performance enhancement. As a basis for SP-based algorithm, an initial step is to calculate the relative proximity between each nomadic AP and the object. To enable proximity determination, we process CSI into time domain and choose the power of the direct path for approaching distance. More specifically, the disturbances caused by NLOS paths can be captured and filtered out. Furthermore, the channel responses relevant to multipath effects can be resolved owing to the $20MHz$ bandwidth of $802.11n$ system. Consequently, it contributes to elimination of both the multipath and NLOS effects.

The NomLoc framework is illustrated in Fig. 2. From a bottom-up perspective, NomLoc consists of three functional components: (1) the object, (2) multiple APs, and (3) the localization server. We describe these components in the order of the outgoing data path.

The object transmits the probe request packages or data packages to the APs. In reality, any target object, for example a person with a WiFi-enabled device, suffices to perform this simple job.

The APs are comprised of both stationary ones that are fixed in the area of interest and nomadic ones that move around. The static APs only maintain the task of collecting CSI samples in the channel estimation block and export the measurements to the server. Likewise, this procedure extends to nomadic APs when they are moving for assisting localization. Concurrently, each nomadic AP will report its coordinates of the current sites with CSI measurements to the server. Here we suppose the coordinates information of static APs have been stored in the server. While for the noomadic APs, we can either employ powerful APs with built-in sensors, or collaborate with complementary technologies like Bluetooth, RFID, which contribute to coordinates acquisition.

The localization server finalizes the task of positioning as to guarantee user experience consistency for a variety of ILBS. To enable the SP method, the server first needs to decide which AP the object is more close to in the positioning region. Upon receiving all the samples, it strives to perform CSI processing to eliminate the severe multipath and NLOS effects that account for the proximity judgement. The correspondingly primary module is PDP-based proximity determination. After the relative proximities are determined, a second localization module is introduced by leveraging the mobility of nomadic APs using SP-based algorithm, which is termed as SP-based location estimation.

IV. Methodology

This section presents the complete description of our design including two key modules, (1) PDP-based proximity determination and (2) SP-based location estimation. As a cornerstone for NomLoc, the first module works by processing CSI to obtain the power of direct path. Based on the results of PDP-based proximity determination, the second module can thereby contribute in locating the object by SP-based algorithm.

A. PDP-based Proximity Determination

To begin with, we consider the PDP-based proximity determination module. The target of this module is to determine the object's relative proximity to two arbitrary APs, which serves as the preliminary of the space partition in the next step. The determination could be based on the comparison of time-of-arrival (TOA) or power of the received signal. Since the radio signal traverses at the same speed of light, the two APs should be tightly time synchronized together to be able to differentiate the TOA of the same signal from the object. Such a tight synchronization module is of substantial cost, and not available at the majority of the commercial APs. Moreover, the results of TOA could be highly misleading when the LOS signal is blocked by obstacles in indoor environments. Therefore, we tend to explore signal power-based approaches.

As mentioned earlier, NomLoc server collects the PHY layer CSI in the frequency domain [17]. Note that CSI describes the channel status from subcarrier level between the transmitter and receiver. It can manifest the LOS transmission as well as multipath and NLOS reflections which are common in indoor environments. With the objective to enable SP-based approach for accurate localization, a premise is to determine at which area an object is located by CSI measurements. The fundamental idea lying behind is to estimate the power of direct path (PDP). We first transform the frequency domain CSI into the time domain channel impulse response (CIR). With Inverse Fast Fourier Transformation (IFFT), we can obtain CIR whose amplitude is proportional to the power

