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Experimental Characterization of Radio Signal Propagation in Indoor Environments with Application to Estimation and Control

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***Abstract*— We study radio signal propagation in indoor environments using low-power devices leveraging the *Zigbee* and *Bluetooth* specifications. We present results from experiments where two robots equipped with radio signal devices and enabled to control and localize autonomously in an indoor hallway and laboratory environment densely sample RSSI at various times over several days. We show that simulated RSSI measurements using existing radio signal models and experimentally gathered RSSI measurements match closely, suggesting that for robotics applications requiring predicted RSSI, low-power radio signal devices are a well-posed sensing modality.**

I. Introduction

Wireless communication is requisite in most multi-robot scenarios and devices for enabling wireless communication protocols through radio signals, such as *Zigbee*, *Bluetooth*, and *802.11*, are readily available and economically priced. It is well-known that environmental effects on radio signal propagation are significant and several models of radio signal propagation are discussed in [1]–[3], including: statistical, empirical direct-path, empirical multi-path, and ray optical models. In the robotics community, several works exploit the fact that radio-propagation is environment dependent by leveraging received signal strength indication (RSSI), a measurement of power present in a radio signal, as a model for localization, including [4]–[6]. By predicting the RSSI for an environment based on experimentally gathered or modeled data, this research suggests that it is possible to localize a robot in an environment. In each of these works, the authors study communication via *802.11 b/g*, with sampling in indoor environments via autonomous [4] or sparse manual [5, 6] methods. RSSI also plays an important role in multi-robot control algorithms which require inter-robot coordination via communication [7]–[9]. The relationship between radio signal strength and bit error rate (and thus communication capability) is well studied and shown to be heavily correlated. Therefore, RSSI prediction is vital to the success of control algorithms requiring inter-robot communication.

In this work, we study radio signal propagation in indoor environments using low-power devices leveraging the *Zigbee* and *Bluetooth* specifications. In particular, we are interested in using RSSI for sensing and control applications where a model of RSSI behavior acts as a measurement model in estimation tasks and as an accurate prediction of possible data transmission capabilities in multi-robot scenarios. We present results from experiments where two robots enabled to control and localize autonomously in an indoor hallway and laboratory environment densely sample RSSI at various times over several days using off-the-shelf radio devices.

The contributions of this work are as follows. (1) We present experimental results for low-power *Zigbee* and *Bluetooth* devices that confirm existing results from prior literature developed via *802.11 b/g* devices. (2) A comparison between a radio signal propagation model and experimental data affirms the model correctness for low-power devices and suggests its applicability for predicting RSSI for a known indoor environment description assuming a quantifiable noise model. (3) We provide a characterization of the effects of non-trivial environmental changes on RSSI as predicted via the radio signal propagation model and observed in experimentation.

The presentation of the paper is as follows. In the next section, we place our results in context with existing studies in the robotics and sensor network communities. We detail the simulated radio signal propagation model and pertinent specification information for *Zigbee* and *Bluetooth* in Sect. III. In Sect. IV we review the approach to experimentally analyzing RSSI in an indoor environment including radio hardware selection and robot control and localization. The experimental results and associated discussion are provided in Sect. V. We conclude in Sect. VI.

II. Related Literature

Due to the fundamental role of RSSI as a quality measure in wireless communication, the estimation and exploitation of RSSI is well-studied in the mobile robot and sensor networks literature. We highlight several works focusing on a similar analysis to our own.

The problem of RSSI estimation as an enabling sensing modality in the robotics community is presented in the context of localization and control. In [4], Howard *et al.* experimentally study the use of RSSI measurements for robot localization. The authors address the localization problem in two steps; by first generating an RSSI map through experimental sampling, using interpolation methods for regions without data samples, then applying Monte-Carlo Localization [10] methods for pose estimation based on the previously generated RSSI maps. The authors conclude that the RSSI map representation is more appropriate for localization than a simple parametric model such as the statistical model discussed in Sect. III. A similar analysis is provided in [5], where Ferris *et al.* show the application of Gaussian processes as a means of generating a likelihood model for signal strength measurements. The choice of model parameters is determined through learning methods applied to experimental data sets. The authors comment on the complexity of model learning for large data sets.

