LOCO: A Location Based Communication Scheme

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Abstract

We present, LOcation based COmmunication (LOCO), a new channel for communication for robots that can act as a fail-safe communication mechanism in contexts of radio failures, given a working localization system. With insights from traditional wireless communication, we formulate a channel model for the location based communication channel where the transmitted data is modulated into a set of discrete locations of a robot. The receiving end employs a localization module to estimate the positions of the robot and to demodulate it into received symbols. We further identify the key factors that control the capacity and error performance of this channel: the symbol grid granularity, variance of the localization noise, the frequency of the localization, and the speed of the robot. In this paper, we also present a set of illustrative examples for LOCO along with pertinent analysis via detailed simulation and real-world data based emulation experiments.

1 Introduction

With the recent breakthroughs in hardware and software developments, robotics and automation have become integral parts of our life. Over the last decade, robots have been employed in a diverse application contexts such as to help first-responders in firefighting, and search and rescue missions, to explore unknown terrains, and to form temporary communication backbones [9, 14]. A key enabler in all these applications is a reliable communication between the robot and a control center. If the communication links fails, say, due to radio damage, the whole purpose of the robot's deployment may be a lost cause. For example, imagine sending a rover to Mars to sense, collect and send information about Mars. If all radios on the rover fails momentarily or permanently, the mission might turn into a lost cause. In such cases, it is pertinent to have an alternate (preferably non-radio based) communication scheme as a fail-safe communication mechanism. One potential choice is to use the motion of robot as a fail-safe mode of communication as we often employ an off-board localization technique such as camera based or RF based to keep track of the robot. There exist many passive localization schemes, such as camera based localization, bi-static radar based localization, and passive RF based localization, where the robot is not required to communicate with the localization module using radio based communication. In Figure 1, we present an illustration of the concept where Message 1 and Message 2 are conveyed in form of locations of the robot, whereas Message 3 is conveyed by the movement of the robot.

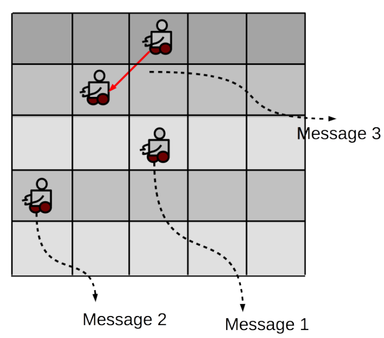

Figure 1: An Illustration of Localization Based Communication

In this paper, we present the first ever (to our knowledge) channel formulation of a LOcation based COmunication (LOCO) system. To this end, we explore the existing well-versed literature on communication channels and information theory [12] to explore the applicability of traditional wireless channel models to our context. We show that, most of the well-known concepts of traditional wireless communication channels such as source coding and source to symbol mapping can be molded to use in our proposed location based communication channel. In this paper, we present a couple of illustrations of such communication channel along with simulation and emulation experiments based effective rate analysis

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International Conference on Embedded Wireless
Systems and Networks (EWSN) 2017
20–22 February, Uppsala, Sweden

ISBN: 978-0-9949886-1-4

with respect to the accuracy of the localization schemes used.

2 Problem Statement

We consider a setting where the entity (say, a robot) wishes to communicate using its location alone. In particular, we assume that robot is mobile and that the intended message recipient (say, a remote control room) is able to estimate the location of the robot accurately upto a certain precision. Consequently, the robot wishes to exploit its mobility to communicate important messages back to the control room. While not intended to replace traditional communication systems, a possible application of this work is the possibility of maintaining a communication link even if the traditional communication system on the robot is rendered unusable in the wake of a disastrous event. Of course, we still assume that the robot is mobile and that the control room is able to estimate the location of the robot, perhaps visually or through use of a remote sensing procedure such as RADAR. For simplicity, we consider only unidirectional communication wherein the robot needs to convey messages to the control room.

2.1 Source Symbol Set

Traditional digital modulation schemes transmit digital data by changing some property of a carrier signal such as the amplitude, frequency, phase or a combination thereof. In our setting, we 'transmit' digital data by varying the robot's position. Specifically, in this paper we shall restrict ourselves to source symbols consisting of only locations. However, for completeness we also include a brief discussion on the design of source symbol sets that incorporate movement or change in location as a symbol.

