Data-Driven Evaluation of Base Station Locations using Signal Strength Prediction and Gaussian Processes

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Abstract

This work combines machine-learning-based signal-strength estimation with planning techniques and Gaussian Processes to assess the utility of potential base station locations. For a robot in an autonomous fleet, being able to connect to a base station means transmitting findings to an operator, receiving additional information from other agents or the operator, coordinating plans with other robots, and much more. Therefore, it is highly advantageous to place the base station at the location with the greatest connectivity within the operational area. However, determining whether locations are within mutual communication distance can be computationally demanding, as it needs to be computed numerous times to evaluate the quality of a potential base-station location. The presented work uses a real-world data-driven linear model of the communication availability to construct a coverage estimation framework that is computationally feasible to execute repeatedly and can be used to evaluate an entire map for potential base-station locations.

Keywords

Communication mapping, Base-station Placement, Gaussian Processes

1. Introduction

For a remotely deployed autonomous robotic team, a communication base station can serve as the central point connecting the team operator and mediating communication among the individual agents. Its placement is therefore a crucial aspect of such robotic field deployments, as it determines the communication availability of the team [1]. For a radio-based communication channel, the signal strength is influenced not only by the properties of the transmitter but also by the environment through which it travels. For aerial drones and aerial mobile base stations, the free-space path loss can be used directly to estimate communication availability, since obstacles are much less likely to obscure the path [2]. However, for communication between ground robots and ground base stations, such a simplification is too generous and leads to much greater error of estimate [3]. There are many methods for estimating signal strength, from physics-based, accurate methods [4] to ray tracing [5] to machine learning approaches [3].

In the presented work, we propose an algorithm to evaluate the communication utility of different potential base-station locations. The approach utilizes a linear regression-based communication solver [6] and a machine-learning approach that uses data gathered during a real-world deployment of a ground robotic platform. The method of estimating signal strength is less computationally demanding than the more accurate methods. However, it is much more accurate than free-space path-loss models or probabilistic path-loss models used in UAV-mounted base-station placement problems, making it suitable for communication among the studied ground robots.

Despite the computational efficiency of the method [6], the number of queries needed to estimate the coverage from a single possible location of the base station remains high. If applied to every point in the map, the computational requirements would be prohibitive. Therefore, the proposed approach introduces two further simplifications. First, we represent the environment by a discrete sampling into a fixed number of locations using a probabilistic roadmap [7]. Graph-based representation has

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been shown to reduce computation time for single-location coverage significantly. Additionally, rather than computing coverage at all sampled locations, we interpolate from a subset of locations using Gaussian Processes (GP) [8]. Thus, we can obtain an estimate for any point in the map, while keeping the computational requirements feasible.

The contribution of our work lies in combining existing techniques to address base-station placement and connectivity estimation, achieving improved accuracy over purely distance-based methods. We propose to leverage the speed and accuracy of machine-learning methods to evaluate a large number of potential base-station locations, enabling us to practically assess the entire map of the operational area.

The paper is structured as follows. A discussion of the prior work is presented in Section 2. The problem statement and the employed communication availability model based on a signal strength estimator are presented in Section 3. The algorithm itself is detailed in Section 4, and its results and evaluation are summarized in Section 5. Finally, a brief conclusion is in Section 6.

2. Related Work

The problem of optimal base station placement is studied in many contexts, with varying levels of signal complexity and different metrics and settings. A scenario in which aerial base stations are deployed on *Unmanned Aerial Vehicles* (UAVs) is addressed in [2]. The authors propose an algorithm that places individual base stations (mounted on fixed-altitude UAVs) until all required locations are covered. In [9], the authors address a similar problem of optimal intermediate relay node placement. Their work assumes that communication is proportional to distance, leading to a geometric disk-cover problem. A more advanced communication model is proposed in [10]. Unlike the free-space path-loss model, the approach uses ray tracing to simulate air-to-ground communication in an urban environment.

Another approach to modeling the communication availability is to assume a probabilistic setting. In [11], such a communication model is proposed. The authors divide the path-loss into two cases: *Line-of-Sight* (LoS) and *Non-Line-of-Sight* (NLoS). Both of these cases assume communication loss, and the model estimates the resulting path loss by first estimating the probability of LoS based on the environment, and then combining the two models accordingly. It still leads to a distance-based communication availability model. However, it allows for more accurate estimation of the size of the region, and takes the altitude of the UAV into account in a realistic way. The approach has been used in [12] and [13].