From the multi-robot control perspective, Hsieh *et al.* present in [11] an experimental study of the effects of radio signal strength on end-to-end communication between multiple robots in an ad-hoc network. The authors propose reactive control laws for communication link maintenance given RSSI measurements. In [12], Lindhé *et al.* exploit the effects of multi-path fading on radio signal propagation in the design of control laws for improving radio signal strength. The authors consider the necessary sampling population for given communication performance and design control strategies for robot positioning to gather samples.

Formulations in the mobile sensor network literature show similar methods as the robotics community. In [6], Ladd *et al.* demonstrate a strategy akin to [4] for solving the localization problem by generating a map of signal strength trained from sparsely sampled data in an indoor environment, which is leveraged in a Baysian inference algorithm for pose estimation. The authors conclude that commodity hardware is suitable for accurate pose estimation in indoor environments.

A related problem is self-configuration in sensor networks. Patwari *et al.* consider in [13] the localization problem in a sensor network by measuring received signal strength and time-of-arrival of messages between neighboring network nodes. The authors formulate Cramér-Rao bounds and maximum-likelihood estimators assuming free space path-loss on received signal strength.

While the motivation of these works is common to our own in that we are interested in studying radio signal propagation in indoor environments, we wish to differentiate the results and discussion in the remainder of the paper from prior work. We are interested in studying RSSI-aware multi-robot estimation and control algorithms via low-power devices and for this reason consider only *Zigbee* and *Bluetooth*, noting that there is already an existing body of work studying *802.11 b/g* for these applications. *802.11 b/g* devices are employed for analysis in the relevant results presented in the prior references. We conclude in Sect. V that it is because of our selection of low-power devices that we see fewer environmental effects as compared to the results leveraging *802.11 b/g* devices which typically have high transmission power. For this reason, it is possible to accurately predict RSSI via existing radio-propagation models, which we detail in the next section. Additionally, in much of the prior work involving robotic estimation tasks, the approach requires a sampling of signal strength (often sparse) that spans the entire configuration space. We seek to develop methods that provide predicitve capabilities for reconfigurations of the transmitters in new regions of the environment.

III. Modeling

A. Indoor Wave Propagation

Indoor radio signal propagation is generally considered to be an extremely uncertain and complex process with heavy correlation to environmental features ranging from electromagnetic interference to physical obstacles. However, due to the pervasiveness of wireless communication needs in and around buildings, there is an extensive body of literature devoted to understanding and modeling the radio propagation process. We seek to draw on this work in order to develop tools that allow us to fully incorporate radio signal information into our estimation and control tasks.

Development of models for indoor wave propagation can be classified into four categories: statistical models, empirical direct-path models, empirical multi-path models, and ray optical models [1]. While ray optical models include the possibility of simulating complex indoor phenomena such as fast-fading and corridor wave-guiding effects, only some approaches such as [3] provide efficient computational methods.

1) Statistical models: The most basic formulation, these models do not incorporate information about specific obstacles in the environment. Power-loss throughout the environment is computed as a function of the distance between antennas d and fit to the entire environment by a power decay n so that loss (in dB) is

$$L = L_0 + 10n \cdot \log(d)$$

where L_0 is a measured loss at 1 m. The decay parameter n must be experimentally fit for each environment.

2) Empirical direct-path models: These models consider the line-segment connecting the source and receiver antenna. Obstacles along the transmission path are considered and result in path-loss prediction that is related to the number and type of obstacles in addition to the total path-length. A typical model (and one we have currently implemented) is the *multi-wall model* from [2] where path-loss is given by

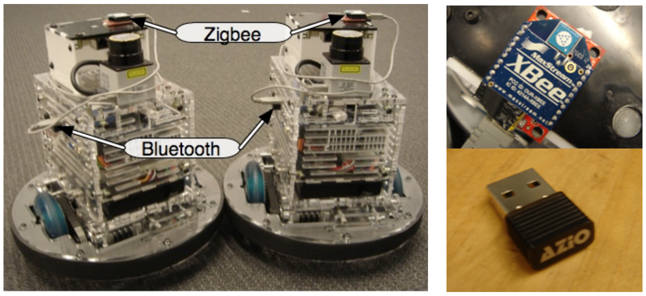
$$L_{mwm} = L_0 + 10n \cdot \log(d) + \sum_{i=1}^{N} k_i L_i$$

where N is the number of wall-types, k_i is the number of walls penetrated with type i, and L_i is the loss factor for a wall of type i. The model is adjusted to the environment by tuning n and L_i.