2.1.1 Location Based Symbol Sets

In this case, our source symbol set $\mathcal{X}$ consists of discrete locations. As an example, consider a robot placed in a square terrain as shown in Figure 1. A simple source symbol set consists of discretized locations possibly distributed in a uniform manner across the terrain. For example, in Figure 1, $\mathcal{X}$ consists of 25 symbols obtained by imposing a 5×5 grid on the square terrain. In this case sixteen locations can be thought of as encoding a four bit message, with the remaining locations possibly reserved for control messages.

In general, a large symbol set will increase the number of bits sent per symbol at the cost making the locations closer to each other and hence harder to resolve. In general, the design of $\mathcal{X}$ must take into account such constraints imposed by the physical terrain in addition to those imposed by the capabilities (or lack thereof) of the receiver. In particular, if the receiver is capable of resolving small changes in the robot location, then our design space for $\mathcal{X}$ is greatly increased. We assume that the capabilities of both the robot and the receiver are decided beforehand and known to each other. More formally, we assume that the symbol set $\mathcal{X}$ is known to each other.

2.1.2 Location and Movement Based Symbol Sets

Analogous to how differential modulation schemes such as DPSK [11] take into account sequences of modulation symbols, consider the case where we can communicate using *changes of location* instead of the location itself. In the simplest case, $\mathcal{X} = \{L, R, U, D\}$ corresponding to the directions (L)eft, (R)ight, (U)p and (D)own. In general, we may use a combination of location and movements for signalling. In particular, we can greatly increase $\mathcal{X}$ by distinguishing between changes in direction at different locations. This corresponds so indexing each direction by a location, $\mathcal{X} = \{L_{\boldsymbol{r}}, R_{\boldsymbol{r}}, U_{\boldsymbol{r}}, D_{\boldsymbol{r}} | \boldsymbol{r} \in S\}$, where we use S to denote the space used by the robot to communicate with a receiver.

While considering location and movement based source symbol sets, particular care needs to be taken in their design. In particular, it may not be possible for the robot to move in all directions at all locations. For instance, mobility is curtailed at the edges of our space and the particulars of the terrain might make it desirable to avoid certain directions in particular locations. Moreover, care needs to be taken to ensure that it is possible to use any combination of the source symbol set. For instance, a naïve design of the source symbol set might render some sequences of symbols unusable which amounts to being unable to send certain messages.

For simplicity, in the remainder of the paper we shall restrict ourselves to the analysis of the LOCO system that uses location based symbol sets exclusively.

2.2 Communication System

The communication channel formulation in LOCO model remains same as standard wireless communication channel model that includes source coding, channel coding, modulation at the sender and demodulation, channel and source decoding at the receiver [12]. The main difference of LOCO compared to traditional wireless communication model is in the modulation-demodulation process and the transmitted symbol set. The symbol set in LOCO model is a set of locations of the communicating robot. For example, in Figure 1, each of 25 grid points can act as a symbol of communication. The modulation and demodulation in LOCO involves mapping a bit stream into a set of locations and mapping a set of observed (by the localization module) locations into a received bit stream, respectively.

2.3 Channel Capacity

Let $\mathcal{X} = \{x_1, x_2, \cdots, x_S\}$ and $\mathcal{Y} = \{y_1, y_2, \cdots, y_T\}$ be the set of source and received symbols, respectively. Let $p(y \mid x)$ be the conditional probability mass functions (PMFs) corresponding to the channel which we assume to be stationary, and $p(x)$ be the PMF of the source symbols. Let $p(x,y)$ be the joint PMF of the source symbols and received symbols. The mutual information between the source symbols and the received symbols can be represented in terms of the PMFs as

$$J(\mathbf{p}_X; \mathbf{P}) = \sum_{i=1}^{S} \sum_{j=1}^{T} p(x_i) p_{ij} \log_2 \left(\frac{p_{ij}}{\sum\limits_{k=1}^{S} p_{kj} p(x_k)} \right) \tag{1}$$

where $\mathbf{p}_X = [p(x_1), p(x_2), \cdots, p(x_S)]$ represents the vector containing the source PMF entries and $\mathbf{P}$ denotes the matrix of transition probabilities where $p_{ij} = p(y_j \mid x_i)$ for $1 \le i \le S$ and $1 \le j \le T$. The channel capacity can be calculated as

$$C = \max_{\mathbf{p}_X} J(\mathbf{p}_X; \mathbf{P}). \tag{2}$$

Note that the channel transition probabilities that we refer to here correspond to the errors in the robot's location estimation. The transition probability $p(y_j \mid x_i)$ corresponds to the case when the robot sends a source symbol x_i, but the localization system detects the symbol y_j. Therefore, the channel transition probability matrix as well as the channel capacity in our proposed communication channel depend on the localization technique employed.

