Adaptive Signal Strength Prediction based on Radio Propagation Models for improving Multi-Robot Navigation Strategies

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***Abstract*— Multi-robot systems, i.e. groups of mobile robots which carry out complex tasks cooperatively, are becoming increasingly important in robotics research. For many applications, like exploration or search and rescue missions, multi-robot systems have great advantages over single robot solutions. Besides their ability to fulfill missions faster, multi-robot systems offer improved fault tolerance and the opportunity to combine a large number of relatively cheap robotic systems with complementary capabilities. For the successful deployment of a multi-robot system, reliable wireless communication plays an important role. Especially if an operator is in the loop, the ability to communicate to every robot at any time can be vital. This article presents a technique to predict the expected signal strength of the wireless communication between mobile robots, based on parametric models of radio wave propagation. The predictor allows to take information about the expected future communication quality into account during mission planning and helps to increase the robustness of navigation strategies for multi-robot systems with respect to communication-loss this way. The presented signal strength predictor adjusts itself on-line to different operation environments and robotic systems being used.**

I. Introduction

In contrast to a collection of individual robots, which solve a problem independently, a multi-robot system gains its advantages from the cooperation of its units. For this reason, a coordinated multi-robot system can reach goals much more efficiently and faster than a single robot or several non-cooperating robots. However, to coordinate themselves, the individual robots of the system need to communicate. Usually, wireless communication is used for this purpose. Because common wireless communication techniques like IEEE802.11 have a rather limited communication range, it is crucial that the ability to communicate is always ensured during the operation of the multi-robot system. To achieve this goal, we are working on extending navigation strategies for multi-robot systems to take the limitations of the communication system into account. As one step into this direction, we present a signal strength predictor in this article that allows to predict how the connectivity between a sender and a receiver will change while the communication partners move through the environment.

Within our robot framework we use an ad-hoc network protocol (see [1]) for the communication between the robots. This protocol allows for multi-hop communication and it is, therefore, unnecessary that every robot has a direct connection to every other robot. However, such a mobile multi-hop network also causes some problems. If one node is moved to a place where it looses connection, this may not only cause this robot to disappear from the network, but the whole network may split up and several robots may no longer have contact to each other. To prevent such failures, the robots' actions need to be planned in such a way, that they stay within a single connected component at all times. For a multi-robot path planning which takes this communication constraint into account, advance knowledge of the signal strength in the environment is extremely useful. Therefore, we designed a signal strength predictor that is able to adjust itself to different environments and robot hardware, and which can also be adapted on-line.

This article is organized as follows: First we present some related works in section II. Section III introduces the radio propagation model we use for signal strength prediction. Section IV then explains how good parameter sets for this propagation model can be estimated from data collected by the robots. The problems and constraints we observed while taking real world data to evaluate the predictor. are described in section V. The evaluation of the predictor itself follows in section VI. We describe some applications which can be enhanced with the signal strength predictor in section VII and conclude in section VIII.

II. Related Work

Navigation strategies for robot systems which take the network connectivity within the system into account are not a novel idea. Several different approaches have been described to achieve this goal. Hoa G. Nguyen et al. [2], for example,

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introduce a solution to maintaining the communication link between a mobile robot and its control station with autonomous mobile relay nodes. They use a reactive control approach that monitors the signal strength all the time. If the signal strength droped below a certain threshold, one of the mobile relays is left at that place to ensure the connection. In [3], Basu et al. present an approach which uses UAVs as relay nodes to improve the connectivity of mobile ground nodes. Once again this is a reactive approach that decides from signal strength measurements what to do next. Additionally, Basu et al. [4] present an algorithm for realizing fault tolerant networks with autonomous and semi-autonomous systems. For this purpose, they use a graph algorithm that provides a doubly connected network where any one robot can fail without causing the network to separate into more than one connected component. Other algorithms for maintaining the connectivity in autonomous systems which are based on graph topology are presented in [5] and [6]. Bekris et al. [7] present a strategy for coordinated exploration of an environment by a multi-robot system while maintain connectivity.

