Multirobot Exploration for Building Communication Maps with Prior from Communication Models

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***Abstract*— This paper addresses the problem of building a communication map of a known environment using multiple robots. A communication map encodes whether two robots are likely to be able to communicate between two arbitrary locations. Such a communication map is fundamental for reliably deploying a multirobot system to accomplish a variety of tasks, including exploration and environmental monitoring. Previous work proposed offline approaches, which did not utilize data measured by robots. This paper, utilizing Gaussian Processes, proposes methods to efficiently build a communication map with multiple robots. Specifically, the number of measurements used to update the communication map, and the number of possible candidate locations where robots should go are reduced, by exploiting communication models that can be built from the physical map of the environment. This allows robots to take fewer measurements, travel less distance, be more efficient in processing the data online, and get similar accuracy to methods that consider all the locations in the environment. Experiments with a team of TurtleBot 2 platforms validate the approach.**

Fig. 1: The robots, TurtleBots 2 equipped with a WiFi dongle, deployed in an environment to build its communication map.

I. Introduction

This paper aims at increasing the efficiency of a multirobot system that builds an ad-hoc network *communication map* by using prior information from the environment map.

A communication map encodes the information about whether robots in two arbitrary locations can communicate or not. Building communication map can not only be a standalone task—for example to decide where to optimally place routers in an indoor environment—but also is important to efficiently accomplish other robotic tasks, such as exploration [1], [2], [3], environmental monitoring [4], and search and rescue [5]. Indeed, it is experimentally shown that communication constraints degrade the system performance [6]. Many recent work is explicitly considering communication in the multi-robot systems design [7], [3], [8]. All these papers share in common the assumption that: robots have a communication map readily available, which is not available in practice [9], or that a conservative communication model is used, such as limited range line-of-sight, limiting the capabilities of the robots. Having a reliable communication map allows robots not to be hindered by the communication constraints, when choosing where to go, and to have a more efficient multirobot coordination.

In this paper, building on our previous work [10], we propose a system for the efficient construction of communication maps, where the communication source is not stationary. We use a team of robots capable of measuring signal strength between them and a Gaussian Process (GP) to model the communication map. Considering every location in the free space where robots can take measurements would make the robots travel extensively. As a result, the construction of a communication map would be too time consuming to be feasible. Thus, limiting the numbers of candidate locations to informative places is important to accomplish such a task in an efficient manner. Specifically, we use *a priori* communication models that can be built out of the physical map of an environment to reduce the number of candidate locations, to decrease the exploration time and the total traveled distance. The key idea is to consider those that provide some distinctiveness, determined with such prior models. In addition, we filter out input measurements to the GP to reduce GP's computational complexity—i.e., $O(n^3)$ [11] for n observations. In this way, the proposed system can be used more effectively for online operations, as it scales better over time and space. We describe four different communication models for WiFi communication along with experiments to test how close to real data they are. We then present how such models can be used to filter observations to update the communication map and to generate candidate locations used by the sampling strategies. A series of experiments with a

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team of TurtleBots 2 (see Figure 1) show the effectiveness compared to methods that do not exploit such information.

Differently from our paper, in the literature, typically, the problem of building a communication map with respect to a fixed router in the environment is considered [12], [13]. Such a communication map can be used to improve indoor localization [14]. Some previous work involved the use of hand-held devices to create a radio map [15]. Other approaches exploited a single robot exploring an environment and localizing a radio source [16] and multiple robots to map a stationary source without any coordination [17]. Kemppainen et al. [18] proposed a method for a single robot to explore a magnetic field that can be measured in an environment so that it can localize. Hsieh et al. [19] propose some offline methods to compute efficient joint paths for small teams of robots, whose task is to collect signal strength measurements from a set of predefined locations.

The paper is structured as follows: the next section describes the problem in detail. Section III presents an overview of the system that our contributions are based on, highlighting the proposed approach in this paper. Section IV describes communication models for WiFi communication and how such information is used by the robots to make the communication map building process more efficient. Section V shows experimental results from numerous experiments with real robots. The paper concludes with lessons learned and a discussion with interesting research directions.