The deployment of UAV-based stations to extend the range of a ground base station is addressed in [12]. The approach optimizes both the UAV location and the transmission power. The energy optimization is further addressed in [14], where the authors consider landing the UAVs, bringing the problem closer to our setting, although their focus is on the energy aspect. The LoS vs. NLoS separation is studied in [15], which takes the geometric properties of the map into account. In an urban scenario, the separation makes the LoS/NLoS model accurate, since the same type of obstacle typically blocks NLoS paths. It yields a vaguely star-shaped covered region.

A completely different approach to communication modeling is used in [16] and later extended in [17]. It uses radio tomography to assess the quality of the connection for a limited number of end users. The approach estimates cell properties in the map and then computes path loss based on the properties of cells along the signal path. The placement of the base station is then solved using numerical methods.

A framework for solving the UAV-mounted base-station placement problem is presented in [18]. It allows for different objective functions to be optimized or different communication schemes to be used. The framework is built on top of the Probabilistic Roadmap (PRM) [7] and addresses both placement and path planning inherent in UAV deployment.

In addition to the signal-strength modeling approaches discussed for the base station placement problem, other methods can be found in the literature. For example, the communication channel can be modeled using ray tracing ([19], [5]) or modeled based on terrain features, as in [20]. Among others, machine learning approaches are being researched, such as [3] and [6], which form the basis of the results presented herein.

3. Preliminaries

In our research, we are focused on finding a single base station location that maximizes the area it can communicate with. This section presents the problem statement and the communication availability model based on a signal strength estimator.

3.1. Problem Statement

We assume a given discrete environment model $\mathcal{S}$ and a communication function $\delta_{\mathcal{S}} : \mathcal{S} \times \mathcal{S} \to \mathcal{R}$ with a communication threshold γ for which we can assume that if $\delta_{\mathcal{S}}(p_1, p_2) \geq \gamma$ for $p_1, p_2 \in \mathcal{S}$, then the location represented by p_1 and p_2 are within communication distance of each other. The *Communication function* $\delta_{\mathcal{S}}$ depends on the environment $\mathcal{S}$ and takes into account terrain obstacles and foliage. Consequently, the area within communication range of a single location (such as a base station) is not a disk; it is not necessarily convex, and it can even be non-continuous. Note that the function $\delta_{\mathcal{S}}$ can be based on *Received Signal Strength Indicator* (RSSI) or *Reference Signal Received Power* (RSRP) in the case of 5G network.

Given a communication function, we can formulate a coverage function $\mathcal{C}_{\mathcal{S}} : \mathcal{S} \to \mathcal{R}$, which assigns to each $p_i \in \mathcal{S}$ in the environment a value corresponding to the proportion of the environment that is within communication distance of p_i:

$$\mathcal{C}_{\mathcal{S}}(p_i) = \frac{|\{p_t \in \mathcal{S} | \delta_{\mathcal{S}}(p_i, p_t) \geq \gamma\}|}{|\mathcal{S}|}. \tag{1}$$

Our overall goal is to find the location $p^* \in \mathcal{S}$ that maximizes $\mathcal{C}_{\mathcal{S}}$ for a given environment $\mathcal{S}$ and a given communication function $\delta_{\mathcal{S}}$:

$$p^*(S, \delta_S) = \arg\max_{p_i \in S} C_S(p_i). \tag{2}$$

3.2. Communication Function

A proper communication function is crucial for ground vehicles, where a direct connection between the robot and the base station is likely to be obscured. Therefore, we employed the communication model presented in [6] to address the base-station placement problem. The model is a machine-learning approach based on real-world measurements rather than an exact physics-based model. While precise models exist, they are impractical because they require detailed information about the environment and its properties. Besides, the methods are also computationally intensive. Even with access to the operational area prior to deployment, it would not be practical to gather all the required data to ensure the accuracy of these approaches. On the contrary, the machine learning-based models can provide relatively precise models with only limited real-life data.