The downside of direct-path models is that they do not model small-scale fading effects that occur due to obstacles in the environment that reflect or refract the signal so that multiple components arrive at the receiver out of phase. This results in fading on the order of $5 - 10$ dB occurring over small length scales and can be modeled probabilistically.

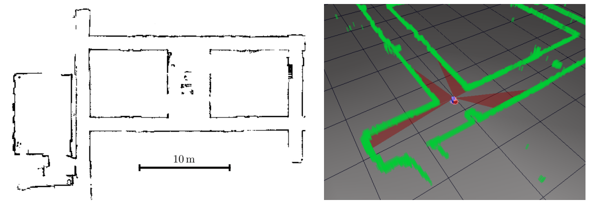
B. Radio Specifications

Since we are not interested in dealing with the low-level interfaces to radio frequency devices, we rely heavily on off-the-shelf technologies. Both *Bluetooth* and *Zigbee* are designed to operate in low-power mesh-style embedded



(a) (b)

Fig. 1. Two *Scarab* robots (Fig. 1(a)). Each robot is equipped with a *MaxStream XBee Zigbee* adapter and an *Azio Micro Bluetooth* adapter (Fig. 1(b)).



(a) (b)

Fig. 2. The map used in laser-based localization (Fig. 2(a)) and a graphic depiction of localization during a trial (Fig. 2(b)).

networking solutions operating in the unlicensed 2.4 GHz ISM (Industrial Scientific Medical) band.

Bluetooth uses frequency hopping technology and every network has a *group ad-hoc network controller* that interconnects nodes and assigns time slots for communication to each node requiring the network to operate on a time division scheme.

Zigbee is a communication protocol built for low-power radios based on the *IEEE 802.15.4* standard which handles all of the physical and media access control layer operation that is important to this work. *IEEE 802.15.4* dictates that each node operates in a carrier sense, multiple access/collision avoidance (CSMA/CA) paradigm.

Important to this work is that both radios must provide methods for reporting the RSSI. The *Zigbee* specification returns this measurement directly as an integer ranging from -40 dBm to receiver sensitivity (-92 dBm for our radios). On the other hand, *Bluetooth* returns RSSI with respect to the notion of a *golden receiver range*. An RSSI of 0 corresponds to a received signal strength within the *golden receiver range*, negative for signals below the range and positive for those above.

IV. Experimental Implementation

In this section we detail the robot hardware, control, and localization for gathering the data required by the analysis in Sect. V.

In the experiments, a single stationary robot transmits data via *Zigbee* and *Bluetooth* radios while a second robot controls autonomously through an indoor hallway and laboratory environment. The mobile robot visits a sequence of waypoints while avoiding obstacles and sampling received signal strength. A dense population of waypoints ensures a rich sampling of the RSSI throughout the environment. Evaluation of each trial occurred at various times over several days. In the results we focus on two trials for data presentation, but note that the data is consistent with the other trials.

A. Hardware

The two robots and communication hardware used in the experiments are shown in Fig. 1. The *Scarab* is a $20 \times 13.5 \times 22.2\ \mathrm{cm}^3$ indoor ground platform. Each *Scarab* is equipped with a differential drive axle placed at the center of the length of the robot with a 21 cm wheel base, onboard computation, and *802.11a* wireless communication. Note that the operational frequency of *802.11a* is 5 GHz and all data logging and experiment monitoring occurred via this alternative frequency to avoid affecting the measurement of RSSI.

A Hokuyo URG 04-LX laser range finder and odometry information provide the necessary sensor information for laser-based localization in the environment similar to the maximum likelihood dead reckoning approach in [14]. The map and a graphical depiction of the localization solution is shown in Fig. 2.

As the duration of these experiments extended over several days, power was a concern. All data logging occurred via SQL database transactions. In this way, data collection was robust to power failures due to drained batteries and experimentation resumed following battery replacement. Battery life for the *Scarab* is approximately 3 h.

The *Zigbee* device is the *MaxStream XBee* with 1 mW (0 dBm) power output and receiver sensitivity of -92 dBm [15]. The *Bluetooth* device is the *Azio BTD-V201 Micro* class 1 adapter with *Bluetooth* version $2.0 +$ EDR and maximum peak output power of 15 mW (11.8 dBm) and antenna gain of 1.0 dBi [16]. Note that nominal output power for this device is unknown. Both devices are pictured in Fig. 1(b).

