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SoLoc: Self-organizing Indoor Localization for Unstructured and Dynamic Environments

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***Abstract*—Self-organization is critical to enable novel indoor Location-Based Services (LBSs) for users and businesses in large, complex and unstructured buildings. Inspired by high densities of smartphones in public indoor spaces, in this paper we propose a self-organizing indoor localization approach that allows the use of available WiFi Access Points (APs) and iBeacons in the area to improve location accuracy and environment adaptability. Our approach is based on a semi-anchored localization that estimates the unknown location of smartphones, given known-location anchors (APs) and unknown-location anchors (iBeacons). We exploit the capabilities of Levenberg-Marquardt optimization algorithm to accurately estimate smartphone locations in real-time, in contrast to fingerprinting methods that require a tedious off-line training phase. Moreover, we use a clustering method based on the Received Signal Strength (RSS) values to obtain the initial estimated location for the optimization. We evaluate our approach using available APs and non-coordinated iBeacons in a large building to localize smartphones. The experimental results confirm that our self-organizing approach not only effortlessly estimates the position of mobile devices, but also provides a higher localization accuracy than other widely used approaches such as extant fingerprinting techniques for both scenarios, with and without iBeacons.**

I. INTRODUCTION

Indoor localization is the primary purpose of numerous mobile computing applications, such as logistics, crowd monitoring, network allocation, and marketing. Although the Global Positioning System (GPS) is definitely the most popular positioning technology, it does not work well indoor due to signal attenuation and scattering. Among alternative localization techniques for indoor environments such as acoustics, magnetic fields, accelerometers, and Received Signal Strength (RSS), RSS is the most popular one because of the proliferation of WiFi and Bluetooth on mobile devices. Moreover, public databases of access point locations are recently available for a large number of buildings [1]. Therefore, using short-range radio communication such as RSS between smartphones and WiFi Access Points (APs) become one of the most practical solutions for indoor localization.

Accurate indoor localization using WiFi infrastructure, however, remains elusive. Although fingerprinting algorithms, such as RADAR [2], Locally Weighted Regression (LWR)-Weighted k-Nearest Neighbours (WKNN) [3], Radial Basis Function (RBF) [4], and Deep Neural Network (DNN) [5], can provide acceptable localization accuracy, they require an enormous amount of measurements, so-called signatures, to build a database for an off-line training phase before real-time position estimation. Such an essential requirement imposes restraints on autonomously deploying a localization system in practice, especially for large and complex space. Even if the laborious fingerprinting can be done, the environment may later change frequently and thus the accuracy of fingerprinting systems decreases. The fingerprinting approach needs to rebuild the fingerprint database frequently to maintain a high accuracy because of the change of multi-path effects in indoor environments. Therefore, a localization approach should be self-organizing, lightweight, and accurate. It also should adapt to any configuration or environment. To this end, the feasibility of leveraging the most prevalent WiFi infrastructure for high accuracy localization on mobile devices in dynamic unstructured environments is still an open question.

In this paper, we first conduct an experiment to empirically study the challenges of WiFi AP-based localization on smartphones in terms of the accuracy and calibration requirement. We find that most current localization algorithms including fingerprinting have a poor performance in terms of accuracy (e.g., > 10 m) when there are an insufficient amount of APs and calibrations. Similar or much larger errors (e.g., > 15 m) also have been reported in previous works [6], [7]. Such large errors are unacceptable for many scenarios. It was shown that a high accuracy of 2 m is possible but only under a high density of APs, which is usually unfeasible in practical settings. Such enormous errors may cause a user to make a wrong turn leading to a different gate in an airport, or an unwanted store in a shopping mall. We reveal that the large errors are due to the possibly faraway locations with similar WiFi signatures. The RSS values typically have a high variability over time even for a fixed location, due to the different multipath effects in dynamic indoor environments.

On the other hand, we observe that smartphones and iBeacons have become very popular in indoor environments, especially in public spaces and smart buildings. We hypothesize that the RSS values between the smartphones and iBeacons would be used as additional information to improve the accuracy of smartphones positioning, even if the absolute coordinates of both smartphones and iBeacons are unknown. We propose a self-organizing localization approach that leverages the relative RSS-based ranging between smartphone-iBeacons, without requiring an offline calibration/fingerprinting phase or special hardware

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yet producing higher accurate location estimates than current approaches.

In particular, the self-organizing localization can be carried out when smartphones have both WiFi and Bluetooth enabled to simultaneously scan RSS from APs and iBeacons, respectively. Smartphones opportunistically scan radio signals emitted from surrounding APs and iBeacons. One should note that our approach does not require that the smartphones have to be connected to the APs and iBeacons to obtain the RSS measurements since smartphones regularly emit ”probes” to scan APs and iBeacons and receive the response including RSS values. Given the RSS measurements, we formulate a semi-anchored localization cost function. The cost function uses APs and iBeacons as anchors; however, only the coordinates of APs are known. We employ the Levenberg-Marquardt optimization algorithm [8] to estimate the coordinates of smartphones as it was proven to be the best for non-linear least squares in [8]–[10]. Moreover, we use a clustering method based on the RSS to obtain the initial estimated location for the optimization. Experiments using data from a real indoor building environment show that our approach is minimally invasive and easy to deploy while providing much higher localization accuracy than most current approaches yet requiring a laborious offline calibration phase. Our specific contributions in this paper are:

i) Semi-anchored localization with non-coordinated iBeacons
ii) Cluster-based initialization for self-organization
iii) Empirically analysis of fingerprinting localization algorithms with calibration
iv) Experiment evaluation with the real-world environment