II. Problem Statement

Similar to [10], m mobile robots are deployed in a known bounded environment with obstacles, where free space is denoted as $\mathcal{A} \subset \mathbb{R}^2$ and $\mathbf{p} \in \mathcal{A}$ denotes a location that can be occupied. Robots with a laser range finder can localize themselves within a global coordinate system. Further, they are equipped with an omni-directional WiFi transceiver, to communicate with peers over the radio channel within a maximum communication range allowed by the device.

Robots select online a sequence of candidate locations, to measure the signal strength between two locations. Measurements are included in the communication map. Note that robots can collect data while traveling to a selected location.

A *communication map* represents information about communication links availability between ordered pairs of locations in $\mathcal{A}$. It is defined as a function $\hat{f} : \mathcal{A} \times \mathcal{A} \rightarrow \mathbb{R}_{\leq 0}$ estimating the received radio signal strength, RSSI, in dBm, f between any two locations $\mathbf{p}_i$ and $\mathbf{p}_j$. The closer it gets to zero, the higher the communication link reliability between $\mathbf{p}_i$ and $\mathbf{p}_j$. Let us call $\mathbf{x}_{ij} = (\mathbf{p}_i, \mathbf{p}_j)$ pair of locations in the freespace and $\hat{f}(\mathbf{x}_{ij})$ the estimate of the signal strength from $\mathbf{p}_i$ to $\mathbf{p}_j$. As communication links not necessarily are symmetric, in general, $f(\mathbf{x}_{ij}) \neq f(\mathbf{x}_{ji})$ [20].

An example of a communication map instance is presented in Figure 2, by fixing the location of the transmitting robot. Obviously, locations with highest RSSI value will be the locations closest to the transmitting robot.

This paper, differently from [10] that considers all possible locations in an environment (up to a discretization), focuses on the following two questions: First, which measurements $\mathbf{x}_{ij}, f(\mathbf{x}_{ij})$ should be used for updating the communication map; second, which candidate locations $\mathbf{p}_j$ should be considered by the robot, to visit and collect data, for a fixed $\mathbf{p}_i$. Given that an environment free space can be arbitrarily large, reducing the number of observations both for building on-line the communication map and deciding where to go is important for reducing the traveled distance and increase the scalability.

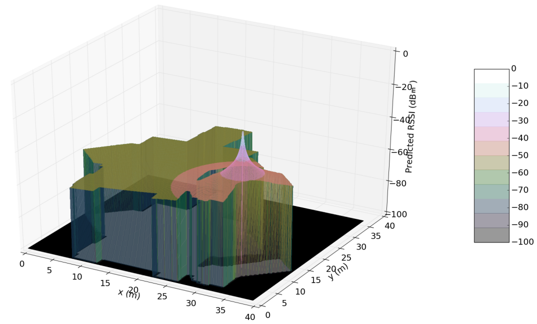


Fig. 2: Example of communication map. For clearly differentiating the locations where robot can not visit in the physical map, we are not allowing the GP to predict (and plot) RSSI values at locations inaccessible to the robots.

III. Background

The multirobot system that the proposed approach is going to be integrated in is composed of two main components, described in the following two subsections: the modeling of the communication map and the robots decision making process on where to go. Please refer to [10] for the full description.

A. Gaussian Process based Communication Map

The communication map is generated from a GP [11], given the spatial correlation that radio signal strength displays. Such a model can also be used to predict signal strengths in areas where measurements have not been collected yet, with an associated uncertainty. Specifically, $\hat{f}$ can be estimated as a posterior distribution fitted over a set of noisy observations made by robots which explore and coordinate in the environment to collect signal strength measurements. Assume that the robot team as a whole collected q measurements over the environment. Let $\mathbf{Y} = [y^1, y^2, \ldots, y^q]^T$ and $\mathbf{X} = [\mathbf{x}^1, \mathbf{x}^2, \ldots, \mathbf{x}^q]^T$ be the set of those measurements and the set of the corresponding pairs of locations from where they have been collected, respectively; recall that $\mathbf{x}^i \in \mathcal{A}^2$. The signal strength observation $y^i = f(\mathbf{x}^i) + \epsilon$ is affected by additive sensing error, which is assumed to be i.i.d. and $\epsilon \sim \mathcal{N}(0, \sigma_n^2)$. As covariance function $k(\mathbf{x}, \mathbf{x}')$, which expresses the spatial correlation between any two values of f, a radial basis kernel (RBF) is used, as done in the mainstream approach:

$$k(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \exp\Big(-\frac{|\mathbf{x} - \mathbf{x}'|^2}{2l^2}\Big), \quad (1)$$

where the signal variance σ_f^2 and length scale l^2 are parameters that indicate the amplitude and the smoothness.