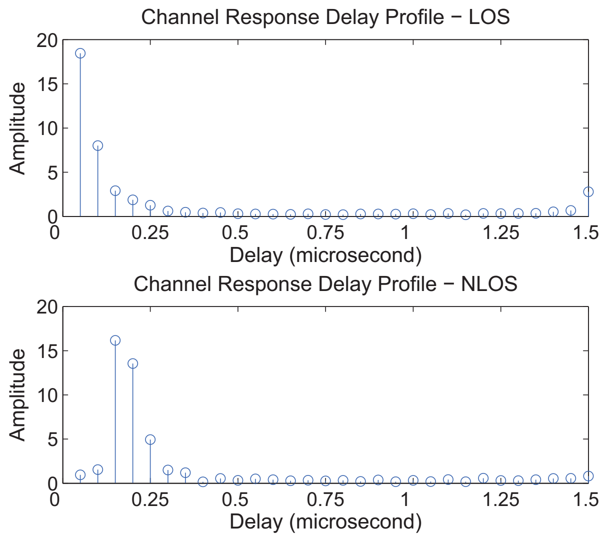


Fig. 3: Channel response delay profile for LOS and NLOS transmissions.

delay profile of the radio link. Regarding the CIR indoors, we observe a following dichotomy:

- If the LOS path exists and the time resolution is high enough, the power of first path is the PDP.
- In some circumstances, the LOS path is blocked by obstacles between the transmitter and receiver. Consequently, the power of the first path will be much lower than the normal one as shown in Fig. 3.

Nevertheless, it is reasonable to assume that the PDP is the highest among all the transmission paths. Hence, we can use the maximum power of the power delay profile to approximate PDP of each link. In this way, no additional efforts need to enforce its viability in the presence of multipath effect as well as NLOS propagation. This is because it naturally alleviates CIR of the NLOS paths since only the maximal amplitude is chosen for PDP. Meanwhile, all the other multipath reflections are filtered out. As such, we suggest to choose the PDP as an indicator for proximity determination.

We next turn our attention to utilize the PDP to determine the distance between the AP and the object. Obviously, larger true value of PDP indicates a shorter distance between the AP and the object whereas a smaller one relates to a longer travel distance. In this manner, we can render the PDP-based proximity determination on which AP the object is closer to, i.e., AP j or AP i. In particular, let P_i and P_j be the PDP of AP i and AP j, respectively. To quantify the probability of proximity, we define the confidence factor w of the judgement as

$$w_{ij} = f(\frac{P_i}{P_j}); \tag{1}$$

where the f function should satisfy the following two conditions simultaneously

$$f(x) + f(\frac{1}{x}) = 1 \tag{2}$$

$$f(1) = \frac{1}{2}, f(x) \geq 0 \tag{3}$$

This is because when the PDP estimations for the two APs are equal, the object is close to each AP with the same probability.

In general, there exists a wide variety of f function that maintains the above properties. In this paper, we select the f function as following:

$$f(x) = \begin{cases} 2^{-x} & 0 < x \leq 1 \\ 1 - 2^{-\frac{1}{x}} & x > 1 \end{cases} \tag{4}$$

Clearly, based on the f function above, the larger w represents the more confidence of PDP-based proximity determination result from the object to the APs. In other words, an optimal value of w will render more reliable prerequisites for the objective of precisely figuring out the object's location.

B. SP-based Location Estimation

With the PDP-based proximity determination derived above, we are now ready to present the SP-based location estimation module of NomLoc, which is imperative for figuring out the position where an object is located. Recently, SP-based algorithm has been applied in RFID-based robot system [3] for navigation and mobile manipulation. In this work, we use space partition method to better leverage the AP mobility.

1) Relative Proximity: Assume the object presents at site q, and $P := p_1, p_2, \dots, p_n$ be a set of n distinct sites where the APs are located in an indoor venue. The distance between the object and AP i can be obtained by Euclidean metric $dist(q, p_i)$ as,

$$dist(q, p_i) := \sqrt{(x - x_i)^2 + (y - y_i)^2} \tag{5}$$

Clearly, if the object is closer to AP j compared to AP i, it must satisfy the following inequality as,

$$(x - x_i)^2 + (y - y_i)^2 \leq (x - x_j)^2 + (y - y_j)^2 \tag{6}$$

Rewriting it in a matrix manner, we get

$$\begin{bmatrix} 2(x_j - x_i) & 2(y_j - y_i) \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} \leq x_j^2 + y_j^2 - x_i^2 - y_i^2; \tag{7}$$

