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 is on-demand by public service providers. Due to the fact that its performance on crowd density monitoring highly depends on how BLE beacons are allocated, BLE beacon placement optimization has been tackled as fundamental research work in the ubiquitous computing community. However, the previous researches focus on the batch optimization and ignore the actual workload to obtain the optimal placement result. In this research, we propose a novel approach to incrementally optimize the beacon placement by detecting the optimal placement of BLE sensors in favor of Bayesian optimization and determining the optimal location to place the beacon. Our proposed method can optimize the beacon placement effectively to improve the signal coverage quality in the given environment and also minimize the human workload. The experiment results on actual BLE sensing results show that our proposed method can provide over 13% area coverage than the average placement while reducing 67% optimization time.

Keywords: placement optimization, crowd density monitoring

1. Introduction

With the development of IoT technology, BLE beacons are widely used in modern society for various purposes, as indoor tracking, peripheral detection, and indoor localization [1]. Bluetooth Low Energy (BLE) technology is capable of providing considerably reduced power consumption and cost while maintaining a similar communication range. By deploying BLE beacons, we can provide localization solutions for a robust indoor environment with great power efficient both for the broadcaster and receiver [2].

During the COVID-19 pandemic, BLE technology is widely used for contact tracing and indoor crowd monitoring to prevent infectious disease. Japanese government urges people to avoid Three Cs (San Mitsu) to prevent factors from leading to clusters of infection. Some public service facilities or organizations take the responsibility to prevent Three Cs [3]. Thus, organizations and companies have promoted indoor crowd monitoring applications to prevent the spreading of the epidemic. Beacapp corporation is one of the companies that provide indoor tracking systems using BLE beacons to customers for the office space [4]. Meanwhile, some education facilities in Japan have also deployed BLE beacons to monitor indoor crowd density.

Indoor localization with BLE beacons has been studied for years [5,6]; especially, the localization algorithm gets most of the attention. However, it is crucial to provide accurate results only with optimal beacon placement. Optimizing BLE beacon placement is a challenging and laborious problem. First, knowing the detection status of beacons is difficult, because the measurement of all the locations is laborious. Second, knowing how to optimize the placement is a more difficult problem, as we will never know the exact propagation of the Bluetooth signal before placing the beacon.

As for the optimization problem itself is not a decidable problem, and one cannot be solved in polynomial time. Many researchers have attempted to solve it by Genetic Algorithm (GA) to derive the optimal results [7–9]. Some other researchers also propose the differentiable objective function and solve it by the neural network [10]. The greedy algorithm is also proposed to optimize the beacon placement. Shimosaka et al. propose the backward greedy algorithm, which needs to place redundant beacons at initial and then apply multiple rounds to reduce the beacons and evaluate the performance [11].

The previous research focuses on analyzing the beacon placement problem of theoretical geometry analysis and the batch installation phases but ignores that the environmental factors can affect actual coverage status in the optimization [12–14]. Also, the optimization workload has seldom been studied, which is important to the actual optimization. However, to apply neural networks, genetic algorithm, or greedy algorithm to solve the problem, those solutions require a large amount of data or a high calculation cost, thus it is not fesiable for real-time optimization.

In this research, we focus on incremental placement optimization placement in the given environment by balancing the workload. Our method generates the BLE radio map from small RSSI samples and decides the next optimal BLE beacon placement lo-

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cation by simulating the signal propagation, and it can optimize the BLE beacon placement in real-time deploying if we acquire a small portion of signal RSSIs from the beacons.

The contributions of this article include the following:

- We propose the approach to place candidate beacons, derive the detection probability map by Bayesian optimization, and estimate the optimal location for the subsequent placement.
- We conducted the experiment on one building floor, and evaluated our proposed method performance.

Related work

Batch beacon optimization from geometry perspectives

Most of the related work studies the batch optimization of sensor optimization. Researchers propose the k-coverage objective for the locations, which means signals should cover the objective area from the k number of beacons. In the most of the case, to solve the coverage optimization problem, the objective function usually is not differentiable, and the genetic algorithm is often used to find the optimal result [7, 13, 15].