The rest of this paper is organized as follows. Section II reviews the related techniques of WiFi localization, especially for indoor environments. Section III states the localization problem and challenges in unstructured and extreme environments. Section IV presents our approach through mathematical model and optimization, followed by performance evaluation and important observations presented in Section V. Finally, we conclude our paper in Section VI.

II. Related Work

Although GPS is definitely the most popular positioning technology, it does not work well in GPS-blocked environments due to signal attenuation and scattering. As alternative technologies, a short-range radio communication such as WiFi is widely used for indoor environments. Most WiFi-based indoor localization systems are mainly categorized into either location-based fingerprinting techniques or ranging based on radio signal propagation models.

Fingerprinting techniques build a fingerprint database that can be used to approximate a location. The database, a so-called radio map, is constructed by measuring RSS at a number of known locations – signatures. The test location is then estimated by comparing the new RSS values to the fingerprint database.

RADAR [2], [6] is a naive fingerprinting technique that determines smartphone's location by finding a known signature that is most similar to the actual RSS measurement of the location. In RADAR, it is shown that the highest accuracy is obtained by computing the mean coordinates of three nearest neighboring signatures. The Nearest Neighbours technique, in addition to its simplicity, turned out to be among the most accurate ones. More advanced techniques such as LWR-WKNN [3] (a data interpolation technique) and RBF [4] (a supervised learning technique) also have been used for fingerprinting. Recently, deep learning techniques are also used to predict smartphone locations [5]. However, building such a fingerprint database is a laborious task as it requires to collect fingerprints from numerous positions. The built fingerprint database generally stays valid only for a short time as the environment may change due to objects and human mobility, among others.

Alternative techniques that are most related to our approach use the characteristic model of radio frequency propagation to avoid the laborious fingerprinting [11]–[17]. As RSS decreases when the distance between the transmitter and receiver increases, the distance can be estimated using a propagation model such as the Log-Normal Shadowing Model (LNSM) [18]. The LNSM in [18] defines the received signal strength as a function of the distance and two environmental parameters, i.e., the transmission power of the reference transmitter and the path loss exponent. These parameters together with unknown coordinates can be estimated using a least-squares fitting technique [12]–[14]. Range-based localization usually gives a relatively poor accuracy due to the intrinsic phenomenon of the radio signal propagation. Most indoor environments cause severe multipath effects that lead to a high variability over time for the same location. Such high variability results in a large error even for a stationary device. Moreover, RSS values do not convey the subcarriers in an Orthogonal Frequency-Division Multiplexing (OFDM) for richer multipath information such as WiFi Channel State Information (CSI) [19], which can be exploited to improve the accuracy. Since WiFi CSI requires expensive hardware and is sensitive to privacy breaching, we do not consider this technique in this paper.

Furthermore, the WiFi APs in public places are generally limited and deployed in the middle of the areas of interests so that they can cover most parts of the areas with a minimum cost. However, in order to achieve a high localization accuracy for both fingerprinting and radio propagation techniques, APs need to be placed abundantly in optimal locations, usually at the boundary of the area. In addition, APs are usually affixed to the ceilings, not in a same horizontal plane with smartphones carried by users. The difference in height increases the variance of measurements. It turned out that existing techniques have a poor performance in terms of accuracy (e.g., > 10 m) in most real environments, albeit they were shown perform well in customized test beds, of which the AP are optimally placed for the purpose of the experiments.

Thanks to their low cost and low power consumption, the use of iBeacons has gained popularity. Many existing solutions including [20]–[22] use iBeacons, in addition to APs, to provide location information. In these works, authors assume that iBeacons are stationary and have a known location, functioning as anchors for localization. Using smartphones of the crowd to sniff both iBeacons and APs is an interesting solution to push the limits of WiFi-based localization.

Using smartphones to sniffs both WiFi APs and Bluetooth iBeacons is not new itself as being proposed in [23], [24]. However, the iBeacons used in such works are deployed at fixed and known locations, functioning as anchors. Conversely,

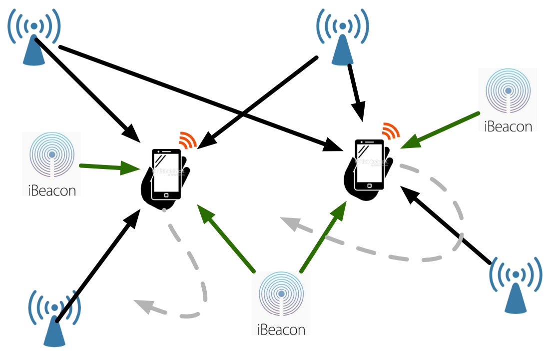

Fig. 1: Illustration of self-organizing localization for unstructured and dynamic environments. Available APs and iBeacons are stationary; however, iBeacons do not have location information. Smartphones are roaming around the area without location information. The main goal is to localize smartphones using APs location with the support of non-coordinated iBeacons.

in this paper iBeacons are non-coordinated since they are mobile and have unknown locations. To the best of our knowledge, none of the previous works has addressed the use of such non-coordinated iBeacons to enhance smartphone localization, especially without using a fingerprinting technique.