Given n APs in the area, we have $N = \frac{n(n-1)}{2}$ inequations which form the matrix inequality as follows,

$$\mathbf{Az} \leq \mathbf{b} \tag{8}$$

where $\mathbf{A}$ is a $N \times 2$ matrix, $\mathbf{z}$ is a vector of 2×1 which is the site coordinates of the object to be estimated, $\mathbf{b}$ is a $N \times 2$ vector.

To solve the above optimization problem, it may come out with a feasible region instead of a single solution. We hence choose the center point of the region as the approximation result for localization.

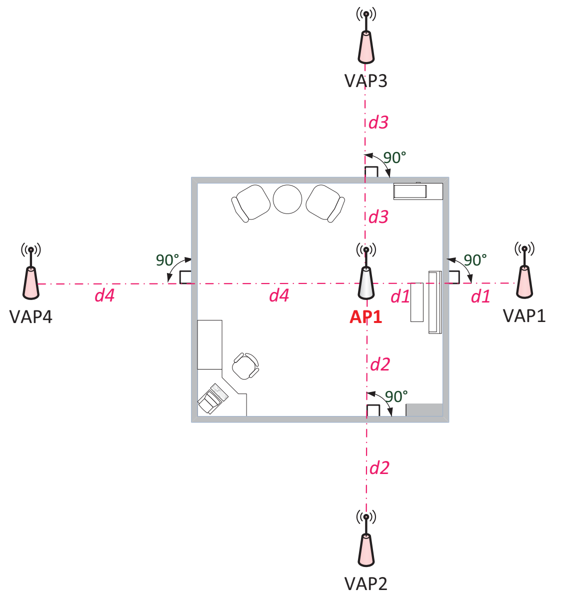


Fig. 4: Illustration of area boundary treatment.

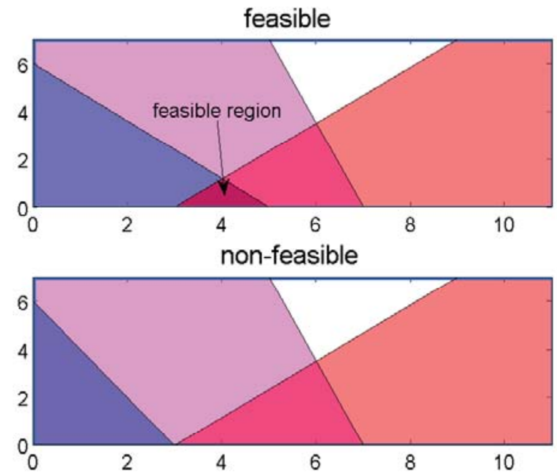


Fig. 5: Illustration of feasibility.

2) Area Boundary Restriction: Moreover, the intrinsic boundary of indoor environments imposes restriction on the range of activity for the object, referred as *area boundary*. In other words, the object must be present within the interior area of interest other than the outside space. For instance, the object is unlikely to appear exterior the third floor of one building normally. It suggests that this boundary constraint is conductive to our SP-based algorithm. Hence, we invoke the use of virtual APs (VAPs) for satisfying area boundary. Suppose the original area has a polygon shape with m edges, where each edge serves as a boundary line. We then depict the VAPs whose positions are the symmetry mirror points of the position of a specific AP, e.g., AP 1 against the boundary lines as shown in Fig. 4. Obviously, the object is much closer to AP 1 than those virtual APs (i.e., VAP 1 - VAP 4). Therefore, we can guarantee the area boundary with the following inequality,

$$\mathbf{A}'\mathbf{z} \leq \mathbf{b}' \tag{9}$$

where

$$\mathbf{A}' = \begin{bmatrix} 2(x_{n+1} - x_1) & 2(y_{n+1} - y_1) \\ \cdots & \cdots \\ 2(x_{n+m} - x_1) & 2(y_{n+m} - y_1) \end{bmatrix} \tag{10}$$

$$\mathbf{b}' = \begin{bmatrix} x_{n+1}^2 + y_{n+1}^2 - x_1^2 - y_1^2 \\ \cdots \\ x_{n+m}^2 + y_{n+m}^2 - x_1^2 - y_1^2 \end{bmatrix}; \tag{11}$$