Wu et al. propose a geometry model of sensor coverage optimization to improve the indoor localization accuracy and focus on the critical-grid coverage problem with accuracy and cost objectives [13]. They define the objective as the k-coverage for the critical-grid and propose the optimization objective as maximizing the average covering critical-girds of the beacons. Falque et al. also propose a heuristic strategy to optimize the beacon placement by defining a cost-function to maximize the average coverage by the beacon and maximize the distance between beacons [7].

However, batch beacon optimization is to find the optimal placement of beacons all at once, and it could not consider the actual beacon signal propagation in the environment. Thus, it is not convincing of the batch optimization.

Batch beacon optimization of selection problem

Some research model the problem as the beacon selection problem and define the differentiable loss function [10, 16, 17]. Schaff et al. propose an approach of beacon selection [10]. The selection of beacon is defined as the 0-1 value. They define the differentiable loss of received signal strength indicator (RSSI) difference at each location between the estimated and measurement. They derive the optimal placement by the neural network training.

However, using deep learning technology requires a large amount of data to avoid overfitting problems. Consequently, this kind of solution requires a large workload.

Iterative optimization using greedy algorithm

On the other hand, some other researchers also employ the iterative optimization approach [11, 18]. Shimosaka et al. propose a backward greedy approach for Zigbee sensor placement optimization in an indoor localization system [11]. This paper proposed the backward and forward greedy algorithms of optimization. For the backward greedy algorithm, all the beacons, including redundant beacons, were placed first and then remove the smallest effective beacon step by step by measurements and calculations. In contrast, forward greedy algorithm starts from none of beacons and decide to place the beacons decided by the full measurements and calculations iteratively. Those approach requires a high calculation cost and requires much more human labor cost. Also, this approach requires a large number of redundant beacons if for a large indoor environment.

2. Problem settings and beacon placement optimization

2.1 Problem settings for incremental beacon placement optimization

Indoor monitoring is realized by the mobile application on the user side and the delicate beacon deployment as the infrastructure. The installed mobile application can provide the user localization information. It will detect the peripheral Bluetooth signals and determine the user's current location. Given radio wave propagation, the power of the signal gets weaker after the long distance. The application can help determine the nearest BLE beacon by finding the maximum RSSI from received Bluetooth signals.

From the BLE beacon's placement location, the user's location can be easily determined. The placement of beacons is fundamental to monitoring functions. Therefore, the beacon placement optimization is important to increase the performance of localization by using BLE beacon efficiently.

Beacon placement optimization finds the optimal number of beacons n as well as the optimal placement locations of beacons, $\boldsymbol{B} = \{\boldsymbol{b_1}, \boldsymbol{b_2}, ..., \boldsymbol{b_n}\}$, $\boldsymbol{b_i} \in \mathbb{R}^2$ is the selected optimal location of beacon i. Beacon placement optimization is defined as the follows:

$$\underset{\boldsymbol{B}^{(A)}}{\operatorname{argmax}} \sum_{\boldsymbol{l}} [\![P(y|\boldsymbol{l}, \boldsymbol{B}^{(I)} \cup \boldsymbol{B}^{(A)}) > t]\!], \tag{1}$$

where $[\![a]\!]$ is the indicator function that $[\![a]\!] = 1$ if a is true, else $[\![a]\!] = 0$. $P(y|\boldsymbol{l}, \boldsymbol{B})$ is the beacon detection probability at location $\boldsymbol{l}$ under the beacon placement $\boldsymbol{B}$, $\boldsymbol{B}^{(I)}$ is initially installed beacon placement, and $\boldsymbol{B}^{(A)}$ are the beacons to be installed. Our research aims to find the optimal locations to place the beacons while achieving $P(y|\boldsymbol{l}) > t$ where t is the thresholding detection probability for each location $\boldsymbol{l}$.