III. Real-world indoor localization problem statement

A. Objectives

As depicted in Figure 1, we aim at a self-organizing localization system for smartphones based on available WiFi and Bluetooth infrastructure in the area. Both APs and iBeacons play the role of anchors; however, only APs have a known location. Since we consider large and complex indoor areas, it is laborious to register the coordinates of all iBeacons when deploying them. Even if that can be done, iBeacons may also be moved afterward because of building renovations or infrastructure replacements. This means that keeping position information of iBeacons up-to-date is either very costly or even infeasible. For the same reason, burdensome fingerprinting or calibration is not preferred in our targeted scenarios, which dynamically changes over time. Smartphones carried by users are mobile. Smartphones opportunistically scan radio signals emitted from surrounding iBeacons and the APs. The collected RSS measurements then are sent to a central server. One should note that our approach does not require that the smartphones are connected to the APs to be able to scan them since WiFi-enabled smartphones regularly emit "probes" to connect to APs and receive the response including the RSS of the radio signals. The most computationally intensive part of our approach is the optimization phase, which is done on the server side. The estimated coordinates of the smartphones will be sent back to the users.

B. Challenges

In dynamic indoor environments, localizing smartphones based on radio signal is challenging since; since, RSS values are coarse information and significantly vary with the environments, which comprise various factors as follows.

1) Unstructured Environment: In many existing works, the environment is well known and calibrated. This makes it possible to apply advanced radio propagation models for high localization accuracy. In our study, the environment is unstructured and dynamic. This means that we do not know the environmental parameters such as the number and type of walls to employ an advanced model. Therefore, in this work we focus on a simple radio propagation model such as LNSM.

2) Already Existing AP Deployment: In many existing works, the APs are thoughtfully deployed at certain positions to obtain as high accuracy as possible, which are usually at the edge of the area. However, the existing APs that were already deployed for maximum WiFi internet coverage are typically not at the border of the area but in the middle. Therefore, it should be noted that in the experiment of this study only already existing APs are used, no additional APs were deployed or no existing APs were moved for the purpose of localization.

3) Non-coordinated iBeacons: In most existing works, iBeacons for assisting localization are carefully distributed across the area and have a known location. In our study, we aim at utilizing the already deployed iBeacons for infrastructure monitoring in large complex buildings. Keeping position information of iBeacons up-to-date is either very costly or even infeasible for such buildings. Therefore, in our experiment we assumed that the locations of iBeacons are unknown.

4) Limited RSS Measurements: In most existing studies, RSS measurements are made at stationary locations for a quite long duration and with various orientation and position of the smartphones, especially for the calibration phase of fingerprinting techniques. Such tedious calibration is what we want to eliminate in this study. Therefore, in our experiment there are only a few measurements at each point and such measurements are under a random smartphone's orientation.

5) Non-deterministic RSS Measurements: The variability of the RSS measurements of most smartphones are also quite large (e.g. the standard deviation of 500 samples is > 2.5 dBm for smartphones we used in our experiment) due to the multipath effects in indoor environmets, even when the smartphones are stationary. A tolerance of 1 dBm causes an error of approximate 0.7 m with the AP, or of 1.5 m with the iBeacons in our experiment. The negative impact of the variability on accuracy was reduced by increasing the number of measurements. However, acquiring numerous measurements is infeasible in our study as discussed above.

6) Limited Radio Range: The area we conduct our experiment is large and complex, with various walls and layouts. Most existing iBeacons in our experiment also have None-line of Sight (NLOS) with smartphones. A smartphone cannot listen to all available APs and iBeacons from an arbitrary point in the area. On average, only 36% APs and 30% iBeacons can be scanned by a smartphone from a location in our experiment.

7) High Ceilings: In many existing studies, anchors and unknown/blind nodes are placed in the same plan. In our study, already existing APs and iBeacons are above the ceiling with a height of more than $4\,\mathrm{m}$, while smartphones are only approximate $1\,\mathrm{m}$ above the floor. Assume that a smartphone is currently $4\,\mathrm{m}$ right under an iBeacon. When the smartphone moves $3\,\mathrm{m}$ horizontally along the floor, the distance between the smartphone and the iBeacon will increase only 1 m due to the 3-dimensional space, instead of $3\,\mathrm{m}$ if the iBeacon and smartphone are in the same horizontal plane. This smaller difference in distance causes a smaller difference in the corresponding RSS measurements. This makes the localization problem definitely challenging for both radio propagation and fingerprinting techniques.

IV. SoLoc: Self-organizing localization Approach

This section is divided into two parts: model presentation and model optimization.