Note that the site of AP 1 could be any other sites within the area for the above calculation. If the objective polygonal area is non-convex, we can divide it into several convex ones. For each convex area, we solve the optimization problem and merge the areas with feasible solutions.

With the above boundary constraint transformation, the location estimation problem can be transformed into the following convex linear optimization formulation:

$$\begin{aligned} &minimize && 0 \\ &s.t. && \begin{bmatrix} \mathbf{A} \\ \mathbf{A}' \end{bmatrix} \mathbf{z} \leq \begin{bmatrix} \mathbf{b} \\ \mathbf{b}' \end{bmatrix} \end{aligned} \tag{12}$$

By solving this linear programming (LP) problem, we can complete the indoor localization with AP coordinates, boundary information, and relative proximity output from the PDP-based proximity determination block.

3) Nomadic AP Downscoping: So far the above linear optimization retains its feasibility on space partition under the static AP deployment. However, the partition results turn out to be of coarse granularity due to the limited number of static APs. To overcome this limitation, we endeavor in narrowing down the partitioned spaces into more small segmentation by exploiting the mobility of nomadic APs.

Without loss of generality, we assume that AP l is a nomadic AP that moves among multiple sites in the positioning area. Let $L = \{L_1, ..., L_S\}$ denote the site set of AP 1 for performing CSI measurements. For each site $L_i = (x_i, y_i)$, suppose the object locates closer to nomadic AP l than any other static APs, the object's coordinates also have to hold the following $n - 1$ constraints:

$$\mathbf{A}''\mathbf{z} \leq \mathbf{b}'' \tag{13}$$

where

$$\mathbf{A}'' = \begin{bmatrix} 2(x_2 - x_l) & 2(y_2 - y_l) \\ \cdots & \cdots \\ 2(x_n - x_l) & 2(y_n - y_l) \end{bmatrix} \tag{14}$$

$$\mathbf{b}'' = \begin{bmatrix} x_2^2 + y_2^2 - x_l^2 - y_l^2 \\ \cdots \\ x_n^2 + y_n^2 - x_l^2 - y_l^2 \end{bmatrix}; \tag{15}$$

The total number of new constraints is $S \times (n-1)$. Apparently, the further the nomadic AP moves, the more CSI measurements will be collected corresponding to the site set L, resulting in finer granularity segmentation. In return, higher accuracy can be expected for SP-based location estimation. Thus mobility of nomadic APs is beneficial for downscoping the feasible region.

The optimization problem for location estimation considering nomadic AP is formulated as follows,

$$\begin{array}{ll} minimize & 0 \\ s.t. & \bar{\mathbf{A}}\mathbf{z} \le \bar{\mathbf{b}} \end{array} \tag{16}$$

where

$$\bar{\mathbf{A}} = \begin{bmatrix} \mathbf{A} \\ \mathbf{A}' \\ \mathbf{A}'' \end{bmatrix} \tag{17}$$

$$\bar{\mathbf{b}} = \begin{bmatrix} \mathbf{b} \\ \mathbf{b}' \\ \mathbf{b}'' \end{bmatrix}; \tag{18}$$

Note that Eq. 16 still yields a LP problem.

4) Constraint Relaxation: However, it is possible that the above optimization problem comes out with no feasible solutions, i.e., the feasible region is empty since the problem is over-constrained. The rationale is that the relative proximity determination of the nomadic APs could be erroneous. Fig. 5 gives an illustration of feasible and infeasible solutions.