Most of the strategies which try to enhance the connectivity by moving the mobile node to certain positions, act on the simple assumption that communication within a certain distance is always possible and that beyond this distance the communication fails. This assumption does not consider obstacles in urban environments and the properties of signal propagation inside of buildings. To reduce the misplacement of relay nodes, the quality of the connection at the new position should be known in advance. The quality of a connection can be described by many different attributes like signal strength, loss-rate, utilization of the link and others. We use the received signal strength as the quality indicator of the connection between two robots, because many of the other attributes are either situation dependent, or cannot be measured by a relay node. The prediction of the signal strength on paths in free space with line of sight can be approximated using simple propagation models. The prediction in buildings and on paths with obstacles between sender and receiver is more complicated. In these cases phenomena like reflection, diffraction or scattering have to be taken into account by the propagation model. These and other phenomena are described in [8].

A few navigation strategies like Reinl and von Stryk [9] provide an interface for more realistic propagation models, but use only a simple propagation model in their evaluation tests. Because of this, a coordination with a realistic propagation model for prediction of the signal strength is required.

For simulating communication a lot of different propagation models are available. Deterministic propagation models like *Ray Tracing*, *Beam Tracing* [10] or *UDel* [11] emulate the physical characteristics of the wave propagation when estimating the signal strength at a given position. However, these models are computationally expensive and need detailed information about the environment. Therefore, they are not practicable for applications like multi-robot exploration.

Empirical propagation models are based on regression using experienced data. They can be classified in two categories: *large-scale* and *small-scale* models. The large-scale models describe the fading of the signal strength over relatively large distances. The fluctuations caused by reflection, diffraction, scattering, and small movements are described by small-scale models. Large-scale models are e.g. the *Free Space Model*, *Two Ray Ground Model*, *Log-Distance Model* or *Shadowing Model* [8]. The Free Space Model is a special case of a Log-Distance Model and describes the logarithmic propagation in non-urban environments with line-of-sight communication. The Two Ray Ground Model takes the path reflected on the ground into account in addition to the line of sight. The Shadowing model, in contrast, introduces a log-normally distributed random variable to account for shadowing effects. In all these models obstacles in the environment can not be specified.

Two well known small-scale models are Rician- and Rayleigh Fading. They assume that signals arrive at the receiver in different ways and interfere with each other. The Rayleigh Fading model describes the resulting amplitude gain by a Rayleigh distribution. The Rician Fading Model is a special case of the Rayleigh Fading Model that considers a single path only – typically the line of sight.

Both empirical and deterministic models have their disadvantages. The selection of an adequate propagation model for a signal strength predictor is a trade-off between complexity, accuracy and processing time. G. Wölfle and F. M. Landstorfer [12] introduced an approach with dominant paths to describe all rays passing the same rooms and walls. For the prediction, neural networks were used. So the trained model depended on static aspects such as the hardware used, the characteristics of obstacles and the character of the environment. In [13] more than thousand measurement were taken within indoor enviroments to find good strategies to measure a local mean signal strength. With the help of this large sample database the best propagation models was identified. But in both approaches, it seems that the environment is known in advance. In our case, especially if the multi-robot system is used for exploring an unknown environment, such detailed information about the environment is not available.

III. Propagation Model

In this work we have chosen to use a rather simplified model. On the one hand, we want to get good predictions for the anticipated signal strength, on the other hand we do not have much information about the environment. Many assumptions made in common propagation models, like the minimal height of the antenna or outdoor conditions (e.g. Nakagami Model [14]), are not true for our scenario. Besides the lack of information about the environment (e.g. damping of different materials) we also have only little computing capacity. Therefore, we do not use a ray-tracing based propagation model, but stick to a fading model.