To make notation easy to follow, given $X_1 = [x_1^1, \ldots, x_1^q]^T$ and $X_2 = [x_2^1, \ldots, x_2^q]^T$ the locations of two robots, we identify with $K(X_1, X_2)$ the $q \times q$ matrix, where $K_{ij} = k(x_1^i, x_2^j)$ and with I_q the $q \times q$ identity matrix. The correlation between the observed function values is represented by the following equation:

$$\mathrm{cov}(\mathbf{Y}) = K(\mathbf{X}, \mathbf{X}) + \sigma_n^2 I_q. \tag{2}$$

Here, the GP is assumed to have a zero mean function, as typically done in literature [11]; therefore it is fully specified by the parameter vector $\theta = [\sigma_n^2, \sigma_f^2, l^2]^T$. Such a parameter vector is computed as the one maximizing the observations log-likelihood, that is,

$$\theta^* = \arg\max_{\theta} \log P(\mathbf{Y} \mid \mathbf{X}, \theta), \tag{3}$$

where $\log P(\mathbf{Y}|\mathbf{X}, \theta) = -\frac{1}{2}\Big(\mathbf{Y}^{\mathbf{T}}\mathrm{cov}(\mathbf{Y})^{-1}\mathbf{Y} - \log|\mathrm{cov}(\mathbf{Y})| - n\log 2\pi\Big)$.

To calculate an estimate of the signal strength, θ^* optimal parameter vector is used in unobserved regions by evaluating the posterior. Specifically, called $\mathbf{W} = [\mathbf{w}^1, \mathbf{w}^2, \ldots, \mathbf{w}^l]^T$ a set of arbitrary location pairs for which a signal strength estimate is requested, $P(f(\mathbf{W}) \mid \mathbf{X}, \mathbf{Y}) \sim \mathcal{N}(\mu_{\mathbf{W}}, \mathbf{\Sigma_W})$, where the mean vector is obtained as $\mu_{\mathbf{W}} = K(\mathbf{W}, \mathbf{X})\mathrm{cov}(\mathbf{Y})^{-1}\mathbf{Y}$ and represents the estimate $\hat{f}(\mathbf{W})$, while the covariance matrix is given by $\mathbf{\Sigma_W} = K(\mathbf{W}, \mathbf{W}) - K(\mathbf{W}, \mathbf{X})\mathrm{cov}(\mathbf{Y})^{-1}K(\mathbf{W}, \mathbf{X})^T$. Note that the main diagonal of $\mathbf{\Sigma_W}$ is called *predictive variance* and quantifies the uncertainty of estimates in $\mathbf{W}$.

Because of the inverse operation of the covariance matrix, the complexity of updating the GP with n number of observations is $O(n^3)$. As such, in this paper we address the following question: is it possible to wisely select observations to include in the update of the GP so that the model is still accurate, but at the same time the multirobot online system is not overloaded?

B. Sensing strategies

In this work, two main sensing strategies are adopted to decide pairs of locations for collecting measurements, and both are based on a *leader-follower* scheme. Specifically, the first one, called *Pairwise Mapping* (PM), divides a team of robots into pairs, where one acts as a leader, and the other one as a follower. Pairs of locations are selected by the leader preferring those that display high predictive variance inferred from the GP. In addition, other robots' plan is considered in this decision: if two selected locations are close to locations selected by other robots, they are discarded. To ensure robustness, a backup pair of locations where robots could communicate is also selected, in case robots cannot communicate from the new locations. The two locations are then assigned to the robots to minimize the maximum traveled distance. The second one, called *Region Mapping* (RM), allows one leader to have more than one follower. The idea is that instead of minimizing the uncertainty of the communication map by iteratively selecting pairs of locations, with RM, the objective is to select and minimize the uncertainty of a given region centered in a selected location from the leader. First, the leader randomly selects a location $\mathbf{p}_c$, as a center for the region, taking into account the associated uncertainty and possible overlaps with other teams of robots. In that region, locations to be assigned to the followers are iteratively chosen, considering the highest sum of predictive variance when paired with $\mathbf{p}_c$ and sufficiently far apart from the already chosen waypoints. Also with the RM strategy, backup locations are decided to avoid any significant disconnection between robots.