Therefore, we relax the constraints of optimization in Eq. 16 as follows:

$$\begin{array}{ll} minimize & \mathbf{w}^T\mathbf{t} \\ s.t. & \bar{\mathbf{A}}\mathbf{z} - \mathbf{t} \le \bar{\mathbf{b}} \\ & \mathbf{t} \ge 0 \end{array} \tag{19}$$

where $\mathbf{t}$ is a matrix of the relaxation variables, that represents the cost for breaking down each constraint, and w is the weight of constraints whose transpose matrix is $\mathbf{w}^T$. It can be proved that Eq. 19 and Eq. 16 are equivalent when feasible solution is available for Eq. 16. In this case, we aim to look for a solution with minimal relaxation cost $\mathbf{w}^T\mathbf{t}$. The basic idea is to retain the constraint with a larger weight (i.e., $t_i = 0$) while sacrificing the one with smaller weight (i.e., $t_i > 0$), as the larger weight, the higher cost we will pay for the relaxation. Generally, given the constraints in Eq. 8 and Eq. 13, w corresponds to a matrix of confidence factor w as defined in Eq. 1. While regarding the area boundary constraint in Eq. 9, w is preset to a large weight to guarantee the corresponding constraint satisfied with high priority. In our implementation, we use an open-source solver CVX [26] based on the interior-point method which can return the center of the feasible region by using logarithmic barrier functions. Nevertheless, it is proved that the LP problem can be solved using interior-point method within weakly polynomial time [27]. Therefore, the scalability of the proposed NomLoc system is very high.

V. Performance Evaluation

In this section, we conduct a thorough evaluation of the NomLoc system. Our evaluation has three primary goals: (1) to study the performance of PDP-based proximity determination, (2) to investigate the performance gain of NomLoc over a static AP deployment, and (3) to analyze the impact of nomadic APs' position estimation error on SP-based localization.

A. Evaluation Methodology

Before going deep into the experiment details, we clarify the evaluation metrics of interest including: (1) spatial localizability variance, and (2) accuracy. In addition, we present the mobility model of Nomadic APs.

Evaluation metrics.

- *Spatial localizability variance.* To validate the effectiveness of leveraging nomadic APs's mobility, we introduce spatial localizability variance (SLV) which is defined as the variance of mean error across all sites in the space. We denote $e(x, y)$ as the mean error of location (x, y), and the SLV over area D is defined as

$$SLV = \iint_D (e(x,y) - \bar{e})^2 dxdy \Big/ \iint_D dxdy \tag{20}$$

where $\bar{e}$ is the error mean of area D,

$$\bar{e} = \iint_D e(x,y) dxdy \Big/ \iint_D dxdy \tag{21}$$

In the evaluation, p sample points will be selected for error statistics. The according SLV is calculated as

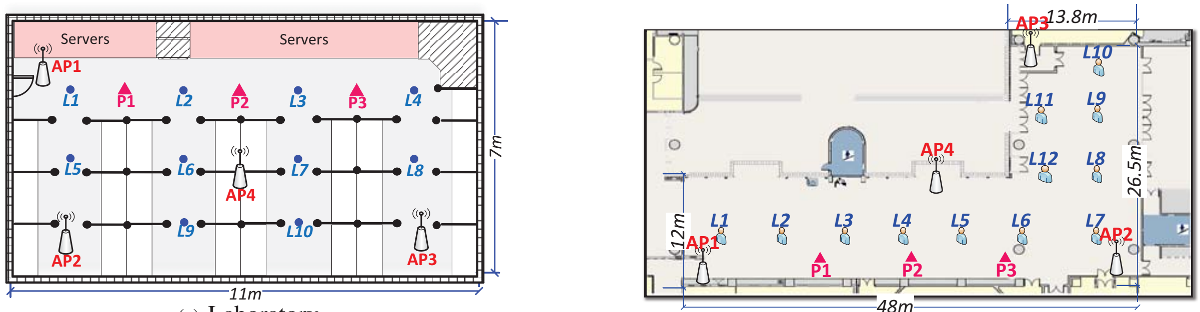
$$SLV = \frac{1}{p}\sum_{i=1}^{p}(e_i - \bar{e})^2 \tag{22}$$

