2

Beacon Placement Problem for Indoor Localization

Indoor Localization is the process of finding the location of a target sensor surrounded by the guiding sensors having known locations. In practical terminology, a target sensor is a location seeking device, and a guiding sensor is a localizing beacon. As described in the previous chapter, the primary step of deploying a localization system demands a proper hardware setup. The problem of finding a set of locations for beacon deployment is called Beacon Placement Problem (BPP). In this direction, the current chapter reviews past research work for solving BPP and presents our proposal for the same. The next section builds a basic understanding for the reader about BPP and describes the steps for solving it.

2.1 Beacon Placement Problem (BPP)

Figure 2.1 presents a 2D bird's eye view of a typical indoor environment setup for localization. Common to all localization deployments, this setup contains two spatial domains, namely beacon and device depicting the possible positions for the placement of beacons and the existence of devices.

Within the setup, environment's periphery marks the beacon domain and the area enclosed, apart from the shaded obstacle regions, is designated as the device domain. Here, the four beacons with coordinates $(x_1, y_1), (x_2, y_2), (x_3, y_3), (x_4, y_4)$ attempt to localize a device with unknown co-

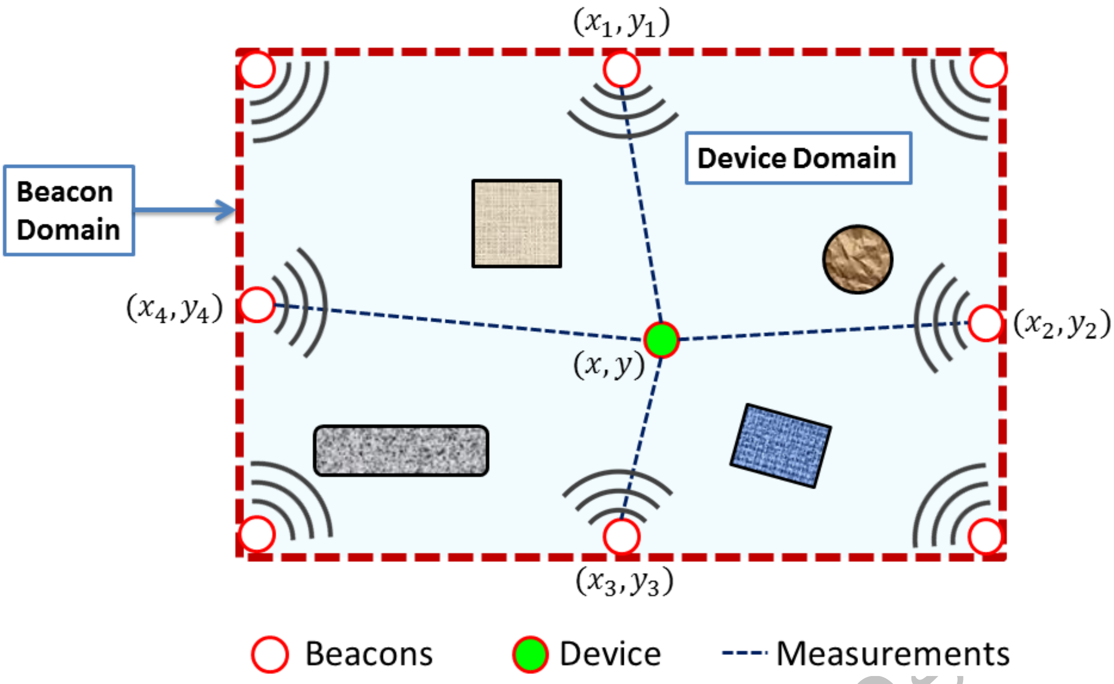

Figure 2.1: 2D bird's eye/floor-plan view of a synthetic indoor environment.

ordinates (x, y), while retaining Line of Sight (LoS) visibility to it.

With reference to the above description, to formalize, finding a configuration of beacons optimal for localization objectives such as accuracy and LoS coverage that conforms to constraints for beacon and device domains is frequently termed as Beacon Placement Problem (BPP) [Rajagopal et al., 2016] or Sensors Placement. Optimization (SPO) [Elsersy et al., 2015]. Solving a BPP is a two-step process consisting of designing and optimization as described in the following:

- **Design:** This step involves choosing the target indoor space and creating its digital representation that can be use in further mathematical formulation. This representation can be a (i) regular 2D geometry e.g. polygons, circles, (2) detailed floor plans and (iii) 3D representations generated by advanced visual imaging methods. These circumscribed spaces contain both beacon and device domains as described earlier in this section. In its fundamental form, the above spatial description of an indoor space is used to formulate the objectives and constraints for BPP.