The model [6] is a linear regression-based model trained on real-world measurements collected by a robotic platform operating in a specific operational area. Connectivity between two locations is represented as a path in a discrete grid environment. However, the connecting path is split into a fixed number of cells. Hence, depending on the path length, the cell size varies. Given a cell and an obstacle type, the area of the cell that is covered by that obstacle is computed, and it is used as one feature in the feature vector. The value is computed for every cell-obstacle combination, since multiple obstacle types can occur in a single cell. Such a model can differentiate between a narrow obstacle that can only partially block the connecting path, a crossing wall, and obstacles clustered around the transmitter.

Using an of-the-shelf solver, such as the one provided in [21], we can determine the parameters F_i and C of the liner model of the RSSI as

$$RSSI = \sum_{i=0}^{m} F_i \log f_i + C, \tag{3}$$

where m denotes the total number of parameters of the model (which is proportional to the cell count and the obstacle-type count) and f_i represents the individual features in the feature vector. The grid

density can be adjusted to improve accuracy, potentially increasing the risk of model overfitting. All the data necessary to compute the features can be obtained from maps such as OpenStreetMaps [22] or [23].

A great advantage of the communication function based on the model (3) is low computational requirements. For example, evaluating $10\,000$ data points takes about $160\,\mathrm{ms}$ on a machine with AMD Ryzen 7 CPU and $32\,\mathrm{GB}$ RAM. Low requirements are crucial for model usage in solving the base-station placement problem, where coverage estimation, which evaluates the communication function, can quickly require millions of assessments for a single possible base-station location. Additionally, computing the model's parameters is relatively cheap. It takes about $109\,\mathrm{ms}$ to compute the regression from precomputed features using the above-mentioned computational environment. Low computational requirements make the method suitable for a quick model update if new data points arrive.

4. Proposed Method

The proposed method for addressing the single base-station placement problem can be reduced to determining coverage at each location in the environment and then selecting the location with the greatest coverage. Although the problem, in its essence, is continuous, we opted for a fixed resolution of the map. Hence, we address the original problem by solving its discrete variant, which is justified by the limited accuracy of the prediction model and the environment map. Thus, increasing the sampling density would improve solution precision up to the point where computational demands would increase without further gains in precision.

In the rest of the text, a location denotes a specific position in the environment map at the specified resolution and sampling unless otherwise described. Similarly, all locations on the maps refer to all sampled discrete locations at the specified resolution. For example, in fixed discrete sampling of the environment map with the resolution of $1\,\mathrm{m}$ and size $100\,\mathrm{m}\times100\,\mathrm{m}$, "all locations" amount to $10\,000$ locations.

4.1. Single Location Coverage

The coverage function $\mathcal{C}_{\mathcal{S}} : \mathcal{S} \to \mathcal{R}$ (1) is a critical part of the problem, as it is the metric used to determine the quality of a potential base-station location. However, using the communication function $\delta_{\mathcal{S}}$ directly to evaluate the coverage of a point would be very computationally intensive. Therefore, we propose further sparsification of the discrete environment representation using a probabilistic roadmap (PRM) [7], thereby alleviating computational requirements.

The communication coverage of a single location is determined by a search algorithm that immediately rejects locations (roadmap nodes) outside the communication range. Thus, the number of communication function evaluations is limited in two ways.

- First, using a relatively sparse discretization based on the roadmap.
- Second, during the search, most nodes outside the communication range are never queried.

The location (roadmap node) coverage is estimated using the proportion of reachable nodes. Additionally, unreachable locations, e.g., those behind an obstacle, are discarded directly during roadmap construction, further reducing real-time computational requirements.

4.2. Global Coverage Function

Discretizations at a single location significantly reduce the number of coverage queries. However, finding the location with the best global coverage would still be too computationally demanding if every location on the map were considered. On the other hand, using roadmap nodes for possible base-station location would be too limiting and inaccurate. Therefore, we mitigate the issue by using a Gaussian Process (GP) with a squared-exponential kernel to interpolate coverage values between nodes on the

roadmap (we omit specifying parameters, as they depend on how the data points are processed, which varies by implementation).