A. Model Presentation

We consider a network that consists of M stationary APs with known position and N iBeacons with unknown positions. All these devices are assumed to be within the area of interest. The main problem is to localize a smartphone at K unknown locations, given a total of K corresponding RSS observations measured by smartphones in the area. We assume that there is no reference information (e.g. trajectories, movement patterns, or ground truth positions) about the smartphones used to scan the APs and iBeacons. We also assume there is no information available about the position of the iBeacons.

Let $S = \{(x_i, y_i, z_i)^T,\ i = 1, .., K\}$ denote the set of K position vectors of the unknown positions of smartphones, where the corresponding RSS observations are measured. Let $A = \{(x_i, y_i, z_i)^T,\ i = K+1, .., K+M\}$ denote the set of M position vectors of known-location APs. Let $B = \{(x_i, y_i, z_i)^T,\ i = K+M+1, .., K+M+N\}$ denote the set of N position vectors of unknown-location iBeacons. Let $\tilde{P} = \{\tilde{P}_{i,j},\ i = 1, .., K,\ j = 1, .., M+N\}$ denote the set of K observations of RSS measurements collected by available smartphones in the area of interest, where $\tilde{P}_{ij}$ denotes the RSS of the measured power of observation i, transmitted from node j. Since the propagation is symmetric, we assume that $\tilde{P}_{i,j} = \tilde{P}_{j,i}$. Note that the vector of the RSS measurements combines both Bluetooth and WiFi measurements. A smartphone can opportunistically scan RSS at multiple positions and we only consider the number of observations. For each observation $i,\ i = 1, .., K$, we have $\tilde{P}_i = \{\tilde{P}_{i,1}, \tilde{P}_{i,2}, .., \tilde{P}_{i,M+N}\}$ that contains $M+N$ RSS values from M APs and N iBeacons at location i.

As advanced models are not suitable for dynamic and complex environments because of laborious calibration, we use the LNSM model for our localization problem. In fact, the LNSM model is still commonly used in many works including [10, 17, 18, 23] as it is simpler and still valid in many indoor environments [22]. Applying the LNSM model, we model $\tilde{P}_{i,j}$ as:

$$\begin{aligned} &\tilde{P}_{i,j} \sim \mathcal{N}(\bar{P}_{i,j}, \sigma_{i,j}^2), \\ &\bar{P}_{i,j} = P_{j,d_0} - 10\beta_j \log_{10}(\frac{d_{i,j}}{d_0}), \end{aligned} \tag{1}$$

where $d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2}$. P_{j,d_0} and β_j are the parameters representing the transmission power of the transmitter j in dBm at a distance of d_0 and the path-loss exponent, respectively. The reference distance d_0 is typically set to $1\,\mathrm{m}$ for computation convenience.

Mathematically, we define the problem as a semi-anchored localization problem, combining cost functions for known-location anchors (APs) and unknown-location anchors (iBeacons):

$$\hat{\theta} = \arg\min_{\theta} \sum_{t=1}^{K} \left(\sum_{i=1}^{M} (\tilde{P}_{t,i} - \bar{P}_{t,i})^2 + \sum_{j=M+1}^{M+N} (\tilde{P}_{t,j} - \bar{P}_{t,j})^2 \right). \tag{2}$$

The unknown parameter matrix $\hat{\theta}$ includes the estimated locations of smartphones at observation points, iBeacons, and environmental parameters.

$$\theta_{2M+N+K,3} = \begin{pmatrix} x_1 & y_1 & z_1 \\ x_2 & y_2 & z_2 \\ \vdots & \vdots & \vdots \\ x_K & y_K & z_K \\ x_{K+M+1} & y_{K+M+1} & z_{K+M+1} \\ x_{K+N+2} & y_{K+N+2} & z_{K+N+2} \\ \vdots & \vdots & \vdots \\ x_{K+M+N} & y_{K+M+N} & z_{K+M+N} \\ P_{1,0} & \beta_1 & 0 \\ P_{2,0} & \beta_2 & 0 \\ \vdots & \vdots & \vdots \\ P_{M+N,0} & \beta_{M+N} & 0 \end{pmatrix}, \tag{3}$$

where $\{(x_i, y_i, z_i)^T,\ i = 1, .., K\}$ are coordinate vectors of K observations and $\{(x_i, y_i, z_i)^T,\ i = K+M+1, .., K+M+N\}$ are coordinate vectors of N iBeacons. $\{P_{i,0},\ i = 1, .., M\}$ are reference power of APs. $\{P_{i,0},\ i = M+1, .., M+N\}$ are the reference power of iBeacons. $\{\beta_{i,0},\ i = 1, .., M\}$ are the path-loss exponents of APs. $\{\beta_{i,0},\ i = M+1, .., M+N\}$ are the path-loss exponents of iBeacons.

B. Model optimization

We employ Levenberg-Marquardt optimization to minimize the least-squares function described in Equation 2. All the unknown parameters in Equation 2 including the locations of smartphones can be estimated simultaneously. To avoid a local minimum, which results in poor estimates, we propose a twofold optimization process, which is executed online and real-time.

- Phase 1: Cluster-based initial values estimation.
- Phase 2: Semi-anchored optimization.