We designed our predictor for improving navigation strategies within large buildings. Thus, we assume an indoor environment, where walls are the predominant obstacles for

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communication. Because of these reasons, we chose a radio propagation model which is similar to the Log-distance path loss model, but additionally considers the damping influence of walls. Define S as the position of the sender and R as the position of the receiver. Then we define the loss of signal strength over distance as

$$L_{dist} = -10 * VD * log(d(S,R)). \quad (1)$$

Here, $d(S,R)$ is the distance between sender and receiver and VD describes the damping effect over distance. VD is constantly adapted while the robot moves around. Additionally we consider the damping of obstacles (e.g. walls) using the term

$$L_{obst} = -VW * \#obstacles. \quad (2)$$

Here, $\#obstacles$ is the number of (known) obstacles in the line of sight between sender and receiver and VW describes the damping of a single obstacle. VW is also adapted by the robots. As the last part of the propagation model we mould the transmission power of the sender as

$$L_{start} = -OD, \quad (3)$$

where OD is again an adaptive parameter.

The overall predicted path loss between a sender and a receiver is

$$L_{all} = L_{start} + L_{dist} + L_{obst}. \quad (4)$$

L_{all} is measured in [dB]. Within this model we assume that all obstacles have the same damping factor. This is obviously not the case, but a rather fair assumption, if the robot moves in a typical indoor environment. There are several other influences to the radio propagation like reflections and refractions. In environments where these influences are dominant the chosen propagation model had to fail and should be expanded.

Please note that we do not have any random term in this prediction model as it is usually the case in signal strength simulations. Randomization makes a simulation more realistic, but in the case of signal strength prediction, we are only interested in expected values (and maybe the variance).

The model is adaptive in three different parameters: loss over distance, loss through damping of walls, and transmit power. We assume that none of these parameters is known in advance. Although the environment is unknown, the robot is capable of mapping the environment while driving through it. This may be done for example by different SLAM approaches ([15], [16]). Additionally, every robot knows the position of every other robot in the map, and also the position of a control station, if one exists. Details on how the necessary measurements are obtained will follow in section V.

IV. Finding the Parameters

As described in section III there are three different parameters we want to adapt, in order to tune the radio propagation model as close to the real physical performance as possible. The parameters are estimated based on measurements taken by the real robots while they start to drive around. Therefore, we need a good initial guess of the parameter values, otherwise we can not use the predictor right from the start. However, the system will improve the model while the robots collect more data.

To decide whether a set of parameters is good, we need to define an error function F that quantifies the difference between predicted signal strength values and true signal strength measurements at positions in the environment. Let K denote a set of points (R_i, S_i) in the environment for which the signal strength is known. The measured signal strength for the i-th element in K is M_i while the predicted value is P_i. Let k be the number of elements in K. Then the error function for a set of parameters $(VD; OD; VW)$ is defined as

$$F_{(VD;OD;VW)} = \sqrt{\Sigma_{i=0}^{k}(P_i - M_i)^2}. \quad (5)$$

As this link-strength prediction should also be used within unknown environments we want a predictor which can be adapted on-line, while the robots are driving.

Therefore the parameters of the propagation model were only linear, a linear regression with a non-polynomial function is possible. Therefor the equation:

$$Ax = y \quad (6)$$

has to be solved, where A represents the non-polynomial function, x is a vector of the parameters and y the measured signal strength. So let a measurement i of the robot be the triplet $\{d_i, n_i, M_i\}$ where d_i is the distance between sender and receiver, n_i is the number of obstacles between sender and receiver and M_i is the measured signal strength at the receiver. If there are m measurements, A is, according to the signal strength propagation model:

$$A = \begin{pmatrix} -1 & -10log_{10}(d_1) & -n_1 \\ -1 & -10log_{10}(d_2) & -n_2 \\ \vdots & \vdots & \vdots \\ -1 & -10log_{10}(d_m) & -n_m \end{pmatrix} \quad (7)$$

and

$$y = \begin{pmatrix} M_1 \\ M_2 \\ \vdots \\ M_m \end{pmatrix} \quad (8)$$

while x is the searched parameter set

$$x = \begin{pmatrix} OD \\ VD \\ VW \end{pmatrix} \quad (9)$$

With Householder transformation [17], this problem is solved in a fast and numerical stable manner. The approach is on-line capable and quite stable against faulty measurements.