where $\bar{e}$ is,

$$\bar{e} = \frac{1}{p}\sum_{i=1}^{p} e_i \tag{23}$$

- *Accuracy.* The first assessment of NomLoc is to verify its capability of indoor localization. To this end, we measure the NomLoc accuracy, in terms of cumulative distribution function (CDF) of the mean error across distinct sites in the space.

Nomadic AP mobility model. The mobile traces of nomadic APs are characterized by random walk built on a Markov chain [28]. The nomadic AP is assumed to be moving among several discrete sites with a preset transition probability. The CSI measurements are collected at these sites. With this mobility model, we can map the ground truth coordinates of the nomadic AP with the CSI measurements, and evaluate the influence of nomadic AP coordinates error by introducing artificial random errors.



(a) Laboratory.

(b) “L-shape” Lobby

Fig. 6: Layout of the experiments.

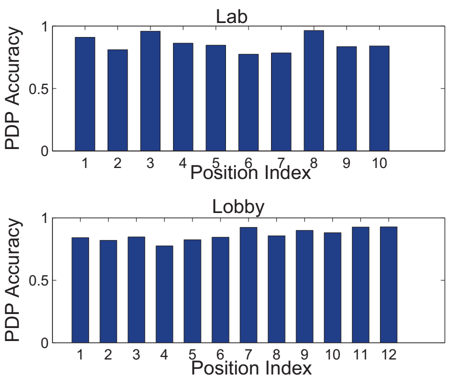


Fig. 7: Performance of PDP-based proximity determination.

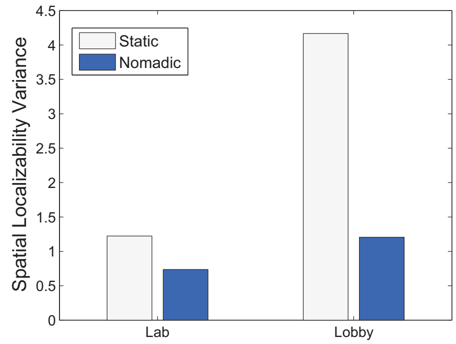


Fig. 8: SLV performance in two scenarios.

B. Experimental Setup

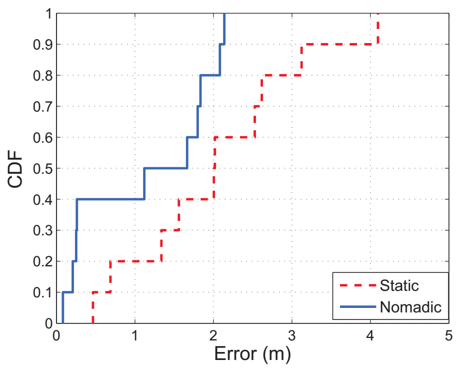
We set up a computer running on Linux platform as the object. The object is equipped with an off-the-shelf WiFi 5300 NIC that enables its driver to export the CSI samples. In our current prototype, the object remains stationary at certain preset sites during the measurement. The TL-WR941ND routers are used as APs that support $802.11n$. The object connects to the APs and then sends PING message in millisecond. Such that the object collects thousands of packages at each site. The NomLoc server is implemented on a PC to process the CSI measurements as to estimate the location of the object.

The first scenario for evaluation is a Lab of academic building in HKUST, with layout specified in Fig. 6(a). The Lab is a typical complex indoor environment with substantial equipments (i.e., PCs and servers) and office facilities. To verify the merits of our design, we deploy multiple APs in the experimental area. Four APs are fixed at specific sites for static deployment benchmark, and AP 1 is chosen as nomadic AP that randomly moves among current location and $\{P_1, P2, P3\}$.