The input to the Gaussian Process is a subset of the PRM nodes with their coverage determined using the single-location coverage method described above. Using all PRM nodes would be possible, but it would be computationally too intensive, as GP methods have cubic complexity in the number of training data points. Any evenly distributed set of nodes would work; the one used in the results presented was obtained by sorting the nodes by their coordinates and selecting every tenth node. Having learned the Gaussian Process, a coverage estimate for an arbitrary location of the environment can be queried. We can use a grid-like discretization, e.g., with a sampling distance of $1\,\mathrm{m}$.

5. Evaluation Results

The proposed solution to the single base station placement problem has been computationally evaluated, focusing on the accuracy and efficacy of the proposed discretization and the employed GP regression model. We assume the communication function is given and do not include an accuracy study in the evaluation. Readers interested in that communication model accuracy are referred to [6, 3].

The evaluation is performed on a real-world dataset, briefly summarized in the following section, along with a description of the computational environment. First, results on the evaluation of the discretization using a probabilistic roadmap for computing a single-location communication coverage are presented in Section 5.2. After that, the GP-based coverage estimation results are presented in Section 5.3.

5.1. Computational Setup

The evaluation is performed on a field deployment dataset collected by mobile ground robots via a radio-based communication system. The RSSI estimation model [6] is computed from roughly $10\,000$ communication data measurements in the area, accounting for terrain difficulties such as buildings, foliage, and forest. The total size of the operational area is roughly $600\,\mathrm{m} \times 600\,\mathrm{m}$.

The computational environment consists of the Intel(R) Xeon(R) Gold 6130 processor with $394\,\mathrm{GB}$ of RAM. The implementation is written in C++ using the GNU Scientific Library [21] for the linear regression model and the Gaussian Process.

The PRM is constructed with 6000 nodes, and the GP model is computed from a roughly evenly spaced subset N of 600 nodes. A denser PRM and a larger subset of nodes used in GP model training would increase accuracy at the cost of computational time. The map in our testing scenario is rather small, which favors naïve methods. Nevertheless, the results suggest that even in such a setup, the proposed simplifications significantly reduce computational demands, achieving a speedup of two orders of magnitude in this scenario.

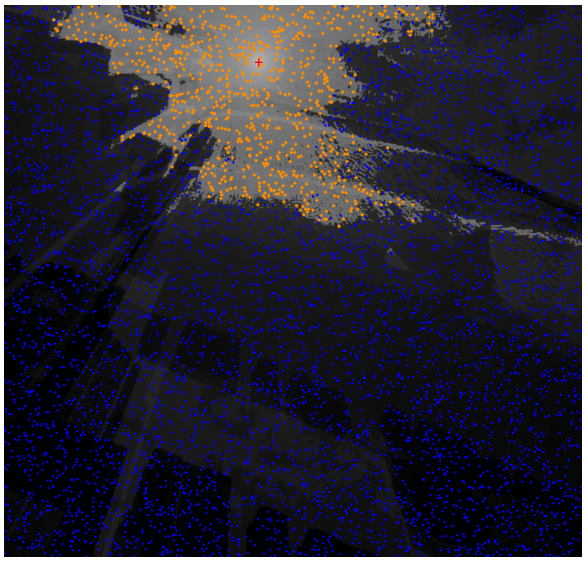
5.2. Probabilistic Roadmap Estimate Evaluation

The accuracy of the single-location coverage using the proposed PRM-based sampling (`PRM Estimation`) is compared with the coverage computed across all grid locations, hereafter referred to as `All-point Evaluation`. The computed coverage is depicted in Fig. 1. Evaluating the signal strength for all cells in the grid map is feasible for individual locations, but for evaluating the utility of a base station, it provides unnecessary detail. Additionally, since the RSSI is a continuous value, the edges of the area are based on a somewhat arbitrary threshold, and the distinction between "just inside" and "just outside" of the communication range is therefore of little consequence.

The PRM-based approach reduces the density of the discrete grid-based environment representation. According to the resulting coverage estimation depicted in Fig. 2, the PRM-based estimation is considerably accurate when compared with the `All-point Evaluation`. The error of the estimation is noticeable only for a few percentage locations, a difference likely to be within the error rate of the signal strength estimator anyway.