V. Experimental Results

The analysis of the experimental results is focused on addressing several concerns related to the applicability of low-power *Zigbee* and *Bluetooth* devices to robotics estimation and control applications and the correctness of the models discussed in Sect. III as compared to experimental data.

Throughout the analysis we make use of figures to depict data acquired experimentally or through simulation. A color mapping is used in these figures to represent variations in RSSI values, where areas of maximum or minimum values or variations, depending contextually on the figure, are depicted by red and blue, respectively.

A. RSSI Sampling Suitability of Zigbee and Bluetooth Devices

Zigbee, *Bluetooth*, and *802.11 b/g* devices have similar operating frequencies around 2.4 Ghz. Therefore it is reasonable to expect similar radio signal propagation models

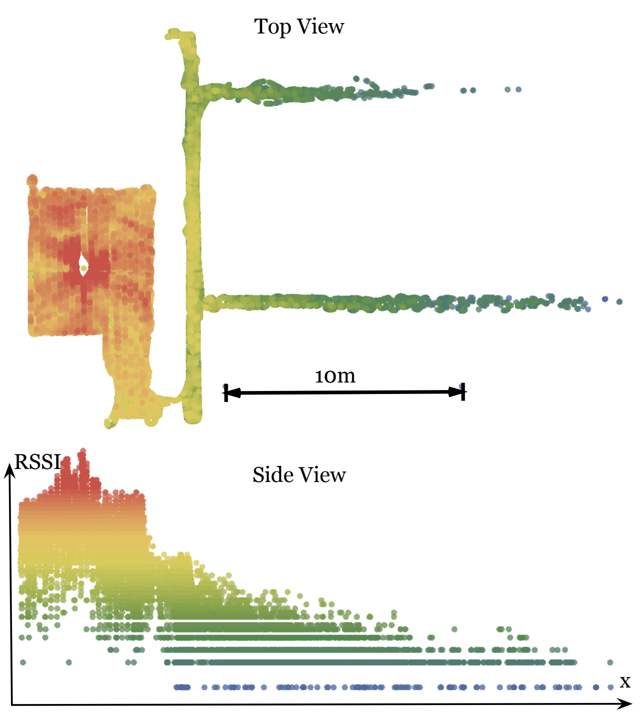


Fig. 3. Visualization of full *Zigbee* data set consisting of over $20,000$ samples from top-view and side-view which demonstrates that radio signal propagation is in fact a stochastic process with uncertainty.

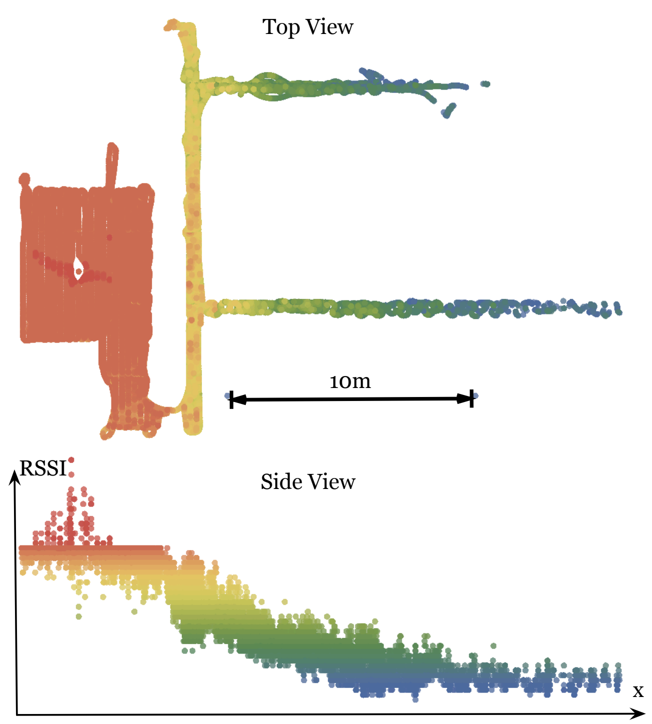


Fig. 4. Visualization of full *Bluetooth* data set consisting of over $20,000$ samples from top-view and side-view. Note that by the *Bluetooth* specification, RSSI data is 0 when within the *golden receiver range*, negative when below this range and positive above. For this reason, *Bluetooth* offers coarser RSSI measurements as compared to *Zigbee* (Fig. 3)