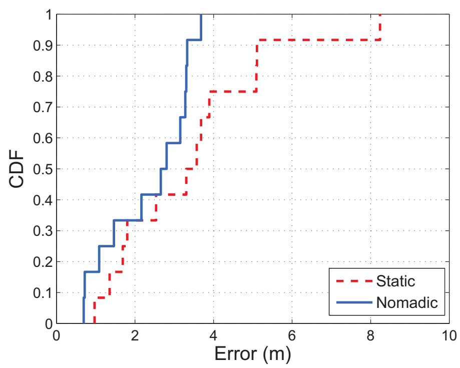
Similarly, we further deploy NomLoc in a larger, more open Lobby for evaluation as shown in Fig. 6(b). In this set of experiments, the NomLoc prototype contains one client, also four APs, and one of them (AP 1) is nomadic. The nomadic AP starts from its current location, and random walks among the sites $\{P_1, P_2, P_3\}$.

C. Performance of PDP-based Proximity Determination

We begin with evaluating the performance of PDP-based proximity determination which serves as the primitive for the SP-based method. In the Lab scenario, we measure the relative proximity of 10 sites corresponding to 4 APs, including the static and nomadic ones. Clearly, the total amount of determination for each site is $C_4^2 = 6$. We then compare our PDP-based proximity to the ground truth. Fig. 7 depicts the statistics of comparison results for 10 sites in Lab. We find that our PDP-based approach is accurate and most of them are more than 85%. Some sites like cite 6 have low accuracy because the distance of this position to several APs are very close which results in similar PDP. Therefore, we can draw the conclusion that most of the PDP-based proximity determination errors happen when the site is at the middle of two APs. Note that according to Eq. 1, the constraint is assigned a low confidence factor when the two PDPs are close. Hence, we can expect that this error will not affect much on the localization performance. In the Lobby scenario, we statistic the accuracy for the 12 sites and show the results in Fig. 7. The PDP-based proximity can also achieve high accuracy, and even outperforms the Lab scenario, because the AP deployment in lobby are more sparse than that in the Lab.

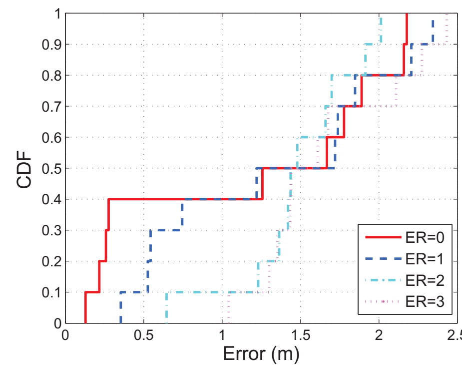


(a) Lab

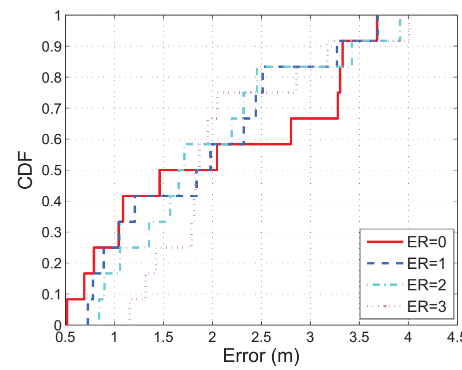


(b) Lobby

Fig. 9: Error CDF in two scenarios.



(a) Lab



(b) Lobby

Fig. 10: Effect of ER in two scenarios.