1) Cluster-based Initial Values Estimation: To the best of our knowledge, the initial estimates of environmental parameters have little impact on the estimation accuracy. Therefore, in order to obtain the initial values of environmental parameters, we simply measure them with an AP and an iBeacon at different distances (e.g., at 1 m and 5 m). The most difficult part of the initial value estimation is the initial positions, which have a significant impact on the estimation accuracy.

We first estimate the initial values of the observation positions using Algorithm 1, which is the position of each smartphone when they are measuring the RSS of radio frequencies from surrounding APs. This estimation is done by applying the Levenberg-Marquardt optimization on the following cost function:

$$\begin{aligned}\hat{\theta} &= \arg\min_{\theta} \sum_{i=1}^{K}\sum_{j=1}^{M}(\tilde{P}_{i,j} - \bar{P}_{i,j})^2 \\ &= \arg\min_{\theta} \sum_{i=1}^{K}\sum_{j=1}^{M}\left(\tilde{P}_{i,j} - P_{j,d_0} + 10\beta_j \log_{10}(\frac{d_{i,j}}{d_0})\right)^2\end{aligned} \tag{4}$$

where $\hat{\theta}$ is the estimated unknown parameter matrix including the estimated locations of smartphones.

To provide the initial positions of observations for the Levenberg-Marquardt optimization, we take the coordinates of the closest APs based on the strongest WiFi RSS measurements of the corresponding observation. It is likely that the AP providing the strongest WiFi RSS is the closest one to the measurement position in most cases, except when there are outliers due to some fading channels. It is possible that at a certain position the smartphone cannot receive WiFi signal from any AP. If that happens, we use the central map coordinates as conventional approach. However, this problem is not expected in most indoor environments, where APs are deliberately placed to cover the area as large as possible.

ALGORITHM 1: Coarse estimation of observation locations

INPUT:
$\{\tilde{P}i, j\}$, reference coordinates $A = \{\boldsymbol{x}_i \ : \ i = K+1, ..., K+M\}$
OUTPUT:
initial observation location values $S^{(0)} = \{\boldsymbol{x}_j^{(0)} \ : \ j = 1, ..., K\}$
INITIALIZE:
for $(j = 1 : K)$ **do**
  $\boldsymbol{x}_j^{(max)} := \arg\max_{\boldsymbol{x}_i}\{\tilde{P}i, j\}, \ i = K+1, ..., K+M$
  $\boldsymbol{x}_j^{(0)} := \arg\min_{\theta} \sum_{j=M+1}^{M+N}\left(\tilde{P}_{i,j} - P_{j,d_0} + 10\beta_j \log_{10}(\frac{d_{i,j}}{d_0})\right)^2$
  (Levenberg-Marquardt with $\boldsymbol{x}_j^{(max)}$ as initial value)
end
$S^{(0)} := \{\boldsymbol{x}_j^{(0)}, \ j = 1, ..., K\}$

The initial-value estimates of the iBeacon positions are more challenging since the iBeacons can be only linked with smartphones that are supposed to have an unknown location. We overcome this issue by clustering observations of iBeacon signals based on their RSS strength. The pseudocode of cluster-based initialization for iBeacons coordinate values is shown in Algorithm 2.

As we want to cluster the observations into subgroups and assign their position to a non-coordinated iBeacon, we set the number of clusters equal to the number of non-coordinated iBeacons. The RSS vector which consists of c values from c surrounding iBeacons is known. Due to the limited coverage of radio frequency, we have $c \leqslant N$. Based on those c values, we cluster the observation to the group of the iBeacon of which RSS is the strongest. It is likely that the position to take the observation is closest to such iBeacon. We repeat this process for all observations to finally obtain N clusters of RSS observations $\{X_j^{cluster}\}$. It is possible that some clusters do not have any observation, albeit it rarely happens because of the proliferation of smartphones. In any case, we deal with such situation by assigning the central map coordinate $\boldsymbol{x}^{center}$ to the iBeacon.

ALGORITHM 2: Cluster-based estimation of iBeacon locations

INPUT:
$\{\tilde{P}i, j\}$, initial observation values $S^{(0)} = \{\boldsymbol{x}_i^{(0)} \ : \ i = 1, ..., K\}$
OUTPUT:
initial observation location values
$B^{(0)} = \{\boldsymbol{x}_j^{(0)} \ : \ j = K+M+1, ..., K+M+N\}$
INITIALIZE:
for $(i = 1 : K)$ **do**
  $\boldsymbol{x}_j^{max} := \arg\max_{\boldsymbol{x}_j}\{\tilde{P}i, j, \ j = K+M+1, ..., K+M+N\}$
  $X_j^{cluster} \leftarrow \boldsymbol{x}_j^{max}$
end
for $(j = K+M+1 : K+M+N)$ **do**
  if $X_j^{cluster} == \emptyset$ **then**
    $\boldsymbol{x}_j^{(0)} := \boldsymbol{x}^{center}$
  end
  else
    $\boldsymbol{x}_j^{(0)} := mean(X_j^{cluster})$
  end
end
$B^{(0)} := \{\boldsymbol{x}_j^{(0)}, \ j = 1, ..., M\}$

2) Semi-anchored Optimization: Given the initial parameter estimates obtained from the first phase and the RSS observations by the smartphones, we employ the Levenberg-Marquardt optimization to estimate the optimal values of unknown parameters including the coordinates of observation points.