In this paper, we tackle the incremental beacon placement optimization problem is to place beacons at optimal location iteratively with the initially installed beacons $\boldsymbol{B}^{(I)}$ to cover expansive space with good-quality signals.

2.2 Existing problems of Beacon placement optimization

Even though we can roughly estimate the BLE signal propagation by path loss model, it is very hard estimate the propagation for the indoor environment. The propagation of the BLE signal is highly affected by environmental factors, such as the walls, doors, and barriers, but current research mostly overlooks the actual propagation. Simply simulating the signal coverage of the new beacon cannot be helpful in the actual environment. Also, the signal detection probability is roughly modeled. In the [7], $0-1$ detection probability is proposed once the RSSI is smaller than a specific value, as shown as the follow. $r(\boldsymbol{l})$ is the RSSI distribution modeling function.

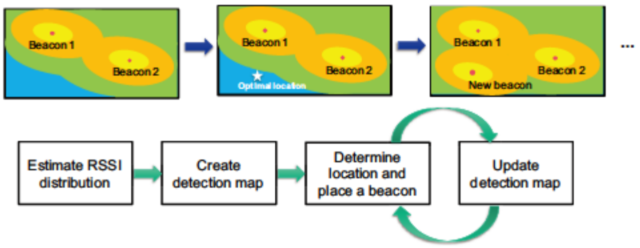


Fig. 1 The overview of optimization process, including estimating RSSI distribution, creating detection map and iterative determining and placing the beacon and updating the detection

$$p(y|l) = \begin{cases} 1 & (r(l) > -100) \\ 0 & (\text{otherwise}) \end{cases},$$

The batch optimization decides the optimal number of beacons n and the optimal placement of B all at once, but it can only use the simulation of signal propagation or large training dataset to determine the beacon's placement. That means the actual environmental factors are hard to be considered or heavy human labour cost is necessary by the batch optimization method.

The greedy algorithm requires multiple rounds of laborious measurements and heavy calculation costs. It can determine the next beacon b_{i+1} to be placed or removed by fully measurement and calculation. Applying this approach in the actual optimization will require much human labor for the measurement, costing the longer walking distance and optimization time.

From the above analysis, we propose the method of incremental optimization. By using incremental optimization, we can consider the environmental factors and balance the workload and calculation.

3. Proposed method: Incremental beacon placement optimization

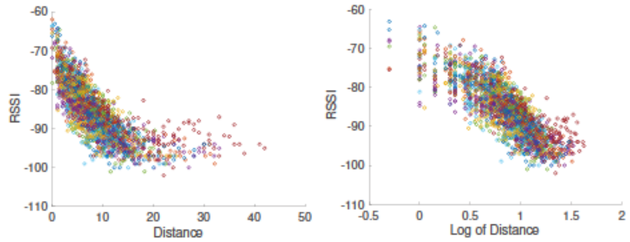
3.1 Overview

Our method, first, models the BLE signal propagation for all initially installed sensors with fewer data by using the Bayesian optimization manner. We discuss the design of the acquisition function and how to model the RSSI propagation for BLE beacons. After constructing the BLE RSSI propagation model, we decide to add the beacons inclemently from the signal detection probability. We also discuss how to calculate the signal detection probability from RSSI distribution and decide placement location iteratively in section.

In order to ensure the availability of the beacon signals, the given environment should be covered with good quality Bluetooth signals. Our proposed method consists of the processes of beacon signal property analysis and incremental beacon optimizations. As for the incremental beacon optimizations, we will obtain the signal detection map of the environment for each round of optimization and determine the new beacon's optimal location. The overview process of our proposed is shown in Fig.1.

3.2 Beacon signal property analysis

Before optimizing the placement, we need to analyze the properties of signal RSSI from observation. This observed information is helpful to determine the signal quality evaluation.



(a) RSSI relationship with distance (b) RSSI relationship with logarithm of distance

Fig. 2 The RSSI relationship with propagation distance

We conclude the following properties of RSSI properties from the observed signal RSSI distribution.