In [10], the whole free space was discretized according to a minimum distance set between locations and sampled, up to a maximum communication range for an arbitrary location. This results in a large number of possible observations. In this paper, we pose the question: can we utilize some prior models to reduce the set of possible candidate locations, to improve the performance of the system?

IV. Communication model based filtering

In this section, first, we present the *a priori* communication models used, with an evaluation of their fidelity; second, we show how such models can be used to filter observations for updating the communication map and locations where robots should go; see Figure 3 to see how the proposed approach modifies the one in [10].

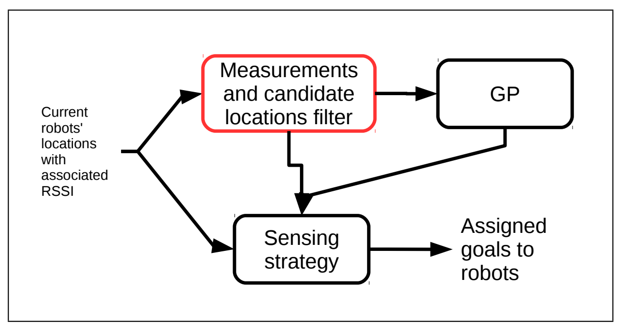


Fig. 3: Block diagram representing the proposed system integrated with that of [10]; in red, the proposed modification to the communication exploration system.

A. Prior from Communication Models

In general, it is hard to directly estimate the RSSI value knowing the map of an environment, because, for example, the compositions of the obstacles are not known. However, in the communication literature, some models—such as Free space, Two-ray, Ten-ray, Wall Attenuation Factor model, and Multi Wall Attenuation Model [21]—have been proposed estimating the signal's power loss during propagation (also known as *path-loss*)[1]. Each of these models vary in terms of computation complexity and accuracy. Further, each model

[1]It should be noted that all these path-loss models are independent of the used communication frequency, i,e., not restricting the analysis to WiFi/LTE etc.

usually has several parameters and quantifying them accurately is hard, as they depend on the considered physical environment. However, such models have been shown to perform relatively well, when the parameters are predicted from the training data obtained from the actual measurements [22].

We selected and evaluated four communication path-loss models with varying complexity that have been tested in indoor environments. In the following, the equations for the different models[2], referring to transmitter $\mathbf{p}_i$ and receiver $\mathbf{p}_j$:

a) Distance Model (DIST): A free space distance based path-loss model assumes the signal is passing through vacuum; the path-loss observed by the signal depends only on the Euclidean distance between locations of transmitter and receiver [23], [21]:

$$L_{\text{dist}}(\mathbf{p}_i, \mathbf{p}_j) = -10 \log_{10} \left[\frac{\sqrt{G_L}\lambda}{4\pi d(\mathbf{p}_i, \mathbf{p}_j)} \right]^2, \tag{4}$$

where G_L is the product of transmitted and receiver antenna gains[3]; λ is the wavelength of the transmitted signal; and $d()$ is the Euclidean distance between transmitter and receiver locations.