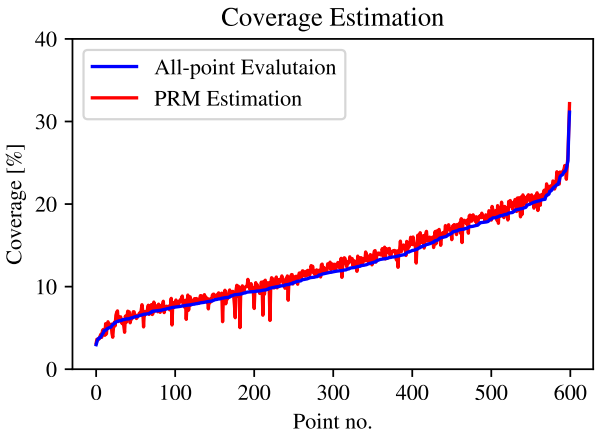


(a) `All-point evaluation` using the RSSI estimator for every pixel in the map. The dark area is out of communication range.

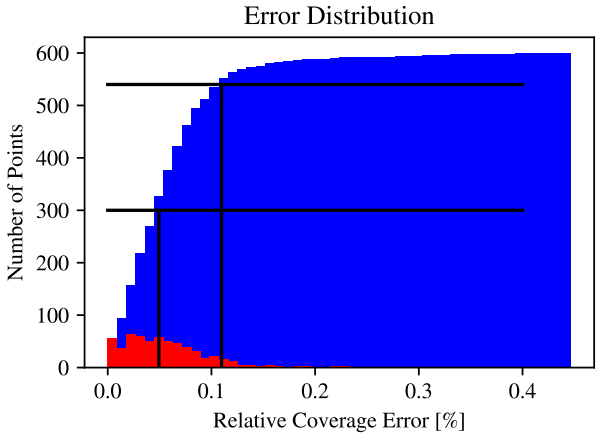


(b) Search-based PRM estimate. Orange pixels represent locations within the communication range of the source (red); blue ones are outside the range.

Figure 1: Visualization of the single-location coverage evaluation for the naïve `All-point evaluation` approach and the proposed search-based PRM method.



(a) PRM vs. `All-point evaluation`.



(b) Error distribution histogram. Blue is cumulative, red is absolute. Black lines highlight median value and 90^{th} percentile values.

Figure 2: Coverage estimation using naïve `All-point evaluation` and the proposed PRM-based approach. The coverage for the `All-point Evaluation` is computed using the RSSI estimator [6] for every cell (pixel) of the 600×600 grid map. The coverage estimate is computed from N locations (and later used for GP training). The percentage coverage is plotted for a sequence of locations, ordered by coverage, using `All-point Evaluation`.

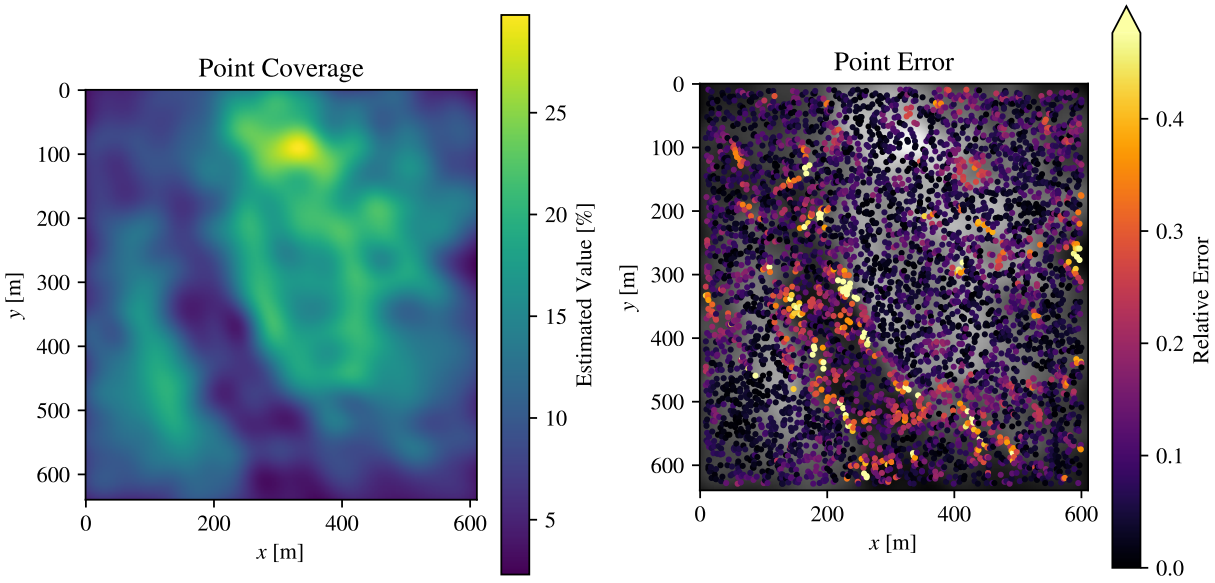
Table 1
Computational times for the evaluation of the two coverage-estimation methods, averaged over multiple hundred function calls. The setup time is the time required to initialize the method and load all necessary data; for the PRM-based method, it also includes time to construct the roadmap, which is done only once at the start.