In particular, we apply the Levenberg-Marquardt optimization in a cooperative manner. This means that all unknown positions of all observations are optimized simultaneously. Equation 2 can be represented as a combination of WiFi and iBeacon channels by:

$$F = \sum_{t=1}^{K}(f_t^{iBeacon} + f_t^{WiFi}). \tag{5}$$

Given K RSS observations, the error function $F = (f_1, f_2, .., f_K)^T$ is a vector of K error functions,

$$f_t = \sum_{j=1}^{M}(\tilde{P}_{t,j}^{WiFi} - \bar{P}_{t,j}^{WiFi})^2 + \sum_{i=M+1}^{M+N}(\tilde{P}_{t,i}^{iBeacon} - \bar{P}_{t,i}^{iBeacon})^2, \tag{6}$$

The optimization starts with initial guess $\theta^{(0)}$ which is estimated in the first phase. The estimated coordinates $\hat{\theta}$ are adjusted by the step h only for downhill steps. The iterative loop stops when the residual $\frac{1}{2}||f(\theta^{(k)})||^2$ is smaller than a predefined ϵ or it reaches the maximum iteration k_{max}. The pseudocode for the semi-anchored optimization based on the Levenberg-Marquardt algorithm is summarized in Algorithm 3.

ALGORITHM 3: Iterative Semi-anchored Optimization

INPUT:
$\{\tilde{P}_{i,j}\}$, $S^{(0)}$, $B^{(0)}$, and A
damping λ, λ_{up}, λ_{down}, accuracy ϵ, maximum iteration k_{max}
OUTPUT:
$\hat{\theta}$ minimizing $F = f(\theta)$ expressed by (5)
INITIALIZE:
$k := 0$; $\hat{\theta} = \theta^{(0)}$;
$f(\theta^{(k)}) := f(\hat{\theta})$;
while $(\frac{1}{2}||f(\theta^{(k)})||^2 > \epsilon)\&(k < k_{max})$ **do**
  $g(\theta) := J(\theta)^T f(\theta)$;
  $h := -(J(\theta)^T J(\theta) + \lambda I)^{-1} g(\theta)$;
  $\theta^{(k+1)} := \theta^{(k)} + h$;
  if $\frac{1}{2}||f(\theta^{(k+1)})||^2 < \frac{1}{2}||f(\theta^{(k)})||^2$ **then**
    $k := k + 1$;
    $\lambda := \lambda/\lambda_{down}$;
  end
  else
    $\lambda := \lambda \times \lambda_{up}$;
  end
end
$\hat{\theta} := \theta^{(k)}$

V. Empirical Results

In this section, we describe a real world experiment and its results when applying our self-organizing approach. Other popular extant localization approaches are also implemented for comparison.

A. Experimental setup

Figure 2 illustrates the real world area for our experiment, which is a laboratory with a quite large and complex structure. In the figure we can observe that the already existing APs are gathered in the middle. Due to the complex architecture and the restriction of the area, iBeacons were already deployed at certain places on the ceiling, along with the beams at about 4 m high (see Figure 3).

The area size is approximate $38\,\mathrm{m} \times 50\,\mathrm{m}$ and has various rooms and sections that are separated by walls made of different materials such as glass, concrete, wood, plastic, steel. We used the *i3 Robust Beacon* made by MINEWTECH (see Figure 3). The transmitting power of iBeacons was set to -59 dBm to save power consumption. There are 11 Cisco APs in the area, deployed previously by the venue owner. To have the highest coverage, the venue owner had mainly placed the APs in the middle of the area. One should note that placement of the WiFi APs to provide the best coverage is not necessarily optimal for WiFi-based localization accuracy. The true location of the iBeacons and the APs were manually measured with a with an error of about ± 0.25 m due to the complexity of the building.

For WiFi and iBeacon scanning, we developed a smartphone application that can scan and record RSS emitted from both iBeacons and APs simultaneously. We set the smartphones scan frequency periodically with an interval of 1 second. This small interval makes it possible for the systems to localize a smartphone moving at a walking speed of approximate 1 m/s. We ignore RSS measurements while moving faster than 1 m/s, which can be detected by the off-the-shelf accelerometers. We do this because the RSS measurements from different APs and iBeacons will not be synchronized in the spatial domain (not at one location) at high mobility. For the evaluation purposes, a person carried the smartphone and walked through 603 grid-based locations. When walking through a marked location, the person pressed the corresponding number to entry the ground truth of the observation locations. For each location, there were roughly 10 measurements.

