AI-BPO: Adaptive incremental BLE beacon placement optimization for crowd density monitoring applications

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Abstract

With the pandemic of COVID-19, indoor crowd density monitoring has become one of the most critical responsibilities of public space managers. Beacon placement optimization has been tackled as fundamental research work as the performance of crowd density monitoring highly depends on how BLE beacons are allocated. In this research, we propose a novel beacon placement optimization approach to incrementally place the beacon on the updated detection status adaptively in favor of Bayesian optimization, which can help to provide the optimal beacon placement. Our proposed method can optimize the beacon placement effectively to improve the signal coverage quality in the given environment and minimize human workload.

CCS Concepts: **• Information systems → Sensor networks**; **• Networks → Mobile networks**.

Keywords: placement optimization, crowd density monitoring, adaptive optimization

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1 Introduction

During the COVID-19 pandemic, Bluetooth Low Energy (BLE) technology is widely used in contact tracing and indoor crowd monitoring systems to prevent infectious diseases. Some public service facilities take the responsibility to prevent such situations and choose to deploy indoor crowd monitoring applications to prevent the spreading of the epidemic. The University of Tokyo released an indoor density monitoring system using BLE beacons to monitor the crowd density of the classroom, laboratory, library, and dining hall[1]. This indoor crowd density monitor system consist of the mobile application at the user's side and the beacon sensor network as the infrastructure.

To obtain accurate result in indoor crowd density monitoring, beacon placement should be carefully designed to cover the spatial area. Finding the optimal beacon placement is a challenging and laborious problem. First, knowing the beacon's detection status is difficult. Second, finding the optimal location to place the beacon is complicated because the actual propagation of Bluetooth signals is unknown until we install the beacon and take the measurement. Hence, most installation of beacons relies on the experience of experts, which significantly impairs their scalability.

Beacon placement optimization has been studied for years in indoor localization, Wireless Sensor Network (WSN), and Robotics communities [2, 3, 5, 10–13, 16]. Some researchers proposed batch simulation-based sensor placement optimization methods which use the radio wave propagation model to estimate the radio map to maximize the coverage of beacon signals [3, 4, 8, 9, 17, 18]. However, they cannot reflect the actual radio map in the target environment because the true received signal strength indication (RSSI), which can

[1] https://mocha.t.u-tokyo.ac.jp/en

be obtained through measurement, is not considered. Some other research proposed optimization methods by selecting beacons from large distributed beacons [1, 6, 7, 13, 15]. This approach can provide the beacon placement considering actual radio propagation. However, it demands an ideal initial beacon placement of adequate beacons and dense data measurement.

This research focuses on the BLE sensor placement optimization problem for the indoor crowd monitor application. Our goal is to enlarge the high-quality Bluetooth signal coverage on the target environment with limited beacons. We propose a novel method named Adaptive Incremental Beacon Placement Optimization (AI-BPO), which effectively suggests beacon placement that maximizes detection coverage with minimal labor cost.

The contributions of this article include the following:

- We propose a beacon placement method AI-BPO by alternating the measurement and beacon placement processes.
- We acquire a dense beacon placed dataset for comparing with all combinations of beacon placement and evaluate the effectiveness of our method.

2 Problem Settings

Mobile application of the user's side detects the peripheral Bluetooth signals and determines user's location by the signal with maximum RSSI from the beacon. Hence, the placement of beacons is fundamental to crowd monitoring.

Beacon placement optimization finds the optimal number of beacons and the optimal locations to place beacons, maximizing the beacon area coverage of expected detection probability. Let the discretized position of target environment be $\mathcal{L} \subset \mathbb{R}^2$, initially placed beacon locations be $\boldsymbol{B}^{(I)} = \{\boldsymbol{b}_1^{(I)}, ..., \boldsymbol{b}_{|B^{(I)}|}^{(I)}\} \subset \mathbb{R}^2$, additional beacon locations be $\boldsymbol{B}^{(A)} = \{\boldsymbol{b}_1^{(A)}, ..., \boldsymbol{b}_{|B^{(A)}|}^{(A)}\} \subset \mathbb{R}^2$, and $y \in \{1, 0\}$ be the beacon signal's detection status where $y = 1$ indicates that the signal is detectable, and $y = 0$ is not, respectively. We define the beacon detection probability at $\boldsymbol{l} \in \mathcal{L}$ under the beacon placement $\boldsymbol{B} = \boldsymbol{B}^{(I)} \cup \boldsymbol{B}^{(A)}$ as $P_{\boldsymbol{B}}(y|\boldsymbol{l})$. We formulate the beacon placement optimization as the follows:

$$\underset{\boldsymbol{B}^{(A)}}{\operatorname{argmax}} \sum_{\boldsymbol{l} \in \mathcal{L}} [[P_{\boldsymbol{B}^{(I)} \cup \boldsymbol{B}^{(A)}}(y = 1|\boldsymbol{l}) > t]], \tag{1}$$

which is to find the additional beacon locations $\boldsymbol{B}^{(A)}$ to improve overall detection probability where $[[a]]$ is the indicator function that $[[a]] = 1$ if a is true, else $[[a]] = 0$, and t is the target signal detection probability. In this paper, we tackle the beacon placement optimization problem to place beacons at optimal location incrementally from the initially installed beacons $\boldsymbol{B}^{(I)}$ to cover expansive space with Bluetooth signals of high detection probability.

3 Proposed Method

Our proposed method evaluates and optimizes the beacon placement using the signal RSSI distribution. Owing to observations, we define the detection probability given RSSI as a sigmoid function, as below,

$$P(y = 1|r) = \frac{1}{1 + \exp(-sr + b)}, \tag{2}$$

where $y = 1$ stands for the detectable status of the signal, r is the RSSI of the received signal, and s, b are the parameters of the sigmoid function.

3.1 Estimation of signal detection probability

To obtain an accurate RSSI distribution map with consideration of environmental factors such as the floor layout, walls, furniture which significantly influence the signal propagation and avoid heavy data gathering, we propose to model RSSI distribution using Gaussian process regression and pick up measurement location using Bayesian optimization to approximate RSSI distribution as accurately as possible with limited measurements.

We estimate the probability of RSSI from the beacon i located at $\boldsymbol{b_i}$, at location $\boldsymbol{l}$ being r by Gaussian process regression as the following,

$$P_{\{\boldsymbol{b}_i\}}(r|\boldsymbol{l}) \sim \mathcal{GP}(\mu_{\boldsymbol{l}_{\boldsymbol{b}_i}}, k(\boldsymbol{l}, \boldsymbol{l}')), \tag{3}$$

where $k(\boldsymbol{l}, \boldsymbol{l}')$ is the Gaussian kernel function. Inspired by the work by Shimosaka et al. [14], the accurate estimation with a reduced number of data via Bayesian optimization. In order to maximize the exploration and reduce the uncertainty of RSSI distribution effectively, we choose to use the sum of the standard deviation of each installed beacon from Gaussian process regression.

Once an RSSI distribution map is generated, a detection probability map can be generated using $P(y|r)$, which is common among all the beacons. An estimated signal detection probability at a location $\boldsymbol{l}$ of a beacon i is given as follows:

$$P_{\{\boldsymbol{b}_i\}}(y|\boldsymbol{l}) = \int P(y|r) P_{\{\boldsymbol{b}_i\}}(r|\boldsymbol{l}) dr. \tag{4}$$

Considering that a certain location is covered with signals from multiple beacons, we estimate the detection probability at location $\boldsymbol{l}$ as a 1-coverage problem. The overall detection probability $P_{\boldsymbol{B}}(y|\boldsymbol{l})$ of installed beacons $\boldsymbol{B}$ at a location $\boldsymbol{l}$ is defined as:

$$P_{\boldsymbol{B}}(y = 1|\boldsymbol{l}) = 1 - \Pi_i (1 - P_{\{\boldsymbol{b}_i\}}(y = 1|\boldsymbol{l})). \tag{5}$$

A detection probability map can be generated by calculating $P_{\boldsymbol{B}}(y|\boldsymbol{l})$ at every location $\boldsymbol{l}$ on $y = 1$.