V. Collecting Data

As the signal strength predictor is developed for a real world multi-robot system, we have to judge if such a simplified radio propagation model will fit real world requirements. All used measurements came from a real indoor environment and were

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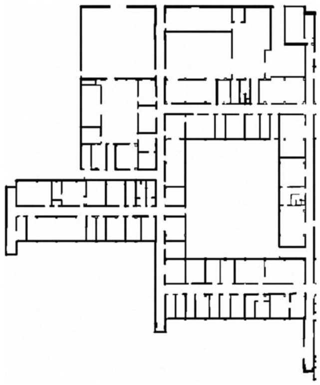

Fig. 1. Footprint of the office environment (full map)

taken by a B21 robot. Radio hardware was a standard atheros chipset WiFi card. As sender we used a laptop which has similar radio hardware. For tests the laptop was used as control station, that did not move within the environment. For more information about the used robot framework please refer to [18].

The environment is an common office environment. Footprint can be seen in Figure 1. The robot localized itself in a self-generated map. So it can only use information about the environment discovered by itself. In Figure 2 you can see the map the robot has built and used for localization. Please notice that the robot did not have information about the rooms that adjoin to the corridor, because the doors were closed. So we expected the parameter for the damping of one obstacle to be higher than it would be if we had measured it. This was because in reality the damping was caused in reality by more walls than were known to the robot.

VI. Evaluation of the Model

To evaluate how well the signal predictor can be used to predict the real signal strength, we performed several tests. Every test is made with the sparse map, the map the robot had built by itself. Additionally the full footprint of the office environment was used as reference to see how important full information about the environment is.

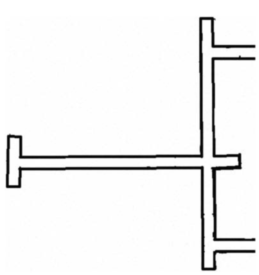

Fig. 2. Cropped map the robot uses to localize itself

We have three different parameters in radio propagation model. To check if all parameters are necessary, we evaluated how much influence each parameter has with respect to prediction quality. Therefore, we evaluated the best found subset of parameters, while one or two parameters were set to zero. Results can be seen in table I.

TABLE I

Performance of the radio propagation model, if only specific parameters were trained in a sparse map

	VD	OD	VW	F_{ges}
VD adaptable $OD, VW = 0$	5.1246	0	0	9.0
VD, OD adaptable $VW = 0$	2.5312	34.415	0	8.9
VD, VW adaptable $OD = 0$	4.6418	0	5.5352	6.7
VD, OD, VW adaptable	1.2359	41.972	8.32024	4.0

Defining VW as zero implies that we do not consider any obstacles. On the other side, taking OD as zero, implies that the transmit power of the sender is not important for the propagation model. As the error values in table I show every parameter is valuable with respect to a better model of the real radio behaviour. Even though the parameter OD does not improve the model without taking obstacle into account, it is important for the full model.

In Figure 3 you can see an example prediction for the sparse map. The predicition is made for the controle station. As you can see, walls do have a certain damping effect. Although the robot did not know all details from the map, the predicted signal strength is usable. Of course this leads to a higher wall-damping factor than in reality.

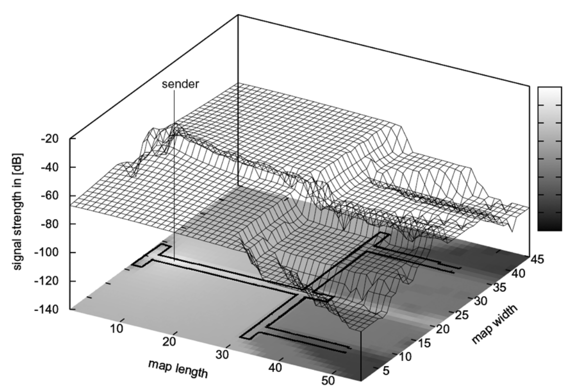

Fig. 3. An example prediction for the learned parameter set.