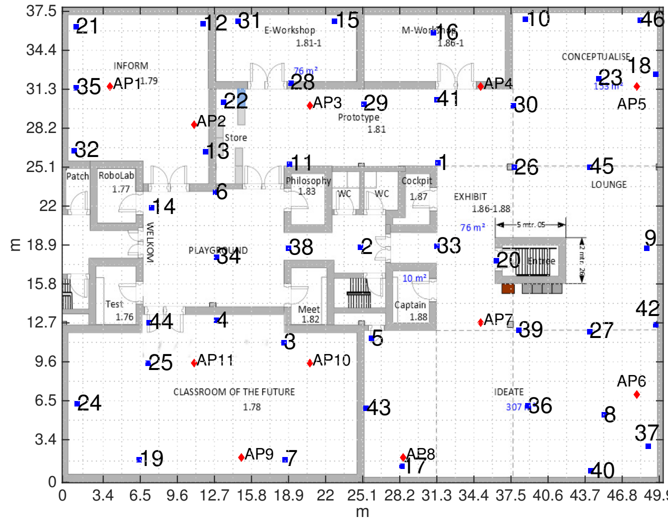

Fig. 2: Deployment area and placement of 46 iBeacons (marked as □) and 11 APs (marked as ♢). Most iBeacons and APs have to be placed between the roof and ceiling due to the constructive constraints.

To investigate the performance of SoLoc, we compare it with four alternative approaches as well as a Cramer-Rao Bound (CRB)-like error bound of our approach. CRB [25] has been widely used for localization.

1) *RADAR* [2]: The well-known naive fingerprinting technique that is based on k-nearest neighbors. We set k to 3 since it was shown to provide the highest accuracy in [2].
2) *LWR-WKNN* [3]: The well-known fingerprinting technique that combines radio-map interpolation and weighted k-nearest neighbor. In [3], the best performance is when k is set to 2.
3) *RBF*: [4] This approach uses a neural network as a regression with a radial function based on Euclidean distance. The network is used to learn the weight of the regression model, which then be used to predict the unknown locations.
4) *DNN* [5] This is an advanced approach that use deep learning as a regression model for node localization. For a fair comparison, we set the network parameters as in [5], which has 9 hidden layers of which the number of neurons decreases over layers from 450 to 50. The rectified linear unit (ReLU) is used.
5) *Error Bound*: According to the optimization theory, when our approach use the Levenberg-Marquardt method with the actual location of observations (smartphones) for initialization and the actual location of iBeacons for references, the estimated locations have the lowest errors. This approach is also considered as the optimal solution for propagation-based localization, of which performance is very close to the lower bound [12].

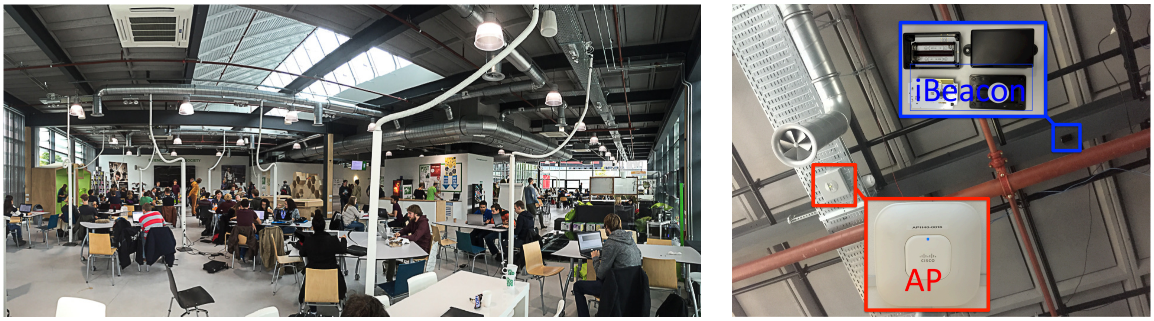

Fig. 3: The $IDEATE$ sub area of our laboratory (see Figure 2). The laboratory has various rooms and sections that are separated by walls made of diverse materials such as glasses, concrete, woods, plastics, steel. Most iBeacons and APs can only placed near the walls and beams, right under the roofs of which heights are about 4 m.

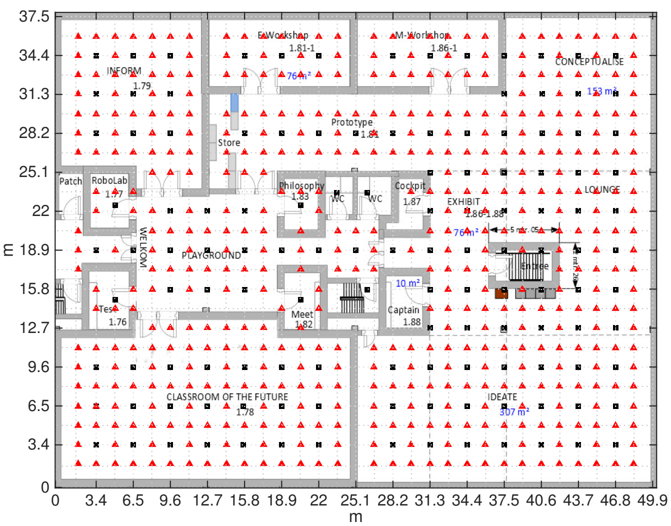

Fig. 4: Signatures (marked as □) and test points (marked as △) for evaluation with fingerprinting techniques.

For the above fingerprinting techniques, we selected 128 locations among 603 locations as signatures to build the fingerprint databases. The remaining 475 observations are for testing. Figure 4 show the distribution of the signatures and test points for fingerprinting approaches in our experiments.