2.4 Modulation and Demodulation

Ideally, given the transition probabilities, $p(y \mid x)$, the capacity achieving source symbol distributions can be determined. Let $\mathbf{p}^*$ denote the optimal source distribution for a given symbol set and a localization scheme. Now, in order to achieve the maximum capacity, the coded bit-stream needs to be mapped to the source symbols such that the effective source symbol distribution is as close to the optimal source symbol distribution as possible. Nonetheless, with analogy from traditional communication channel, we do not focus on the optimal bit-stream to symbol mapping. Instead, we consider mapping schemes with equal probabilities for each of the source symbols. For source coding we use standard optimal prefix free source coding techniques like Huffman coding [10] with simple parity based block coding as the channel coding. The function of the modulator in this context is to map the input coded bit-stream to a set of locations. We assume that the robot is arbitrarily fast or the symbol time is large enough for the robot to travel between any two locations, for simplicity. We intend to account for the movement speed of the robot in our future works. The demodulator in this context is the localization module that can be camera based or RF based. The localization module estimates the location of the robot periodically with a fixed period (say, T seconds). Note that, we need to have at least one location dedicated to null communication. Now, if the robot has noting to transmit, it moves to the null communication location and stays there. For example, a robot can simply move out of the localization arena in order to pause or stop the location based communication.

2.5 Location Based Signalling

As an illustration of the above idea, we consider the following simple example. Assume that our bot is confined to a unit square $S \subset \mathbb{R}^2$ centered on the origin. We define the symbol set $\mathcal{X}_n$ indexed by $n \in \{2,3,\dots\}$ as follows. Divide each side of S in to n equal segments. This corresponds to dividing the area of S in to n^2 squares each with area $\frac{1}{n^2}$. The geometric center of the square corresponds to a symbol that is used for communication. See Fig. 1 for an example where $n = 5$. Henceforth we shall refer to n as the granularity of the symbol set $\mathcal{X}_n$. At the receiver side, this symbol needs to be estimated in some manner. Assume that we have some observations, say a picture, RADAR signals or RSSI, that allows us to estimate the location.

More formally, assume that we have a vector of observations $\boldsymbol{o}$ with the marginal distribution $f_{\boldsymbol{O}}(\boldsymbol{o}|\boldsymbol{R} = \boldsymbol{r})$. A popular method of deriving an estimate from this distribution is MLE. The MLE estimate given by

$$\hat{\boldsymbol{r}} = \arg\max_{\boldsymbol{r}} f_{\boldsymbol{O}}(\boldsymbol{o}|\boldsymbol{R} = \boldsymbol{r}). \tag{3}$$

While we are certainly free to derive our estimate by other means, unless otherwise specified, we shall use MLE in the paper for ease of exposition.

Due to errors in estimation, the receiver estimate $\hat{\boldsymbol{r}}$ typically does not correspond exactly to $\boldsymbol{r}$. Consequently, the receiver obtains the decoded symbol $\boldsymbol{y}$ by computing the element in $\mathcal{X}_n$ that is closest to $\hat{\boldsymbol{r}}$. In other words,

$$\boldsymbol{y} = \arg\min_{\boldsymbol{x} \in \mathcal{X}_n} ||\hat{\boldsymbol{r}} - \boldsymbol{x}||_2. \tag{4}$$