Method	**Average Computational Time** [s]	**Setup Time** [s]
All-point Evaluation	16.100	0.212
PRM-based Estimation	0.182	0.710

Real computational requirements depicted in Table 1 show a clear benefit of the proposed PRM-based method. The PRM-based coverage estimator is much faster than naïve `All-point Evaluation`, running well under 1 s, which is about two orders of magnitude faster. The setup time is much faster for the `All-point Evaluation` because the PRM-based method must first construct the roadmap, in addition to initializing the RSSI estimator, which is not needed when a grid map is used directly. However, the difference is completely outweighed by the speedup provided in the computation itself.

5.3. GP-based Coverage Estimation

The location coverage estimator can be used to evaluate possible candidate locations for base station placement. The naïve approach is to examine all map locations. For a grid-based discretization with the cell size 1 m, for the map 600 m × 600 m large with 360 000 potential locations, it would be prohibitively demanding with about 18 h of computational time on the used computational environment. Therefore, the GP-based model is trained on a subset of N nodes from the roadmap, which took about 230 s. Figure 3 shows a result for the map used in the testing.



(a) GP-based estimated coverage values, trained on PRM-based estimator predictions

(b) The error rate between the coverage estimates of the GP-based and PRM-based estimator. The highest 1 % values are clamped to better differentiate the lower values (the maximum value is 1.73)

Figure 3: The result of the GP-based coverage estimates and its accuracy verification.

Table 2
Percentile values for GP-based prediction errors.

Median	80^{th} Percentile	90^{th} Percentile	95^{th} Percentile	Maximum value
0.065	0.147	0.218	0.283	1.733

The accuracy of the GP-based interpolation is compared with that of the proposed PRM-based estimator at additional locations on the map. The results are shown in Fig. 3b and Table 2, where most of the map has very low error, except for a few areas where the coverage changes more abruptly, and a small number of outliers.

Note that the accuracy of both the PRM-based estimator and the GP-based estimator can be further increased by increasing the number of samples. However, the trade-off is in computational requirements, especially for GP, as it is cubic in the number of data points.

6. Conclusions

In this paper, we address the single communication base station placement problem using a novel method for estimating communication coverage. The employed point-to-point communication estimation is performed using a linear model based on real-world data collected with robotic platforms. The model has been selected for its low computational demands. However, evaluating communication accessibility for all pairs of potential locations is infeasible, even for a relatively small discrete map representation of the operational environment. Therefore, two additional methods are proposed to reduce the computational burden, enabling us to eventually estimate coverage for all locations on the map and thus identify the location with the highest communication coverage. First, a discrete probabilistic roadmap is used to represent the environment. The roadmap is used to estimate the communication coverage for a single location in the map. The second method employs a Gaussian Process model to predict communication coverage at an arbitrary location on the map. The model is trained using a subset of the roadmap nodes (locations). Both methods together yielded a significant reduction of the required computational time by two orders of magnitude without a noticeable impact on the overall accuracy.

In future research, the method can be deployed in a real-world scenario and evaluated in an actual robotic setting with limited communication, with further generalization to communication range extension using robots as relays.

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Declaration on Generative AI

The authors have not employed any generative AI tools.

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