- The signals whose RSSI is less than -100 [dbm] is nearly not detected.
- The RSSI of detected signals is centered at -80 [dbm].

In this research, we analyze the detection problem from the probabilistic perspective. By analyzing the RSSI distribution, we can see that the detection probability reduces sharply when the received signal RSSI is less than -90. Thus we define a conditional probability of detection given RSSI.

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

In Equation 2, y stands for the detection probability of the signal, r is RSSI of the received signal, and s, b are the parameters for the sigmoid function.

3.3 Estimation of signal RSSI distribution

The RSSI of signals is the only measurement data in our proposed method, and we can get the detection probability signals from the RSSI distribution. It is essential to estimate the RSSI distribution accurately and effectively.

As the path loss equation is shown in Equation 3, the logarithm RSSI r forms the linear relationship with the distance d to the beacon, while r_0 is the RSSI at the location from the 1m distance to the beacon. Figure 2(b) shows this relationship from our observations.

$$r = r_0 - \eta \log_{10} d, \tag{3}$$

However, the radio wave can be reflected or weakened by the environment, such as the floor layout, walls, and existing barriers. As a result, it is impossible to estimate signal RSSI distribution without any measurement. Also, it is infeasible to estimate the RSSI by measuring the RSSI of every location in the given environment because not every location is assessable, and it will lead to a heavy workload of measurement.

In order to obtain accurate RSSI distribution of a beacon with less effort, we propose the method to estimate the RSSI distribution by Gaussian process regression via Bayesian optimization to reduce measurement workload.

Estimation of RSSI distribution by Bayesian optimization

We model the signal RSSI distribution from the beacon as a probabilistic model $P(r|l)$, which is the probability of RSSI r given location l. Because it is infeasible to acquire all the RSSI from the measurement, we consider using Gaussian process regression to derive the mean of RSSI μ_l for every location l. However, as for Gaussian process regression, it still needs many data to generate the accurate RSSI. Consequently, the probability of RSSI r at location l forms the Gaussian distribution. σ_l is the standard deviation at location l.

$$P(r|l) \sim \mathcal{N}(\mu_l, \sigma_l), \quad (4)$$

Bayesian optimization is a sequential strategy for global optimization, and it can suggest the following optimal location to acquire the data. Because we want to reduce the uncertainty of RSSI distribution, we employ the standard deviation of Gaussian process regression as the acquisition function, shown in Equation 5. We can derive the next measuring location where exists the most significant standard deviation.

$$A_Q(l) = \underset{l}{\operatorname{argmax}}\, \sigma_l, \quad (5)$$

Also, as it is impossible to measure the RSSI of every location, to avoid the useless exploration of those unmeasurable areas, we propose generating the artificial RSSI of those locations.

Using Equation 3, we can generate the artificial RSSI of a beacon with the distance d. With the generated RSSI, the uncertainty of the unmeasurable locations can be eliminated. Furthermore, because we set the artificial RSSI for all the measurable locations and the acquisition function for all the beacons is uncertain, the acquisition function value for every beacon is the same. In other words, we can obtain the RSSI estimation accurately of every beacon at the same time. It helps us to reduce the workload much less.

3.4 Creation of the signals detection map

As we optimize the placement in the probabilistic coverage approach, the high-quality signal detection probability of can be derived using the RSSI distribution of beacon i $P(r_i|l)$ and signal detection evaluation probability $P(y|r)$ which is the same for each beacon. As for single beacon i, we first define the signal detection probability at location l as $P(y_i|l)$. By convoluting those probabilities, we can derive the beacon i detection status y_i of beacon i given the location l.

$$P(y_i|l) = \int P(y_i|r_i)P(r_i|l)dr_i, \quad (6)$$

As we want to derive the joint signals detection probability of multiple beacons, which is the probability for the full-coverage problem, we can use the coverage equation shown in Equation 7.

$$P(y|l) = 1 - \Pi_i(1 - P(y_i|l)), \quad (7)$$

With the probability of $P(y|l)$, we can acknowledge the coverage of good-quality signal status at the given location l quantitatively.