To find the probability of error, we'll first compute the probability of misclassifying a symbol. For some $\boldsymbol{y} \in \mathcal{X}_n$, define the set $\boldsymbol{O_y} = \left\{\boldsymbol{o} : \boldsymbol{y} = \arg\min_{\boldsymbol{x} \in \mathcal{X}_n} ||\hat{\boldsymbol{r}} - \boldsymbol{x}||_2\right\}$. $\boldsymbol{O_y}$ represents the set of observations at the receiver that results in a decoded symbol $\boldsymbol{y}$. This allows us to define the probability of misclassification as,

$$P(\boldsymbol{y}|\boldsymbol{R} = \boldsymbol{x}) = \int_{\boldsymbol{o} \in \boldsymbol{O_y}} f_{\boldsymbol{O}}(\boldsymbol{o}|\boldsymbol{R} = \boldsymbol{x})\, \mathrm{d}\boldsymbol{o} \tag{5}$$

where $\boldsymbol{x} \in \mathcal{X}_n$. Thus for a given source symbol $\boldsymbol{x}$, the probability that $\boldsymbol{x}$ is decoded in error is given by,

$$P_{se}(\boldsymbol{x}) = \sum_{\boldsymbol{y} \in \mathcal{X}_n \setminus \{\boldsymbol{x}\}} P(\boldsymbol{y}|\boldsymbol{R} = \boldsymbol{x}). \tag{6}$$

The probability of error directly influences the throughput of our channel by limiting the density of the symbols in $\mathcal{S}$. Denote the number of bit errors introduced by decoding a transmitted symbol $\boldsymbol{x}$ as $\boldsymbol{y}$ by $n_e(\boldsymbol{x}, \boldsymbol{y})$. Then the average bit error introduced by the channel in a symbol $\boldsymbol{x}$ is given by

$$P_{be}(\boldsymbol{x}) = \sum_{\boldsymbol{y} \in \mathcal{X}_n \setminus \{\boldsymbol{x}\}} n_e(\boldsymbol{x}, \boldsymbol{y}) P(\boldsymbol{y}|\boldsymbol{R} = \boldsymbol{x}) \leq 2\log_2(n) P_{se}(\boldsymbol{x}). \tag{7}$$

3 Localization Techniques

In this section, we briefly discuss different methods of localization that can be used in our localization driven communication model.

Camera Based and Laser Range Finder Based: The most common architectures for localization are based on Vision and Laser Range Finder systems. In this class of localization, an object can be localized with respect to the camera's field of vision with millimeter level accuracy. To this extent, researchers have proposed a class of efficient sampling and filtering algorithms for vision based localization and tracking such as the Kalman filtering and the particle filtering [4, 13, 4, 7]. Simultaneous localization and mapping [15] architectures in robotics are also very common in this context. On the other hand, there exists a class of range finder based systems that can measure the distance to a object with millimeter level accuracy, given the object is in the line of sight. The works of Lindström and Eklundh [6], and Kleinehagenbrock *et al.* [5] are mentionable in this context.

RF Based Localization In addition to camera-based systems, we also consider RF-based systems in this paper, because they do not require visibility or direct line of sight. As a popular alternative to the camera/range finder based localization, there exists a large body of works [3] that exploits different properties of RF signal for localization. The most common techniques in this context employ three or more reference nodes to triangulate a RF emitting object with centimeter level accuracy (illustrated in Figure 2a). There are also techniques that employ time of arrival (TOA) or time difference of arrival (TDOA) signals to localize the target [2]. However, in such contexts, the object being located requires to

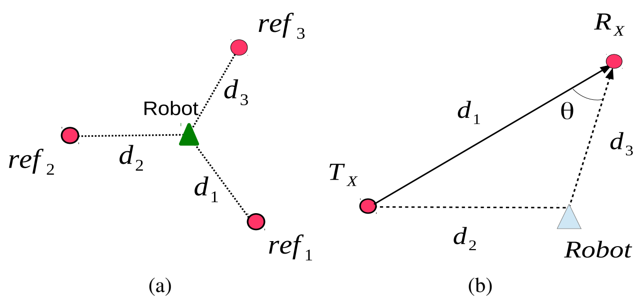

Figure 2: (a) Active RF Localization Illustration (b) Passive RF based Localization Illustration

have an active RF transmitter, thus voids our purpose of localization driven communication. Nonetheless, we aren't ruling out this type of localization completely. There might be situations, where the robot is equipped with an active radio and a low power radio beacon without complicated communication capabilities. The robot can also have passive RF devices that can reflect the RF beacons from the reference nodes. In such cases, our formulation is valid as well.