b) Wall Attenuation Factor Model (WAF): An empirical model [22], which assumes the physical map of the environment to be available beforehand, as path-loss is influenced by the number of walls between transmitter and receiver, in addition to the Euclidean distance:

$$L_{\text{waf}}(\mathbf{p}_i, \mathbf{p}_j) = L_{\text{dist}}(\mathbf{p}_i, \mathbf{p}_0) - 10n \log_{10} \frac{(d(\mathbf{p}_i, \mathbf{p}_j))}{d_0} - \begin{cases} w(\mathbf{p}_i, \mathbf{p}_j) \times \mathit{WAF} & \text{if } w(\mathbf{p}_i, \mathbf{p}_j) < \text{C}, \\ C \times \mathit{WAF} & \text{otherwise} \end{cases}, \tag{5}$$

where $L_{\text{dist}}(\mathbf{p}_i, \mathbf{p}_0)$ is the path loss at reference distance between transmitter $\mathbf{p}_i$ and arbitrary $\mathbf{p}_0$; n indicates the rate of change in path-loss; $w(\mathbf{p}_i, \mathbf{p}_j)$ is the number of walls on a straight line between transmitter and receiver, C is an empirical constant—i.e., the maximum number of walls that can make a difference in path-loss; *WAF* is a constant factor specific to the type of each wall.

c) Multi-Wall Model (MWM): Another empirical model [24] following Equation 6 as:

$$L_{\text{mwm}}(\mathbf{p}_i, \mathbf{p}_j) = L_{\text{FSL}}(\mathbf{p}_i, \mathbf{p}_j) + \sum_{l=1}^{N} k_l w_l(\mathbf{p}_i, \mathbf{p}_j) + k_f \mathfrak{f}(\mathbf{p}_i, \mathbf{p}_j) , \tag{6}$$

where $L_{\text{FSL}}(\mathbf{p}_i, \mathbf{p}_j) = L_{\text{dist}}(\mathbf{p}_i, \mathbf{p}_0) + 10n \log(d(\mathbf{p}_i, \mathbf{p}_j))$ models a free space path-loss model; $w_l()$ is the number of walls of l^{th} type between transmitter and receiver, k_l is a parameter for the attenuation affecting the signal for wall of type l; $\mathfrak{f}(\mathbf{p}_i, \mathbf{p}_j)$ is the number of floors between transmitter and receiver, and k_f is the attenuation parameter observed by signal due to the type of that floor.

d) ITU Radio communication Model (ITU): An empirical model, used by *IEEE 802.15 Working Group for Wireless Personal Area Networks* [25], for testing the proposed channel model of a signal propagating in an arbitrary environment:

$$L_{\text{itu}}(\mathbf{p}_i, \mathbf{p}_j) = 20 \log_{10} f + n \log_{10} d((\mathbf{p}_i, \mathbf{p}_j)) + k_f \mathfrak{f}((\mathbf{p}_i, \mathbf{p}_j)) - 28 , \tag{7}$$

[2]Note a slight change of notation compared to the original papers to make notation uniform and highlight variables and parameters.

[3]Gain is defined in terms of the antenna's capability to send/receive signals in a direction.

TABLE I: Errors observed in the calculated RSSI values, for 6 experiments performed varying locations of fixed robot; while moving robot follows a stable fixed path and collects data

Path-loss	Experiment 1		Experiment 2		Experiment 3		Experiment 4		Experiment 5		Experiment 6	
Model	Mean	stdev	Mean	stdev	Mean	stdev	Mean	stdev	Mean	stdev	Mean	stdev
Distance	8.09	4.98	9.40	7.27	9.40	7.28	17.56	9.27	10.89	8.54	6.14	5.62
WAF	12.02	10.24	15.33	12.08	15.34	12.09	27.29	10.87	20.06	11.85	17.47	7.04
MWM	7.98	5.01	9.37	7.26	9.38	7.27	17.66	9.29	11.15	8.58	4.03	3.66
ITU	11.33	7.84	15.49	10.28	17.79	7.09	29.02	11.74	20.51	9.66	15.40	6.43

where n is the distance power loss coefficient; f is the communication frequency (MHz); $d()$ is the distance between the transmitter and receiver (in m); k_f is the floor penetration loss factor (dBm); $\mathfrak{f}()$ is the number of floors between transmitter and receiver.

Each parameter should be fine-tuned according to the specific environment. Values for parameters are heuristically suggested in the related papers, usually for a communication signal at $2.4\,\text{GHz}$ (WiFi) for different scenarios, including indoor office environment.