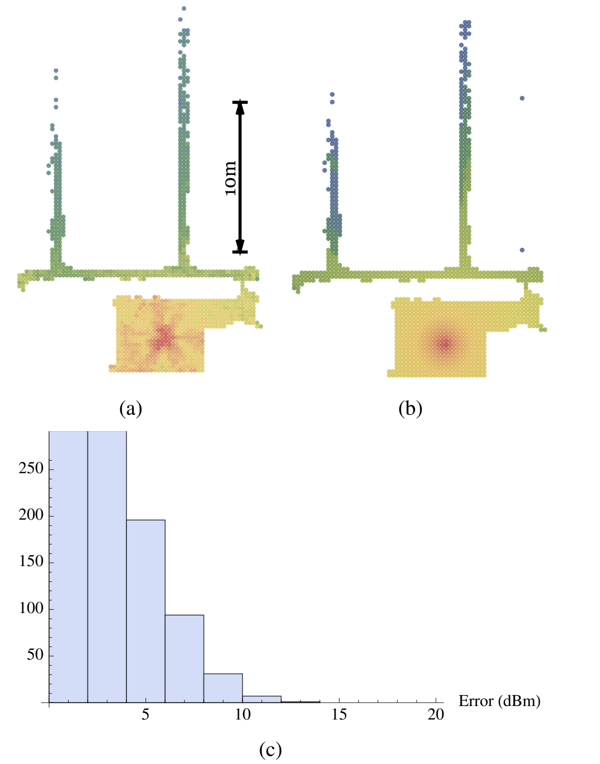


Fig. 5. Comparison of experimental data with the stationary robot at $(0, 0)$. Figure 5(a) depicts average behavior when samples are grouped in 0.25 m cells. Figure 5(b) shows the result of applying the same averaging procedure to simulated samples. Figure 5(c) shows the error between the simulated and experimentally determined RSSI as a histogram representation with bins determined by the average RSSI error between each data point in simulation and experiment.

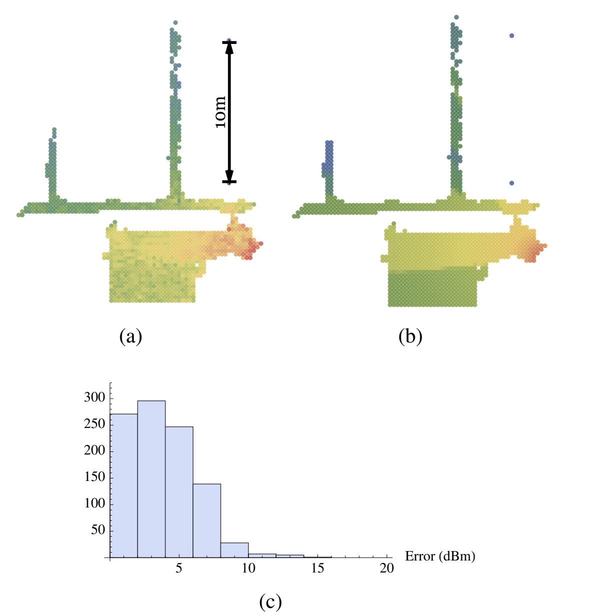


Fig. 6. Demonstration of the predictive capabilities of the model when the stationary robot is moved to a new location. Figures 6(a) and 6(b) depict average RSSI behavior across the map in experimentation and simulation respectively. Figure 6(c) represents the average RSSI error at each cell with a histogram that indicates accuracy of the model to generally be within 10 dBm.