To decide if the prediction of the signal strength is usable in real world environments, we looked at the fault distribution of the model. In Figure 4 you can see such a distribution from a parameter set. The parameter set was trained within the sparse map.

The x-axis shows the difference between the predicted value and the measured value during one run. The y-axis show the number of measurements with this relative error. So there

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are for example about 88 measurements which are correct or differ by less than 0.5 dB from the prediction and e.g. six measurements which differ by -6dB from the predicted value. Please notice that the three predictions which differ by -30dB, results from three errors produced by the localization algorithm. The robot did not have a correct position estimation in these cases.

Figure 4 shows that most of the predicted signal strengths are within an interval of [-4;4] dB. This shows that, although the radio propagation model is not always correct and has difficulties in some cases, it is valuable to predict a trend how the signal strength will behave if the robot will drive to a certain position.

In Figure 5 the error during a run of a robot is displayed. The x-axis shows the number of measurements taken until then while the y-axis shows the error of the parameter set found at that time step once for the cropped map build by the robot itself and once for the full map provided by the blueprint of the building. Note that in the beginning, both error are identical because we used exactly the same measurements but only different underlying maps. Most remarkable is the point in time when the robot began to disappear behind the walls (at measurement 740). While the error was very low during the line of sight movement (always with respect to the control station) the error raised significantly when there was no LoS but the error is not so high that the propagation model failed for this situation. While using the cropped map, it shows out that the prediction error is relatively high (around 4dB). When using the full map the error rises not so fast and reaches only a value of 3.5db. So the full information about all walls helps the predictor to adapt more likely to the real environment. But the differences are not that substantial that a full map is necessary.

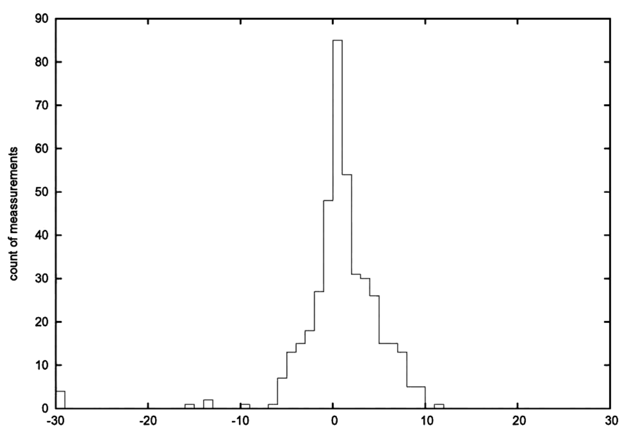

Fig. 4. Fault distribution. Measurements on far left side are wrong localization from the robot

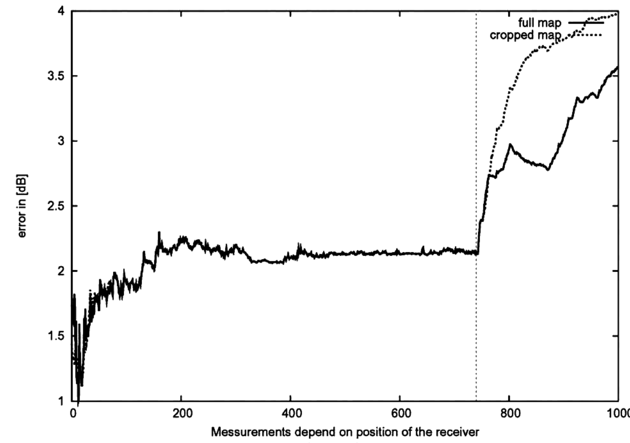

Fig. 5. Error of the propagation model in respect to the cropped map and the full map. At measurement 740 the robot dissappeared behind the wall.