Considering the transmitting power T_{power} (dBm), the RSSI between transmitter and receiver can be then calculated as:

$$\text{RSSI}(\mathbf{p}_i, \mathbf{p}_j) = T_{\text{power}} - L_{()}(\mathbf{p}_i, \mathbf{p}_j). \tag{8}$$

As a physical map of the environment is available, a prior communication map can be computed for every location reachable by a receiver robot, given a fixed location for a transmitting robot. Note that as robots cannot access some locations—e.g., because of doors—and maps are pre-built by the robots, the number of walls is an estimate of the actual number of walls. Specifically, every change from freespace cell and occupied cell in the grid is counted as one wall. Maps are preprocessed in such a way that small objects are removed from the map and thus not counted as wall. Generating a prior communication map using the different models shows that locations closer to the fixed robot observe higher RSSI values, while distant locations have lower values. While the trend seems to be similar, the RSSI values from these priors are different; among them, WAF model seems to weigh more the different terms and as such the returned values are smaller.

We evaluate the accuracy of such models, calculating the difference between the measurements collected by two robots described in Section V and the RSSI values from the communication models (error). In particular, we conducted 6 different experiments in the engineering building of the University of South Carolina[4]. Each experiment involved one robot fixed at a different location, and the other robot following a precomputed coverage path. Each robot measures the WiFi signal 10 times a second along with its position in the map. The physical environment used for these experiments is depicted in Figure 4a.

Table I shows mean (and standard deviation) error for the 6 different experiments. It is worth mentioning that:

[4]All experiments were conducted at night time, so the interference due to moving objects/humans is minimal, except for the people performing the experiment.

we observed a change of $8\,\mathrm{dBm}$ to $10\,\mathrm{dBm}$ in the RSSI value while changing the height of the antenna (by a few centimetres) at the moving robot multiple times. An accuracy error of $<20\,\mathrm{dBm}$ is comparable to what is shown, for example in [22]. As such models display a relatively low error, especially MWM, it is justified to use such models as priors for the robots constructing a communication map, as shown in the next section.

B. Use of Communication Models Prior

For a given location of a transmitting robot—leader in the strategies described in Section III—we propose an algorithm to automatically generate a set of locations that can be provided as goal to the followers and can be used also for integrating measurements in the GP. The main idea is to choose locations that are informative, namely those which present some change in the field, as constant values can be easily approximated by a model.

Mathematically speaking, the RSSI slope is determined at each location, based on the prior communication map built from the communication models. This is basically the first order derivative of the RSSI value at every location. We also determine the change of slope between neighbor locations in the map. If the change of slope between two locations crosses a threshold (τ), we select that location as one of the possible goals of the moving robot (follower). This idea is explained in detail in Algorithm 1.

Algorithm 1 Goals for Moving Robot to Pick Observations

Input: $\mathcal{A}$ (physical map of the environment), $\mathbf{p}_i$ (possible locations that robots can occupy), $N = |\mathcal{A}|$, comm_model, $(x_1, y_1) \in \mathcal{A}$ (considered location of transmitter), τ (threshold)

Output: List of candidate goals for the moving robot $\{(x_i^d, y_i^d)\},\ \forall i \in goals$

for $(x_2, y_2) \in p_i - (x_1, y_1)$ **do**
  $rssi_{(x_1,y_1)}^{(x_2,y_2)} = calculate\_rssi(x_1, y_1, x_2, y_2, comm\_model)$; ▷ Using appropriate Equation from 4,5,6,7
end for
$goals =$ get_goals($rssi, x_1, y_1, N, p_i$);
return *goals*
procedure GET_GOALS($rssi, x_1, y_1, N, p_i$)
  goals={} ▷ Return variable
  for $(x_2, y_2) \in p_i$ **do** ▷ Calculate the slope of RSSI
    $rssi\_slope_{(x_1,y_1)}^{(x_i,y_i)} = calculate\_slope(x_1, y_1, x_2, y_2, rssi)$
  end for
  for $(x_2, y_2) \in \mathcal{A}$ **do** ▷ Calculate the slope of rate of change of RSSI
    $rssi\_change\_slope_{(x_1,y_1)}^{(x_i,y_i)} = calculate\_slope(x_1, y_1, x_2, y_2, rssi\_slope)$
  end for
  for $(x_2, y_2) \in p_i$ **do**
    if $rssi\_change\_slope_{(x_1,y_1)}^{(x_i,y_i)} > \tau$ **then**
      $goals.add((x_i, y_i))$
    end if
  end for
  return *goals*
end procedure