  BPP is typically approached by linear programming or meta-heuristics optimization methods and proved to be NP-Hard [Falque et al., 2018] with reference to the classical art gallery problem. Hardship in BPP's tractability is primarily attributed to the size of its beacon and device domains within the Region of Interest (RoI) in indoor environment. The complexity of BPP's implementation gets severe with the transition from two dimensional (2D) to three dimensional (3D) localization perspective due to exponential increase in coordinate counts within the RoI [Poduri et al., 2006]. Also, due to the presence of static and dynamic obstacles in indoor spaces and signal propagation anomalies such as fading and shadowing which vary with the choice of communication standard, makes it infeasible in finding a generalized optimization strategy.

- **Optimization:** BPP in its core is intended to deliver a set of locations for beacon placement that satisfies the constraints chosen for the target indoor space. For any such space, objectives of solving a BPP are directly mapped to the expectations from an efficiently working localization system in it. Thus, achieving (i) minimum localization error, (ii) maximum indoor beacon coverage, (iii) maximum observation availability to a device and, (iv) minimum cost of deployment are primary objectives for a BPP design. On the other hand, (i) ensuring minimum beacon count available to a device with LoS, (ii) keeping beacon's sensing range in check, (iii) taking the effect of beacon-device geometry are prominent restriction to be implemented as constraint for BPP. We now explain the interplay of objectives and constrains in the following points:

  – Minimization of *Localization Error* as an objective requires high quality sensor observations for RSSI approaches. The high quality of RSSI observations for short range wireless standards such as WiFi and Bluetooth is inversely proportional to the beacon-to-device distance due to corresponding decrease in *Error Propagation*. More precisely, the propagation of observation noise is a function of beacon-to-device geometry, frequently formulated as GDoP metric in satellite as well as indoor positioning. A lower GDoP value (≈ 1) is preferred for both 2D and 3D localizations.

    Also, ensuring a higher beacon count within the LoS visibility of a device improves the quality of RSSI observations by minimizing potential signal propagation anomalies as mentioned earlier in this section.

– Maximizing the *Indoor Coverage* is essentially the objective of provisioning localization network connectivity at as many possible candidate device locations as possible. Achieving higher coverage is proportional to increasing the count of beacons to be deployed as well as increasing the communication range. An increase in both count and sensing range of beacons results in increasing the hardware cost and power consumption. Both objectives of hardware cost and power consumption will be collectively addressed as *Beacon Count* from here on.

– Maximizing availability of observations from beacons to a device location is essential for robust functioning and adequate accuracy of an indoor localization system. The count of beacons in LoS range to a device location will be termed as *Beacon Density* throughout the scope of this thesis.

With the above discussion, it is understandable that the objectives and constrains required for a localization system carry a strong mutual correlation in formulating BPP. Thus, in the next section we analyse relevant research works for their usages of single and multiple objectives in solving BPP.

2.2 Related Works

As detailed in Chapter 1, Indoor Localization carries application oriented diversity in its hardware and software requirements. Considering sensors and communication links as resources, BPP has been researched as an optimization problem over the years. This resource management frequently surfaces the objectives as coverage, accuracy and cost in a communication network. While single objectives tend to produce configurations peculiar to target applications, potential of multiple objectives remains yet to be explored for BPP. Taking this basis, the following subsections explore relevant single and multi objective approaches for BPP to clarify the formulation of premise, objectives and constraints for present thesis.

2.2.1 Single Objective Approaches

Accuracy being a dominant concern for Beacon Placement Problem (BPP), the error propagation, resulting from the least square adjustment of multi-lateration of noisy range measurements, has been a primary source of SOO formulation. In this regard, the use of Fisher Information Matrix (FIM), Cramer Rao Lower Bound (CRLB) and GDoP, have been adopted as a de-facto method for deriving optimization metrics. For example, [Zhou et al., 2010] presents a CRLB based localization accuracy assessment for rectangular shaped industrial facilities. In this approach, using four beacons on the horizontal edges of two target regions, the localization performance is compared among the four optimization objectives as: 1) Expected CRLB, 2) Probability of lower CRLB, 3) Minimum CRLB and 4) Maximum CRLB. Using Monte Carlo simulation, the literature identifies that the localization performance significantly decreases with an increase in the region's length to width aspect ratio and the failure of a beacon. The outcome of this approach is limited to 2D rectangular shapes and the use of CRLB puts a computational disadvantage over GDoP for its projection in 3D Li [2006]; Patwari et al. [2005].

In order to quantify the effect of beacon placement geometry over localization accuracy in 2D, a GDoP based metric is utilized in [Yibei Ling et al., 2012]. With randomly generated beacon locations in rectangular regions, the performances of gradient descent and least-squares methods are evaluated against the proposed two-phase localization algorithm which outperforms the earlier two.