We implemented SoLoc and compared algorithms except DNN in Matlab using the *fsolve* function with the Levenberg-Marquardt optimization. DNN-based localization is implemented with the RapidMiner machine learning toolbox. Since our scenario does not have fully-pairwise RSS measurements among pairwise devices, the common CRB [25] is not applicable to compute the lower error bound. That is why we come up with the Error Bound defined above as a benchmark to compare localization accuracy.

B. Experimental Results

Figure 5 shows the localization results of SoLoc as well as the extant algorithms for both cases: when using only APs' measurements and when adding iBeacons' measurements. Overall, SoLoc performs significantly better than others. For example, SoLoc has a Mean Absolute Error (MAE) of $4.3\,\mathrm{m}$ when using both APs and iBeacons to assist the localization; whereas, the advanced fingerprinting technique DNN has a median of $6.6\,\mathrm{m}$. In other words, SoLoc performs $35\,\%$ better than DNN. Moreover, the performance of SoLoc in terms of accuracy is very close to the lower error bound, of which the median error is also $3.9\,\mathrm{m}$. RBF performs poorly due to insufficient training data.

It is also interesting to observer that the simple RADAR technique performs much better than the complex RBF when using such a coarse fingerprint database in our study. RADAR also performs slightly better than LWR-WKNN. The reason is that the environment is extremely complex, with a lot of different types of walls. Therefore, the interpolation of radio propagation is incorrect and results in higher localization errors. DNN scores best among fingerprinting techniques; however, it is still far from SoLoc.

Figure 5 also shows the improvement in terms of accuracy when adding the RSS measurements of already existing iBeacons. Overall, all localization techniques can provide a better accuracy (smaller error). We observe that DNN could exploit the additional measurement very well. When using only APs for localization, DNN performs worst than RADAR. However, it outperforms RADAR when using both APs and iBeacons. This implies that the DNN technique is promising in environments with high density of iBeacons.

Besides having lower performance than SoLoc, the extant fingerprinting approaches demand an offline laborious calibration phase while SoLoc does not. For example, in [2] it requires 30 observations per location and per direction. The data needs to be measured with 4 directions (West, East, South, and North). Thus when applying the same calibration process for our experiment space with 128 signature location, it will consume at least 4 hrs and 16 min (1 s per observation), which still does not take the time for walking among the calibration points and fixing mistakes.

VI. Conclusion

In this paper we propose a novel self-organizing approach for smartphone localization in extreme environments, which are large, unstructured, complex, and dynamic. The proposed approach, named SoLoc, use the already-deployed iBeacons to enhance the localization accuracy. We employ the Levenberg-Marquardt algorithm to estimate the location of smartphones without requiring any knowledge of environment parameters, calibration, and the location information of iBeacons. Real-world experimental results show that SoLoc outperforms at

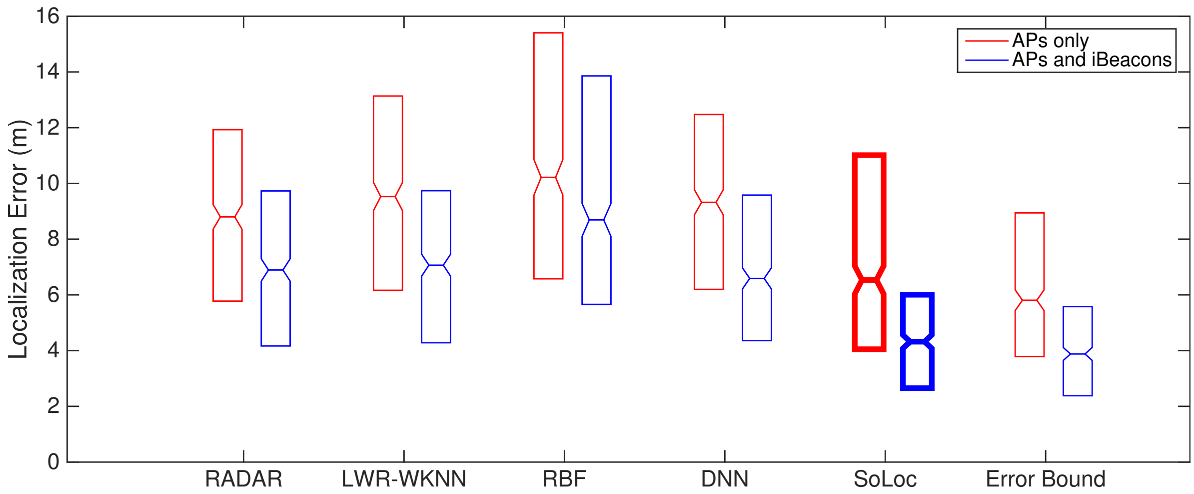

Fig. 5: Boxplot of smartphone localization experiment results: with only already existing APs; with all already existing APs and iBeacons.

least 35 % the compared approaches that including the advanced Deep Neural Network. This work shows that SoLoc not only effortlessly estimates the position of mobile devices but also provides a higher localization accuracy.

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