Another related class of RF based localization applies Bistatic Radar type system for localization. In such techniques there is one RF transmitter and a RF receiver separated by a known distance (say, d_1), The robot is made of some material that can reflect RF signals. In such cases, the receiver Rx receives two signal from the Transmitter (Tx) : one for the direct path and another for the reflected path from the robot (as illustrated in Figure 2). Next, we can employ a directional antenna to separate such multi-path signal components and determine their directions of arrival . Next, we can estimate the distance ($d_2 + d_3$) based on the reflected signal and use the angle θ and the known distance d_1 to estimate the location of the robot. One simple case will be when both the Tx and Rx are located at the same point and the robot just bounces back the signal. Then we will get only one signal and the estimated distance will be twice the actual distance to the robot.

4 Pieces of the Puzzle

Assume that a specific arena is assigned to the robot for communication. Given the arena parameters, the constraints on the robot's movements and the frequency and the technique employed for localization, various parameters for the communication system need to be decided. In this section we discuss the impact of different parameters on the communication ability of the robot.

1. *Grid Granularity*: Given the arena, it needs to be quantized into zones or regions. Robot's presence in a zone corresponds to a particular symbol being communicated. Finer the granularity more is the number of symbols available for transmission, which means higher is the number of bits mapped to each symbol. Ideally we would want the granularity to be as fine as possible in order to improve the communication bit-rate.

2. *Noise Variance*: The noise corresponds to errors in estimating the robot's location. The localization errors can cause the robot's location to be inferred incorrectly and lead to the receiver mistaking it as some different symbol. Depending on the localization technique used and the errors in its location estimates, the grid granularity needs to be decided which determines the size of the symbol set and the total number of bits that are mapped to each symbol. The noise, therefore, plays a major role in determining the effective bit-rate of the system.

3. *Localization Frequency*: The symbol rate also depends on the rate of localization of the robot. Faster the localization, higher are the symbol and the bit rates.

4. *Mobility of the Robot*: Another important factor that affects the communication is the speed of the robot. Depending on whether the relative movements or the actual positions are mapped to the symbols, the robot needs to move from one location to another within one symbol duration. Slower the movements of the robot, lower will be the symbol rate. This shows that the hardware constraints also affect the communication rate.

In our system simulation, however, we assume that the robot can move from one symbol location to another symbol location with the symbol duration. Incorporating the mobility constraints is left as a future work.

5 Proof of Concept

In this section, we demonstrate our idea through concrete examples. We analyze a Gaussian noise model and provide simulations as well as real-world data based emulation performance of LOCO using the RSSI-based localization scheme.

For each evaluation setting below, assume that we assign equal number of bits to each location. For a granularity of n, this would mean that each location represents $\log(n^2)$ bits. We use a single parity bit per location for channel coding that allows us to detect all odd number of bit errors. The performance of the communication channel is measured using the effective number of bits communicated by each symbol (N_s), which is directly related to the symbol error rate as given by the following equation:

$$N_s = (\log(n^2) - 1)\,\mathbb{E}\left[(1 - P_{se}(\boldsymbol{x}))\right]. \tag{8}$$

The effective number of bits that is successfully communicated per location is plotted as a function of the granularity for different noise variances.

5.1 Gaussian Noise Model

There are multiple sources which can cause errors in the localization of the robot, like errors in the actual movement of the robot and noise in the measurements of the devices used in the localization. The errors could also be introduced due to the channel fading, if passive RF based schemes are used. Since it is not always possible to model all these factors, we can use a simplified noise model like the Gaussian noise model. In fact, as the number of sources of error increases, this model gets better and better due to the central limit theorem.

Let us assume that our location estimate is corrupted by Gaussian noise, of known variance, independently in each dimension. More formally, assume that if the robot is located at $\boldsymbol{x} = (x_1, x_2) \in \mathcal{X}_n$, then the receiver obtains the estimate $\boldsymbol{x}' = (x'_1, x'_2)$ where

$$x_i' = x_i + \varepsilon_i \; \forall i \in \{1,2\}, \tag{9}$$

and ε_1, ε_2 are i.i.d normal $\mathcal{N}(0,\sigma_g^2)$. Then the probability that the receiver estimates the position of the robot as $\boldsymbol{y} = (y_1,y_2) \in \mathcal{X}_n$ is given by

$$P(\boldsymbol{y}|\boldsymbol{R}=\boldsymbol{x}) = P\left(x_1' \in [y_1 - l_s, y_1 + l_s], x_2' \in [y_2 - l_s, y_2 + l_s]\right),$$