Another beacon placement approach which minimizes beacon count using a GDoP based constraint metric is presented in [Kirchhof, 2013]. The method utilizes a visual sensor with restricted field of view and range to identify field visibility and performs beacon count minimization using binary and mixed integer programming over 2D indoor designs.

Among the few research works targeting BPP for 3D localization, a GDoP based optimization tool-chain AP15 is presented in [Leune et al., 2016]. In their tool-chain, first, using Poisson-Disc sampling, a set of random beacons is generated. Then, using a) the 3D model of target space stored in an octree, b) target device location and c) the beacon set, the LoS detection is carried out. Finally, a genetic algorithm based optimizer calculates the beacon set for which the

Root Mean Square Deviation (RMSD) of position estimates is compared for random and proposed AP15 placement.

Another GDoP based optimization approach for 2D floor maps is presented in [Rajagopal et al., 2016]. In order to resolve the flip ambiguity, an augmented GDoP metric for unique localization is proposed. With the given floor map and propagation model, their algorithm iteratively estimates the suitability of chosen candidate beacon set with respect to the unique localizability metric.

Falque et. al. have presented an optimization strategy in [Falque et al., 2018] that maximizes 3-coverage and inter-beacon distance over 2D floor plans. They utilize a Genetic Algorithm (GA) based greedy selection approach that iterates up to achieving 90% 3-coverage, which generates a seed solution of beacon location that is further fed to a GA based global optimizer. The performance of resulting optimization is compared against Linear Least Square and Particle Filter based localization.

Another approach of optimal beacon placement for autonomous guided vehicle (AGV) is presented in [Perez-Ramirez et al., 2013]. Based on two groups of beacon sets, they perform a min-max optimization for an FIM based objective function. Simulations were carried out for 2D and 3D environments assuming the dependency of measurement noise over range estimations.

For 3D environments, Leune et. al. have proposed a GA based optimizer in [Leune et al., 2013] that uses DoP for the quality assessment of each generation's genomes. For each genome, a fitness value based on the LoS visibility between target device locations and genome's beacon nodes is calculated. Then, using a random probabilistic draw, the selected genome is crossed over and mutated till the maximum permissible iterations are reached without finding a better solution than the current one.

2.2.2 Multi Objective Approaches

To the best of our knowledge, the proposed methodology in this thesis is the first to analyse BPP for indoor localization by MOO with a 3D point cloud perspective. However, for nonlocalization objectives, [Lin et al., 2018] has utilized MOO to derive an optimal sensor configuration for structural health monitoring of a three dimension frame structure model. Using response covariance sensitivity and response independence, a two objective SPO is approached with Non-dominated Sorting Genetic Algorithm (NSGA)-II. Their proposed algorithm is evaluated for three different damage scenarios that demonstrated the stiffness reduction with resulting sensor configuration.

Similarly, another SPO approach for SHM has been presented in [Elsersy et al., 2015] that incorporates the conflicting trade-off between information quality and total energy consumption for MOO. The two versions of Effective Sensor Placement Model (SPEM) namely, power aware SPEM (p-SPEM) and multi objective p-SPEM (mop-SPEM) were adopted for simulations with a nine-storey building. The resulting configurations demonstrated a comparative assessment of reduction in energy consumption and increment in information quality over varying sensor node count for p-SPEM and mop-SPEM.

Among most recent efforts, Zan et. al. have used a three objective MOO approach for SPO in designing a monitoring system for natural gas distribution in [Zan et al., 2018]. The three objectives of minimizing Time-to-Detection and Impact Propagation while maximizing sensitivity are evaluated with Greedy, GRASP, NSGA II, FrameSense, and Particle Swarm Optimization (PSO) algorithms. The performances of these algorithms are compared for synthetic and real gas pipeline distribution systems against resulting design cost and computation time.

2.3 Motivation

2.3.1 Technological Gaps

Summarizing the previous section, the drawbacks of past efforts have been listed as the following:

1. Consideration of 2D design model for indoor environment has been a major drawback with most of the earlier approaches [Zhou et al., 2010; Yibei Ling et al., 2012; Kirchhof, 2013; Rajagopal et al., 2016; Falque et al., 2018]. Most importantly, its underlying assumption of

the same height of operation for beacon and device locations stands highly impractical for real world 3D spaces.

2. Disregarding the presence of obstacles [Zhou et al., 2010; Yibei Ling et al., 2012; Perez-Ramirez et al., 2013] puts a practical limitation for the adoption of any BPP optimization approach in real world. Actual LoS conditions and restriction on feasible beacon placement locations are few of the noteworthy issues attributed to the obstacle locations. Similarly, single target localization approaches present promising theoretical bounds on accuracy and beacon locations but, they fail to incorporate the practical limitations as above for achieving a generalized solution.