D. Performance Gain over Static AP Deployment

The ultimate goal of NomLoc design is to produce precise localization through alleviating spatial localizability variance. To this end, we assess the spatial localizablity variance of NomLoc system and compare it against static AP deployment in both Lab and Lobby scenarios. We calculate SLV followed by Eq. 22 for NomLoc and static AP deployment respectively, and plot the results in Fig. 8. The observations of SLV comparison are two-fold: first, NomLoc outperforms static AP deployment with much smaller SLV in both scenarios; second, the superiority is more evident in Lobby where the static AP deployment has larger SLV. The former one confirms the benefits of exploiting mobility of NomLoc for spatial localizability variance reduction, while the latter one infers that NomLoc performs even better with larger sites of measurements.

We further evaluate the localization accuracy for both deployments in Lab. Fig. 9(a) illustrates the results, where the blue solid line represents the CDF of mean error obtained by the proposed NomLoc system, and the red dot line stands for the CDF of mean error under the static AP deployment. We can observe that both deployment can achieve mean accuracy of less than 2 m, while the advantage of NomLoc is obvious due to fine-grained space partition with the nomadic AP. Likewise, we repeat the evaluation in the Lobby scenario. From Fig. 9(b), NomLoc yields 2.5 m mean accuracy and 3.6 m with 90 percent. In contrast, the counterpart reveals significantly performance degradation without the nomadic APs' assistance. In this way, we are further confirmed that NomLoc is able to provide higher accuracy than that of the static AP deployment. The current accuracy is meter scale relying on the fact that the system is calibration-free, and we only take one nomadic AP for evaluation. Hopefully, the performance can be greatly improved by employing multiple nomadic APs which is left for our future work.

In summary, NomLoc exhibits a preferable capability in performance enhancement stemming from the beneficial mobility of nomadic APs.

E. Analysis on Position Error of Nomadic APs

We have illustrated the performance improvement of NomLoc over the static AP deployment. In these evaluations, the position of the nomadic AP is assumed to be precisely known by the sever. In this subsection, we evaluate the performance of NomLoc in terms of nomadic APs's position error. Under nomadic APs' mobility, we aim to quantify the impact resulting from erroneous estimation of their locations. We intentionally add random errors to the position information of the nomadic AP with error range (ER) from 0 to 3m. Then we plot the results of CDF of mean error with respect to the ER of this nomadic AP in two scenarios, which are shown in Fig. 10(a). From Fig. 10(a), we find that generally the larger position error of the nomadic AP, the worse performance on location estimation of the object in Lab. However, the performance degradation is ignorable when the error range is small. This is because our SP-based method does not highly depend on the accurate location of these APs as those range-based localization methods do. Moreover, since only the position information of the nomadic AP contains error, the over-constrained optimization problem Eq. 19 still can find a most promising solution for position estimation of the object. Similar results can be obtained in Lobby as plotted in Fig. 10(b). Therefore, the proposed NomLoc system is robust to the position error of nomadic APs which makes it more practical.

VI. Concluding Remarks

WLAN-based localization techniques are ubiquitous for providing today's prevailing ILBS. However, the WLAN-based positioning performance at different locations exhibits distinguishable diversity. Such spatial localizability variance leads to severe user experience inconsistence. In this paper, we investigate into its primary cause - the static AP deployment. We take a radical tact to advocate the use of nomadic APs for dynamically adjusting the network topology without calibration efforts. The NomLoc system is proposed based on space partition method that harnesses the mobility of APs for locating the object. As a prerequisite for the SP-based algorithm, we propose a novel PDP-based proximity determination mechanism to judge the approximation of the AP and object. By mitigating the influence of multipath and NLOS, the relative proximities are further produced to perform SP-based location estimation. Extensive experiments are conducted to evaluate the performance of NomLoc. The results show that NomLoc can effectively reduce the spatial localizability variance while achieve high accuracy as compared with the corresponding static AP deployment.

In current study, we consider to aggregate one nomadic AP for solving the spatial localizability variance. This is the tip of the iceberg in terms of leveraging nomadic APs for precise indoor localization. An potential direction for future work is effectively aggregating multiple nomadic APs. Another extension to our NomLoc system would be to understand the impact of moving patterns of nomadic APs on the overall performance.

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