3.2 Determination of a new beacon placement

Although it is hard to estimate the actual RSSI distribution of a new beacon, we hypothesize that approximating it with a circular shape is sufficient. We calculate the RSSI distribution after placing beacon i at candidate location $\boldsymbol{l}$ using the circular shape signal coverage. We can obtain simulated detection probability $P_{\{\boldsymbol{b}_i\}}(y|\boldsymbol{l})$ of new beacon i placed at location $\boldsymbol{b}_i$ by applying the calculated RSSI to detection model Equation 2. Using the previous estimated joint detection probability of already installed beacons $P_{\boldsymbol{B}}(y|\boldsymbol{l})$, we can derive the estimated joint detection probability when with new beacon i placed at $\boldsymbol{b}_i$ as follows:

$$P_{\boldsymbol{B}\cup\{\boldsymbol{b}_i\}}(y=1|\boldsymbol{l}) = 1-(1-P_{\boldsymbol{B}}(y=1|\boldsymbol{l}))(1-P_{\{\boldsymbol{b}_i\}}(y=1|\boldsymbol{l})). \tag{6}$$

Comparing all the improvement of beacon placement candidate locations $\mathcal{L}\backslash\boldsymbol{B}$, we can determine the optimal location by selecting the location $\boldsymbol{b}$ obtaining the maximum detection improvement as,

$$\boldsymbol{b} = \underset{\boldsymbol{b}\in\mathcal{L}\backslash\boldsymbol{B}}{\operatorname{argmax}} \sum_{\boldsymbol{l}\in\mathcal{L}} \min(P_{\boldsymbol{B}\cup\{\boldsymbol{b}\}}(y=1|\boldsymbol{l}),t) - \min(P_{\boldsymbol{B}}(y=1|\boldsymbol{l}),t). \tag{7}$$

3.3 Iterative adaptive optimization

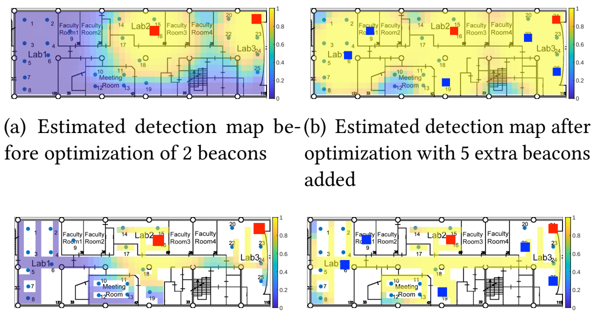
Admittedly, regarding the detection probability of the newly placed beacon, the gap between estimated and ground truth cannot assure we always place the new beacon at the optimal location. More importantly, the updated overall detection probability $P_{\{\boldsymbol{b}_i\}}(y|\boldsymbol{l})$ cannot indicate the actual detection probability since the detection probability of the new beacon i is simulated. Hence, we propose updating the detection map after placing the new beacon by taking measurements. After this exploration process, we obtain the accurate estimated detection map, reflecting the status the newly placed beacon. Accordingly, we can estimate and incrementally place the next location adaptive to the latest detection map until the complete detection of every location.

4 Experiment

4.1 Experiment settings

To evaluate the effectiveness of our proposed method, we conducted the experiment in the dense beacon placed environment. The experiment location is one floor of a building in a university, whose area size is around 300 m^2, as shown in Figure 1; including 3 research laboratories, 4 faculty rooms, and a meeting room. The rooms are separated by concrete walls. The orange dots in the floor-map shown in Figure 1 indicate the measurable locations in the experiments in 1 m distance.

Optimization via the selection of distributed candidate beacons. In this experiment, to compare our optimization result with the ground truth value, we distributed all the beacons to each candidate location initially and obtained all the beacons' detection statuses by the measurement at every measurable location. In the optimization process, we simulated data measurement by providing RSSI of only currently "installed" beacons at the required location and simulated



(a) Estimated detection map before optimization of 2 beacons

(b) Estimated detection map after optimization with 5 extra beacons added

(c) Ground truth detection map before optimization of 2 beacons

(d) Ground truth detection map after optimization with 5 extra beacons added

Figure 1. Detection map of optimization (white space indicates unmeasurable areas)

the beacon placement process by changing the beacon status as installed. Regarding the candidate locations, 25 candidate locations were chosen with candidate locations marked with blue dots shown in Figure 1.