3. Absence of a sufficiently exhaustive search strategy within the parameter domain of optimization has also been seen in past researches [Zhou et al., 2010; Yibei Ling et al., 2012]. For example, limiting the count of CDL and CBL to application specific usages curtails the possibility of solution's practical endorsement [Leune et al., 2016; Rajagopal et al., 2016; Perez-Ramirez et al., 2013].

4. Utilized in most of the research works, assumption of independence between distance measurement noise and actual range induces a geometric disadvantage as the length of propagated signal carries a direct proportionality with inherited degradation noise [Yibei Ling et al., 2012].

5. As a popular technique of LoS detection, procedures such as ray-tracing which involve calculation of ray-plane interaction $O(n^2)$ for each beacon-device configuration $O(n^2)$ adds substantial computation overhead of $O(n^4)$ [Leune et al., 2016; Rajagopal et al., 2016; Falque et al., 2018; Leune et al., 2013].

2.3.2 Proposal

With reference to the above mentioned drawbacks, this subsection highlights the research contributions of this thesis which will be detailed in the upcoming chapters:

1. We conceptualized indoor environment as a 3D point cloud divided into three classes of

beacon, device and obstacle coordinates with following advantages:

- Over the last decade, modelling of indoor environment with laser scanning and photogrammetry has gained wide application in research and development [Adán et al., 2017; Turner et al., 2015], which frequently deliver 3D clouds of coordinate points.

- Coordinate cloud provides an exhaustive search space for optimization by allowing the user to finalize the approximation of indoor space by varying the density of CDLs and CBLs.

- Unlike 2D designs, 3D point cloud representation not only alleviates the issue of planarity between beacon and device existence, but also provides a flexibility of choosing application feasible deployment locations such as ceiling and walls.

2. In order to a-priori estimate the existence of LoS between CDL-CBL pairs for coverage optimization, a novel LoS detection algorithm is created. The algorithm presents a $O(n^3)$ overhead in terms of number of CDL, CBL and Obstacle coordinates unlike the computationally intensive ray-tracing and ray-casting as mentioned earlier in this section. This will further be detailed in Chapter 4.

3. Common to all the range based localization algorithms, inaccuracy in distance modeling propagates to overall positioning error. Hence, to incorporate the range dependency of noise due to strength degradation of propagating signal, a weighted GDoP approach [Teng et al., 2018] is incorporated. We assume 1) the measurement noises to be varying as a percentage of actual travelled distances and 2) the inverse proportionality of variance of range measurements to that of propagated distance in formulating weight matrix for the observations. Moreover, as the proposed methodology optimizes over varying range of input noise percentages, the resulting beacon configurations are independent of the choice of localization algorithm and range modeling.

4. We analyse the two objectives of 1) total beacon count minimization and 2) beacon density maximization for contradictory pareto optimization of BPP. To the best of our knowledge, our approach is the first to utilize MOO for BPP in 3D Indoor Localization. This will further

be detailed in Chapter 5.

Table 2.1 presents the comparison of aforementioned SOO and MOO approaches for respective (i) applicability to 2D/3D, (ii) consideration of obstacles in environment, (iii) type of error bound used and (iv) the number of objectives used. To summarize, this research presents a strategy to systematically analyse any indoor environment for its capability in delivering beacon configurations that, in the presence of obstacles and observation noise can output desired accuracy levels. As the first step to this approach, the next chapter describes important elements for proposed point cloud paradigm and the choice of parameters that leads to the BPP formulation in the subsequent chapters.

Table 2.1: A comparison of SOO and MOO approaches with respect to present work

Work	Dimension	Obstacles	Bound	Optimization
[Zhou et al., 2010]	2D	No	CRLB	SOO
[Yibei Ling et al., 2012]	2D	No	GDoP	SOO
[Kirchhof, 2013]	2D	Yes	GDoP	SOO
[Leune et al., 2016]	3D	Yes	GDoP	SOO
[Rajagopal et al., 2016]	2D	Yes	GDoP	SOO
[Falque et al., 2018]	2D	Yes	None	SOO
[Perez-Ramirez et al., 2013]	2D/3D	No	FIM	SOO
[Leune et al., 2013]	2D/3D	Yes	DoP	SOO
[Lin et al., 2018]	3D	Not Applicable	Not Applicable	MOO
[Elsersy et al., 2015]	2D	Not Applicable	Not Applicable	MOO
[Zan et al., 2018]	2D	Not Applicable	Not Applicable	MOO
Proposed MOO	2D/3D	Yes	GDoP	MOO