3.5 Iterative estimation of the optimal location to place new beacon

After knowing the quantitative coverage status by the probability $P(y|l)$, we can estimate the optimal beacon placement location.

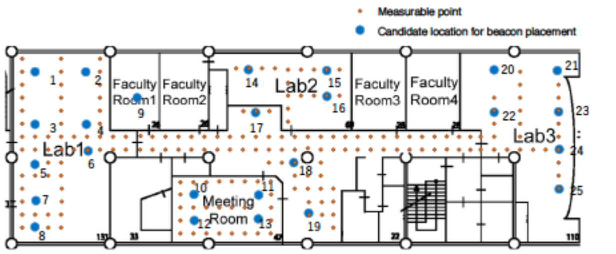


Fig. 3 Floor-plan with candidate locations for beacon placement

The RSSI distribution of a new beacon at any location can be estimated by Equation 3 if the location is known, and we can also get the new detection probability using Equation 2. With the estimated new beacon detection probability, we can estimate the updated detection probability of the given environment. We can determine the optimal location by selecting the maximum detection improvement I_j when the new beacon at location j from all the candidates from the candidates of different locations to place.

$$I_j = \sum_l \min(P(y_j|l), t) - \min(P(y|l), t), \quad (8)$$

As shown in Equation 8, $P(y_j|l)$ is the new joint detection probability after adding new beacon at location j, and t is the expected threshold of detection probability.

By conducting the processes of updating the latest signals detection map and the optimal location to place by estimation iteratively, we can finally derive the optimal placement of beacons when the improvement I is reduced relatively small.

4. Experiment

We conducted the experiment to evaluate the effectiveness of our proposed method. We wanted to optimize the beacon placement from different initialization placement with our proposed experiment.

4.1 Experiment settings

We experimented on one floor inside the university building, and the floor plan is shown in Fig.3. The area of the floor is about 300 m^2. The orange dots on the figure indicates the measurement point to measure the RSSI from beacons, and they are by 1m distance. As for the faculty rooms, students cannot enter due to administrative concerns, so these places are inaccessible locations.

We used the FeasyBeacon FSC-BP104 beacons for the experiment and set the same options for each beacon to ensure that every beacon has the same property in the experiment. We had up to 25 beacons for this experiment, and it was the redundant number of beacons to place on this floor.

We chose 25 candidate locations for the experiment, as shown in Fig.3. Our goal here was to validate the effectiveness; we considered making the experiment setting that the beacons could only be placed at those candidate locations. Also, due to the limited human labor, we placed 25 beacons to the candidate locations at the beginning of the experiment. We only used the RSSI data of the beacons assumed to be already placed in the optimization process. This technique allowed us to evaluate our method performance of the same dataset. To prove the generality of our proposed method, we chose the different groups of initial placement of beacons.

4.2 Evaluation metrics

In order to evaluate the effectiveness and labor cost of our proposed method, we employed the following evaluation metrics.

Area coverage with given number of beacons

This metric was to evaluate the signal coverage status of the entire environment. We evaluated the percentage of the counted number of locations over expected detection probability t by the number of total locations N. $c(x_i, t)$ was the 0-1 function to evaluate whether the detection probability of grid i was above detection threshold t.

We showed this metric with the different number of beacons placed. In the comparison, we also used the calculated best, worst, and median percentage with the same number of beacons from all the permutations.

$$p = \frac{\sum_{i=1}^{N} c(x_i, t)}{N}, \tag{9}$$

$$c(x_i, t) = \begin{cases} 1 & (x_i \geq t) \\ 0 & (x_i < t) \end{cases}$$

Detection probability improvement

This metric was defined in Equation 8. It was to show the change of detection probability improvement with the increased number of beacons. We presented the result of three groups with bad, medium and good initial coverage. This metric could conclude the optimal number of beacons for each initial status.