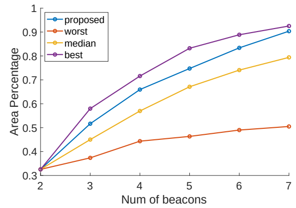
We calculate the performance on all beacon combinations to evaluate our method and show the best, median, and worst performance under several beacons. In other words, the best beacon placement indicates the upper bound of the performance, and the worst indicates the lower bound of performance. We evaluated the percentage z of the counted number of locations over expected detection probability t by the total number of locations $|\mathcal{L}|$, as follows,

$$z = \frac{\sum_{\boldsymbol{l}\in\mathcal{L}} [[P_{\boldsymbol{B}}(y=1|\boldsymbol{l}) > t]]}{|\mathcal{L}|}. \tag{8}$$

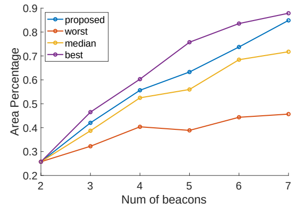
4.2 Experimental result

We evaluate the optimization results of the initial worst, median, and best detection placements, and Figure 1 shows the initial detection map of 2 beacons and the optimization result of the initial median placement, where Figure 1(a) and Figure 1(c) are the estimated and ground-truth initial beacon placement indicated in red rectangles. Figure 1(b) and Figure 1(d) show the estimated and ground truth detection map after adding to place 5 extra beacons indicated in blue rectangles.

Figure 2(a) shows our proposed method can cover 90.37% of the area of signals over 80% detection probability with 2.15% lower than the ground truth optimal result. Figure 2(b) shows our proposed method can cover 84.88% of the area of signals over 90% detection probability with 2.99% lower than the ground truth optimal result. For the worst initial placement case, our placement can cover 89.04% of the area of signals over 80% detection probability with 3.15% lower than the ground truth optimal result and 82.56% of the area of signals over 90% detection probability with 4.82%



(a) Area percentage over 80% detection with number of beacons of the initial **median** detection placement



(b) Area percentage over 90% detection with number of beacons of the initial **median** detection placement

Figure 2. Area percentages changes over the different number of beacons

lower than the ground truth optimal result. Also, comparing with non-adaptive placement, our placement can cover 2.32% more space of over 80% detection probability and 4.49% more space of over 90% detection probability. For the best initial placement case, our placement can cover 90.03% of the area of signals over 80% detection probability with 3.82% lower than the ground truth optimal result and 83.55% of the area of signals over 90% detection probability with 4.66% lower than the ground truth optimal result.

We compare the labor cost of our proposed method with the dense data gathering method in the walking distance and time-consuming. We suppose the walking speed is 1 m/s and the time consuming of gathering data at each location is 10 s. With dense data gathering, the walking distance is 962.24 m, and the time is 2952 s for the initial placement estimation. With our proposed method, the walking distance is 322.88 m and the time is 572 s for the initial placement estimation. Our proposed method can reduce 66.4% walking distance and 80% time-consuming for the data gathering.

From these results, we can see that our proposed AI-BPO effectively enlarges high detection probability areas with less human labor cost.

5 Conclusion

In this research, we focus on the beacon placement optimization problem for indoor crowd monitoring applications and propose AI-BPO to incrementally optimize the placement of BLE beacons to improve the signal of high detection coverage for the given environment. By conducting the experiment of selection from candidate beacons, the results show that our proposed method can optimize the placement of beacons effectively in generality with less human labor.

However, the experiment result still shows a gap between our proposed method and the ground truth best optimization. We plan to optimize the model to estimate the RSSI distribution considering the environmental factors instead of the current only distance-based estimation for future work. Also, we plan to optimize the walking distance in the measurement process by applying a route optimization approach.

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