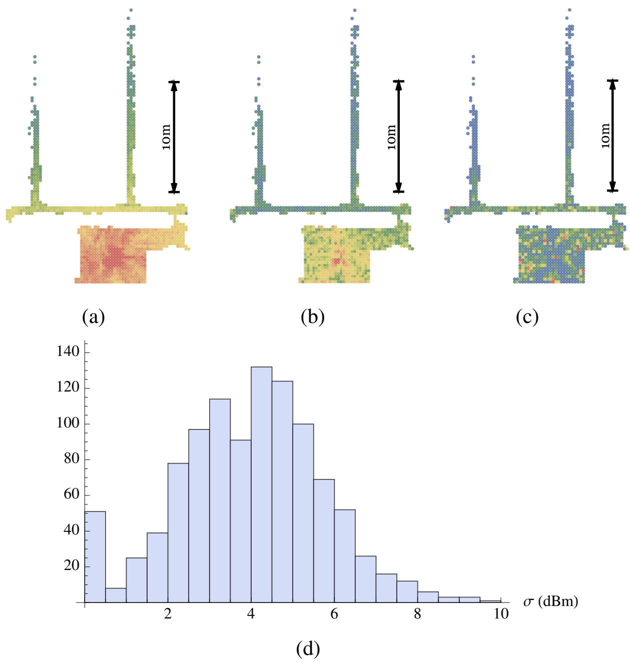


Fig. 7. RSSI is clearly not a deterministic process. Figures 7(a) and 7(b) show the upper and lower bounds for each $0.25\,\mathrm{m}$ cell in our experiments. Figure 7(c) depicts the variance in each cell. With seemingly no correlation between location in the map and variance, we conclude that a constant noise model can be considered. Figure 7(d) depicts a histogram of standard deviation across all cells in the map which indicates Gaussian noise with $\sigma = 5\,\mathrm{dBm}$ is appropriate for the *Zigbee* device.

between the different specifications assuming similar power output, receiver sensitivity, and antenna gain. However, *802.11 b/g* infrastructure access points typically have maximum output power ratings of $20\,\mathrm{dBm}$ or greater, resulting in differing performance from *Zigbee* and *Bluetooth* in indoor environments.

Figures 3 and 4 show visualizations of the data sampled from the same trial via the *Zigbee* and *Bluetooth* devices. It is clear that while both devices provide similar functional communication capabilities, *Zigbee* offers RSSI measurements with higher resolution in line-of-sight regions. This difference is due to the notion of RSSI as defined by the separate specifications (see Sect. III). Due to the *Bluetooth* specification definition of RSSI, these measurements offer a coarse granularity when reporting signal strength changes. We conclude that *Bluetooth* devices provide less suitable measurements of RSSI for applications such as localization and focus the remainder of our analysis and discussion on *Zigbee* devices for this reason.

B. Simulated RSSI Measurements as a Means of Prediction

In the following discussion, we present experimental results which suggest that not only can we fit a direct-path propagation model to our data, but also that it provides predictive capabilities and continues to perform well for an alternate stationary robot location.

1) Direct-Path Model Fit: Given a complete description of our experimental environment and the location of both

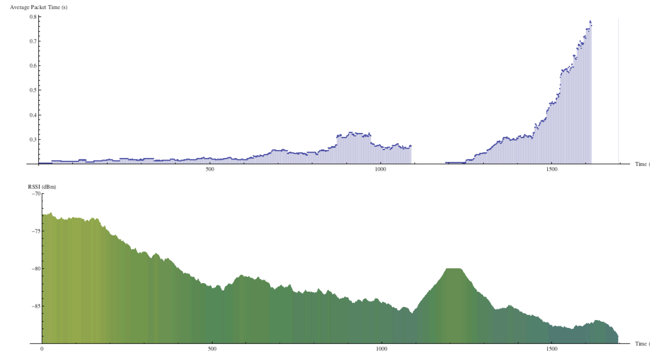


Fig. 8. While it is widely known that there is an inverse relationship between signal strength and packet errors resulting in dropped packets, our data further supports this fact. In our experiments, packets are transmitted from the stationary robot at $0.2\,\mathrm{s}$ intervals so longer inter-arrival times (top) indicate dropped packets. There is clearly a correlation in our data that as RSSI decreases, the number of dropped packets increases, leading to longer inter-arrival times.

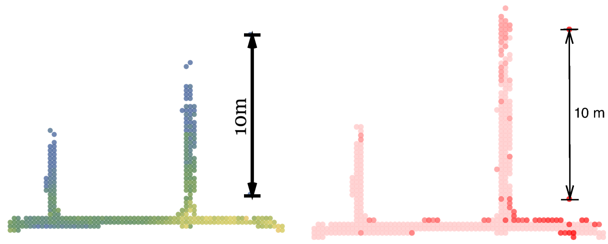
stationary and mobile robot, we can compute a description of the *direct* radio signal path including total distance and wall intersections. By performing spatio-temporal averaging and tuning the parameters described in Sec. III, we are able to closely match the model with the average behavior across our trial as depicted in Fig. 5. The result of tuning is the following: $L_0 = -9.83$, $n = 2$, $L_1 = 6.4$ (for these experiments we assume a single wall-type).