Additionally, locations generated from the algorithm can be used to filter the measurements. If measurements are taken close to those locations within a given range, they are included in the communication model. It is important to note that: τ needs to be generated heuristically, for each communication model separately. When τ is high, robot may not receive sufficient number of goals to predict accurately, while lower τ could result in too many goals for the robot. From our preliminary experiments, $\tau = 11$ ($\pm 10\%$) is a reasonable value to all the four models, and provided between 30-120 goals for various communication models—among 212 possible locations—in the tested environments. Note that, to account for inaccuracies of the prior model, locations within a given radius are added to the list of candidate locations.

The proposed method to select locations is integrated in the PM and RM strategies by filtering the locations considered for the follower. PM and RM algorithm chooses the set of goals, i.e., leader choosing one (or) many followers according to the strategy briefly described in Section III. Further, such selected locations are also used to determine which measurement to include in the communication map.

Using the data collected during our experiments described in the previous section—i.e., one robot fixed at a location, while the other moving along a fixed, known path—we evaluate the GP with all measurements, and the GP with filtered measurements from the proposed method.

In general, the GP with filtered data maintains low variance in GP predictions and low Root Mean Square Error (RMSE), and at the same time the GP training time reduces by 50%, compared to the GP with all data. For example, the Root Mean Square error between the observed data and the predicted values from the GPs, in one of the experiments, is 11.014 for the GP with all data and 11.03 for the GP with filtered data.

These experimental results validate the use of such a filtering approach. Note that such a priori information could also be used within a GP, by changing the mean function; however, the standard definition for the GP worked well enough, without adding complexities for estimating the hyperparameters.

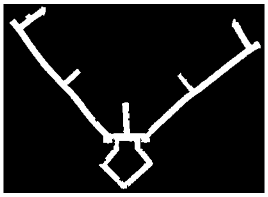
The next section shows the proposed method in an online scenario where robots decide "where to go" to build the communication map.

V. Experimental Evaluations

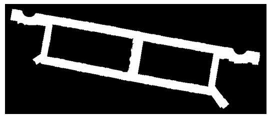
As we already showed a validation for filtering the training data on the GP and as we are assessing whether such prior communication models could work in a real scenario, simulations are not run as they would not reflect the real world communication channel performance. We use a fleet of TurtleBot 2 platforms[5], equipped with an RGB-d sensor (Microsoft Kinect) that allows the robots to localize together with odometry information. The maps used for localization are built in a setup phase and are represented as an occupancy grid. Specifically, a single robot is manually driven around the environment to collect RGB-d readings which are then processed using the ROS gmapping package [26].

We considered two relatively big indoor environments with different characteristics in the Swearingen Engineering Center at the University of South Carolina, depicted in Figure 4. Figure 4a is characterized by long corridors with some intersecting short corridors and one small loop. Note that between the two long corridors, there is an outdoor

[5]http://www.turtlebot.com

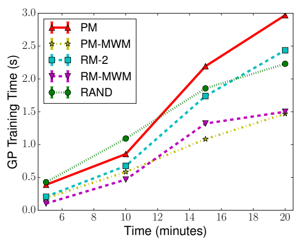


(a) Corridor surrounding Lab Workspace (Lab-Corridors $66\,\mathrm{m} \times 92\,\mathrm{m}$)

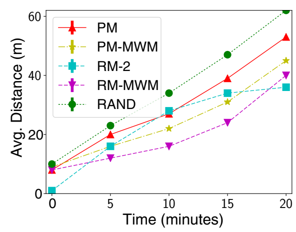


(b) Corridor surrounding the Faculty Workspace (Office-Corridors $30\,\mathrm{m} \times 70\,\mathrm{m}$).

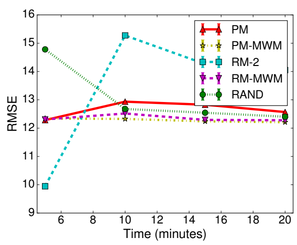
Fig. 4: Two environments, portions of third floor at Swearingen Engineering Center, University of South Carolina.