Labor cost

We presented the labor cost by the walking distance and the total optimization time. Walking distance and total time could show the workload to obtain the optimal placement. We compared the walking distance with the dense data measurement. Also, we assumed the walking speed of the maintainer as $1\ \mathrm{m/s}$, and once measurement time as $10\ \mathrm{s}$. From this setting, we could estimate the total optimization time.

4.3 Experiment results

We chose 10 sets of different initial placement of 2 beacons, and we chose those initial conditions from all the permutations, including 3 sets of initial low detection probability, 4 sets of initial median detection probability and 3 sets of high detection probability.

Fig.4 shows the bad initial detection optimization process, and in which we estimated the optimal location to place and updated the detection map iteratively. Fig.4(d) shows the final result of optimization after placing 3 extra beacons. Fig.5 shows the joint detection probability when placing the beacon at certain locations.

Fig.6, Fig.7 and Fig.8 show the changes of percentage of locations of expected detection probability metric of the different number of beacons. The best, median and worst results are the results we choose from the permutation results of given the same initial beacons. Fig.6 shows our proposed method can cover 20% more areas than the median result for the bad initial placement, Fig.7 shows our proposed method can cover 17% more areas than the median result for the medium initial placement, and Fig.8 shows our proposed method can cover 13% more areas than the median result. However, there is still a gap between the best solution given from the all permutations.

Fig.9 shows the improvement metric goes down with the growth of beacons. The normal and good line shows the improvement changes when placing a new beacon at the optimal position suggested by our method, and the bad one shows that for the initial bad case. We can see that the improvement gives near 0 improvement after we place 6th beacons. That means the optimal number of beacons is 5 for good and normal initial placement.

Table 1 Measurement labor cost

Method	measurements	walking distance [m]	time [s]
Dense data	199	412.79	2411.79
Proposed	25	528.88	778.88

Table 1 shows the measurement times, walking distance, and required time of our proposed method compared to the dense data approach, which is to measure all the measurable locations. This result shows that our proposed method can save much of the measurements and reduce 67% of the total time for optimization. However, our proposed method make people walk $100\ \mathrm{m}$ more distance than the dense measurement as for the walking distance, because the walking route is optimized for the measurement. We think the proposed method still reduces the labor cost because the $100\ \mathrm{m}$ is not a significant burden, and we can reduce most of the total time.

5. Conclusion

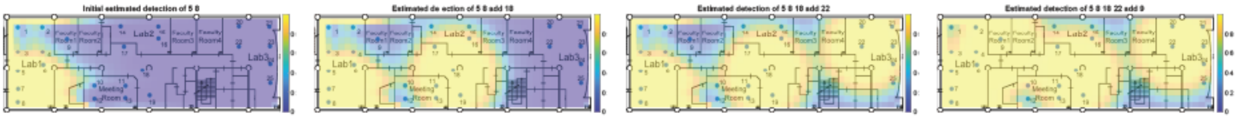
In this research, we focus on the beacon placement optimization problem for the indoor crowd monitoring applications. We propose a method to incrementally optimize the placement of BLE beacons from the initial placement to improve the signal quality coverage for the given environment. By conducting the experiment on a floor inside a building, the result shows our proposed method can optimize the placement of beacons effectively in generality with less human labor.

Applying our proposed method makes it easy to optimize the beacon placement with the consideration of the environmental effect. Also, it will require much less time and labor cost.

However, the experiment result still shows a tiny gap between using our proposed method and the best optimization from the permutation.

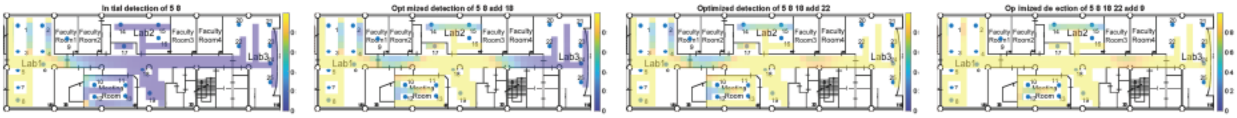
For future work, we want to improve the process of detection map update. Currently, the detection map update uses the estimation of a new beacon, but the new beacon propagation is unknown status to us, and it is necessary to update the detection map with the measurement data. We need to propose an effective exploration to update the detection map after the new beacon is placed in the future.