2) Model Prediction: In order to test the generalization of the model we have chosen for radio propagation, we continue by conducting another large-scale trial with a new location for the stationary robot. Figures 6(a) and 6(b) depict average RSSI behavior across the map in experimentation and simulation respectively while Fig. 6(c) represents the average RSSI error at each cell with a histogram that indicates accuracy of the model to generally be within $10\,\mathrm{dBm}$. It is clear that despite fitting the direct-path model to another location in the environment, the model generalizes well and provides accurate RSSI estimation.

3) Noise Model: In order to utilize radio signal strength measurements for estimation and control, it is necessary to have a suitable model of the noise that is expected on the measurement [1]. Figure 7 depicts statistical properties of RSSI measurements. With seemingly no correlation between location in the map and variance, we conclude that a constant noise model may be considered. Figure 7(d) shows a histogram of standard deviation within all 0.25 m cells in the map which indicates Gaussian noise with $\sigma = 5\,\mathrm{dBm}$ is appropriate for the *Zigbee* device. These findings agree with the noise results presented for *802.11 b/g* in [4, 12]

4) Considerations for Multi-Robot Algorithms Requiring Communication: Of note is the expected correspondence between RSSI and dropped packets which has significant bearing to multi-robot control algorithms requiring communication. While it is widely known that there is an

[1]Given a direct-path model of the signal propagation, we consider small-scale fading effects to be noise.



(a) (b)

Fig. 9. Environmental changes are generally limited to fringe effects. Figure 9(a) depicts an experimental repetition of the trial in Fig. 6(a) where a metal door has been closed between the stationary and mobile robots. Figure 9(b) acts as a visualization of the difference between the two data sets – darker red indicates large errors. Note that most significant errors occur at the edge of the reception range.

inverse relationship between signal strength and packet errors resulting in dropped packets, our data further supports this fact. In Fig. 8 there is clearly a correlation in our data that as RSSI decreases, the number of dropped packets increases, leading to longer inter-arrival times.

C. Transient Environmental Effects on RSSI Maps

Transient environmental effects are a consideration when using RSSI measurements as a sensing modality. To study these transient changes we compared the experimentally gathered data from two different trials, where in the first trial a metal door 2 m from the stationary robot location is open (Fig. 6(a)) and for the second the metal door is closed (Fig. 9(a)). The difference in RSSI between the trials is shown in Fig. 9(b). While it is clear that environmental changes do have an effect on the average signal behavior, the changes are localized to the region of disturbance.

VI. Conclusion and Future Work

We study radio signal propagation in indoor environments using low-power devices leveraging the *Zigbee* and *Bluetooth* specifications. In particular, we are interested in the role of RSSI as a measurement model for sensing and control. We present results from experiments where two robots equipped with radio signal devices and enabled to control and localize autonomously in an indoor environment densely sample RSSI at various times over several days. We show that simulated RSSI measurements using existing radio signal models and experimentally gathered RSSI measurements match closely after spatial averaging. This suggests that for robotics applications requiring predicted radio signal strength, low-power radios are a well-posed sensing modality. We conclude through our analysis that while *Zigbee* and *Bluetooth* devices offer similar communication range capability, *Zigbee* devices yield finer granularity in RSSI measurements (due to specification differences) and are therefore more suitable for applications leveraging RSSI as a means of estimation. Additionally, we find that non-trivial transient changes in the environment resulted in expected RSSI changes consistent with radio propagation models.

In this work we focused on contrasting experimentally gathered data to simulation models. The goal of this work is to develop an understanding of the applicability of low-power radio signal devices to estimation and control in the context of multi-robot applications. Based on the positive results from this work, we are currently pursuing real-time estimation and control for mobile robot networks with low-power *Zigbee* devices. In particular, we are interested in exploiting these devices for enabling predictive RSSI capabilities in multi-robot control for network connectivity and low-cost sensors for pose estimation in environments with known maps and construction materials.

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