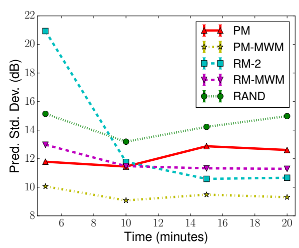
(a) Computation Time by Gaussian Process to Converge over mission time.



(b) Distance Covered by Turtlebot 2 over mission time.



(c) RMSE calculated between Predictions from GP and Measured Values.



(d) Predicted standard deviation of the Gaussian Process.

Fig. 5: Evaluating the Proposed (PM-MWM and RM-MWM) Approaches with Experiments Performed by TurtleBot 2 in Lab-Corridors.

space, which the robots cannot access. Figure 4b is instead an environment with corridors surrounding small office rooms.

After running some preliminary experiments, we decided to use *MWM* as the communication model to generate candidate locations using Algorithm 1, because it provides a good number of candidate locations and has good accuracy (see Section IV-A). We execute the updated algorithm on a real system with two Turtlebot 2 robots. The modified versions of PM and RM are compared against the basic version defined in [10], and on a baseline strategy, RAND, where robots independently move to random destinations over the environment while taking WiFi measurements with respect to other teammates.

For each of the two physical environments mentioned in Figure 4, we verified the performance of both proposed and base line methods; by using two Turtlebot 2 robots, for a $20\,\mathrm{min}$ duration. The strategies are evaluated by considering the quality of the GPs throughout the mission; by merging all the collected data in a global rendez-vous after every $5\,\mathrm{min}$, i.e., traveled distance and the GP processing time. Quality is measured both in terms of RMSE, calculated as the difference between measurements collected with locations along fixed trajectories (described in the previous section) and the predicted values at those locations by the GP trained online, as well as in terms of the average predictive standard deviation of the predictions. Note that, obviously, it is impossible to have a full ground truth as it would take too long for the robots to cover continuously the 4D space.

Figure 5 shows results for experiments performed on the map shown in Figure 4a. Our proposed PM-MWM approach spends less time updating the GP-based communication map—e.g., at $20\,\mathrm{min}$, about $1.2\,\mathrm{s}$ for PM-MWM, compared to $3\,\mathrm{s}$ for PM. Moreover, robots consistently travel less distance at a given time slice (about 30%), preserving good quality in terms of RMSE and predictive standard deviation compared to the other strategies without communication prior—e.g., at $5\,\mathrm{min}$ with PM-MWM the traveled distance is about $15\,\mathrm{m}$ with a predictive standard deviation of $10\,\mathrm{dBm}$, compared to $20\,\mathrm{m}$ with PM and $12\,\mathrm{dBm}$ as standard deviation. Also, note that, with Random strategy, robots cover longer distance but has higher predictive standard deviation. Figures 5c and 5d show that the predictive standard deviation of the proposed approach is lower than the compared methods while maintaining approximately the same RMSE value. Similar results are obtained in the other environment.

VI. Conclusion

In this paper, we presented a method for making the process of building communication maps more efficient. In particular, measurements to be integrated into a communication map and candidate locations to be chosen as goals by robots are filtered, by using communication models as prior. Communication models, which are built starting from the physical environment map, can provide information about distinctiveness of locations, by calculating first and second order derivatives. Experiments with real robots validate the accuracy of such models for the purpose of building communication maps. Moreover, the proposed approach showed an improvement over other methods in terms of traveled distance and computation time, while maintaining comparable RMSE and predictive variance.

Extending the approach to efficiently consider noise in the input space is currently under research. Future work will consider more complex models that consider multiple paths. Further, online update of the communication model prior according to measurements and possible direct integration in the Gaussian Process would be beneficial for improving the selection of candidate locations. This would allow robots to replan as they acquire new measurements. In addition, a method that allows long-term monitoring of WiFi signal is in our plan. The task of building communication maps and its use in the end will be integrated together with other missions robots might have, such as exploration [3] or environmental monitoring [27]. Extrapolating this work to outdoors/underwater/aerial environments can be considered for future work.

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