For another thing, we have experimented in a given environment with setting up all the beacons at the beginning. As for future work, we plan to conduct the experiment on the on-play



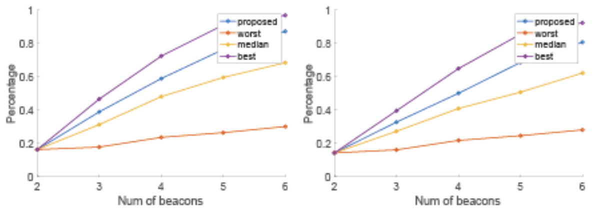
(a) Orignal detection (b) Add 1 beacon (c) Add 2 beacons (d) Add 3 beacons

Fig. 4 The estimated detection probability of optimization process



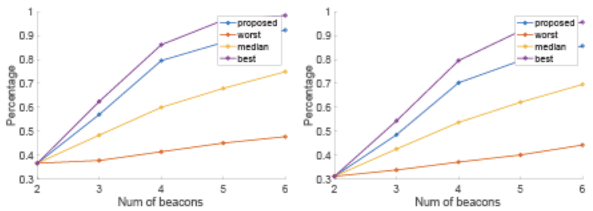
(a) Original measurement (b) Add 1 beacon (c) Add 2 beacons (d) Add 3 beacons

Fig. 5 The ground truth detection probabilities of optimization process



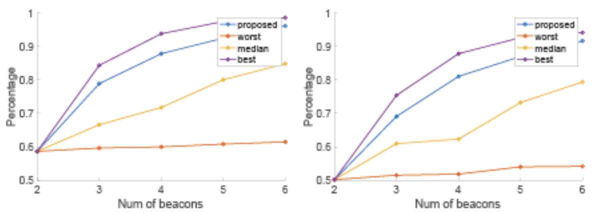
(a) Coverage (with 80% detection) with given number of beacons (b) Coverage (with 90% detection) with given number of beacons

Fig. 6 Percentage changes of bad initial placement



(a) Coverage (with 80% detection) with given number of beacons (b) Coverage (with 90% detection) with given number of beacons

Fig. 7 Percentage changes of medium initial placement



(a) Coverage (with 80% detection) with given number of beacons (b) Coverage (with 90% detection) with given number of beacons

Fig. 8 Percentage changes of good initial placement

indoor monitoring system environment to evaluate our proposed method.

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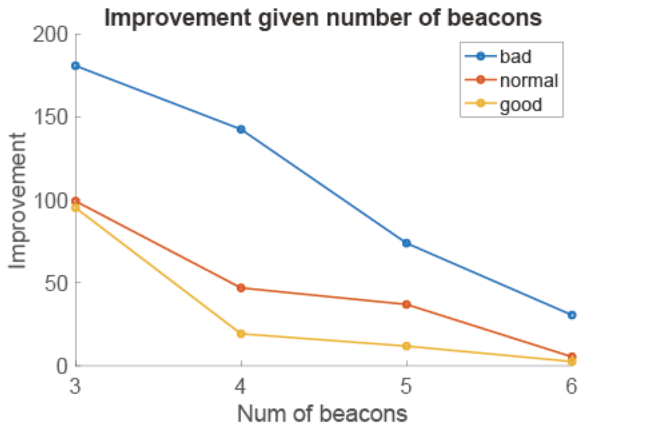

Fig. 9 Improvement given the number of beacons. Legend bad indicates the improvement changes from a low coverage, legend normal indicates the improvement changes from a median coverage, and legend good indicates the improvement changes from a high coverage

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