VII. Using signal strength prediction for Multi Robot Systems

The signal strength predictor should be a tool to gain more information to control single and multi-robot systems. With its help, coordination of multi-robot systems should be improved. Additionally the decision where to go next can be influenced. Most current navigation algorithms for multi-robot systems either ignore communication and assume an always available communication or they just assume that the connection only depends on distance: If the robots are nearer to each other than a certain threshold, there is communication, if not, there is no communication. In real world experiments, especially when covering a huge area, such assumptions are not feasible. We want to present just two applications which might gain advantages from using the signal strength predictor, but several other are possible.

A. Exploration

A coordinated exploration with a multi-robot system shows a much better performance than a single robot exploration, especially in respect of exploration time [19]. But the coordination is crucial. To coordinate the different robots there must be communication between them. Not necessarily to tell the other robots where to go, but mainly to share each other's maps. The signal strength predictor can be used to assure connection between the robots. As mentioned in [19] the necessity of always keeping a communication link between all robots is not given if your concern is only about exploration time. But the predictor becomes more valuable if there is e.g. a control station from where the exploration is controlled and observed. With knowledge how the signal strength will change while moving the robot, it is possible to make connection loss much less likely and keep the data collected at the control station always up to date. Also, in dangerous environments it is easier to distingish if a robot is lost due to connection or due to outside influences.

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B. Building an Infrastructure

In trouble areas like environments after a disaster, there is usually no communication infrastructure available. If robots are used for search and rescue missions, they carry everything with them to establish at least a wireless communication. Therefore they have to be positioned in a way that they maximize the area from where they can receive radio, but also have to make sure that they have a connection to each other. Thus helpers which enter the area have access to a communication network to communicate with other helpers or a control station.

This problem is a variant of the *Art Gallery Problem* (for a description and the art gallery theorem see [20]), which is known as NP-complete. The difference lies in the unusual metric, implied by the signal strength predictor.

When the parameter set of the environment is learned, the predictor can be used to solve such problems (see Fig. 6).

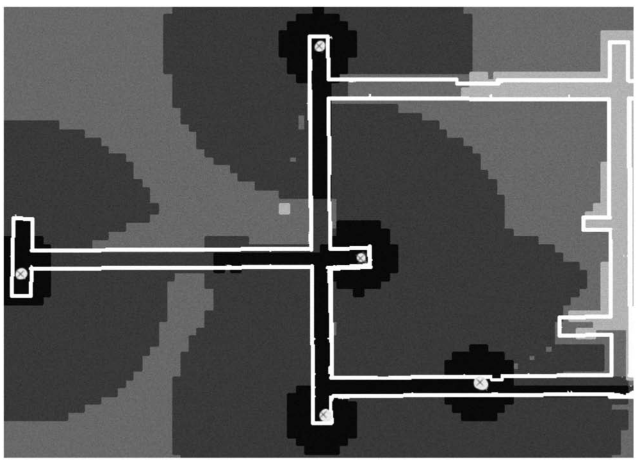

Fig. 6. Building an infrastructure with the help of the signal strength predictor. One solution for 5 robots found with a swarming approach. Darker colour means better connection to at least one robot.

VIII. Conclusion

We presented a signal strength predictor based on radio propagation models. We propose it to improve navigation strategies and coordination of multi robot systems. The predictor is customizable to the environment and can be adapted on-line while using the robots. With the approach we showed a possibility to adapt the predictor even with erroneous measurements. We have shown that for indoor environments the grade of accuracy of the prediction is high enough to predict the tendency of the signal strength when moving the robot. So it is possible to navigate robots with a much lower chance of losing contact.

Additionally we suggested two applications in the field of navigation which can be improved and expanded in functionality with the help of the signal strength predictor.

Further improvements of navigation strategies should be made with the radio propagation model. We want to evaluate in which way more sophisticated propagation models will affect computing time and prediction accuracy. One special feature will be to expand the model to distinguish between different types of obstacles and to learn their damping. Additionally we want to estimate in which way navigation strategies like exploration are affected by using a signal strength predictor. Especially aspects like the time needed until a goal is reached and the number of connection losses are interesting.

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