where $l_s = \frac{1}{2n}$. This may be represented in matrix form as

$$p_{ij} = \left(Q\left(\frac{x_{j1}-x_{i1}-l_s}{\sigma_g}\right) - Q\left(\frac{x_{j1}-x_{i1}+l_s}{\sigma_g}\right)\right) \times \left(Q\left(\frac{x_{j2}-x_{i2}-l_s}{\sigma_g}\right) - Q\left(\frac{x_{j2}-x_{i2}+l_s}{\sigma_g}\right)\right),$$

where the Q-function returns the tail probability of the standard normal distribution and $i, j \in \{1 \ldots n^2\}$. So, if the noise variance σ_g^2 is known, the capacity Eqn. 2 can be used to determine the capacity and the optimal source distribution.

To evaluate this model, we consider a $20\,\text{m} \times 20\,\text{m}$ arena, quantize it into $n \times n$ symbol zones and assign equal number of bits to each symbol. The area outside our arena is regarded as an extra symbol which represents the failure to localize the robot within the grid. This symbol does not convey any information about the location of the robot inside the grid. In Figure 3, we plot the variation in N_s obtained analytically from Eqn. 8. As seen in the figure, high granularity doesn't necessarily lead to improvements in N_s due to constraints imposed by the noise variance.

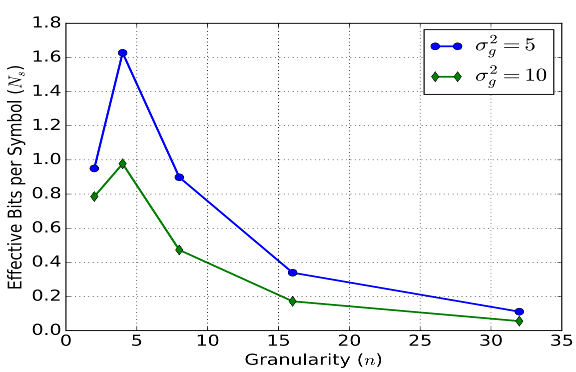

Figure 3: Performance of LOCO Using Parity Bit Channel Coding under Gaussian Noise Model

5.2 RSSI Based Passive Localization

In this section, we present an illustration of the LOCO channel where the localization system employs passive RF based localization algorithm. Let us have m stations with known locations outside the localization arena, S, that function in league to estimate the robot's location. Each station estimates the location of the robot by bouncing beacon signals off the robot surface and measuring the RSSI of the reflected signal. For simplicity, assume that the incident signal is reflected back along the incident path without any extra attenuation due to the reflecting material. Assuming log-normal fading [1], we have

$$P_r^i|_{\text{dBm}} = P_t^i|_{\text{dBm}} + K|_{\text{dB}} - 10\eta\log_{10}\left[\frac{2d_i}{d_0}\right] + W_i|_{\text{dB}} \tag{10}$$

where P_r^i and P_t^i denote the received and transmitted powers, respectively, for the i-th station, d_i represents the distance of the robot from the i-th station, K is the path loss at the reference distance d_0 and W_i is a zero mean log-normal random variable representing the noise with variance σ_r^2. Using (10) we can estimate the distance of the robot from each station and with $m \geq 3$ stations, we can estimate its precise location within limits imposed by the noise (discussed in Section 3) as illustrated in Figure 2a.

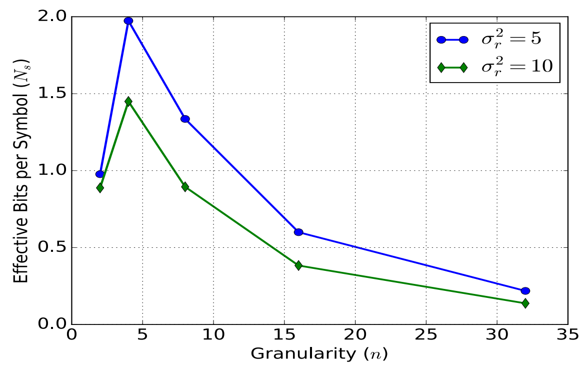

Figure 4: Channel Performance for RSSI Based Location Signaling Using Parity Bit Channel Coding

To analyze the properties as well as performances of this channel, we perform a set of simulation experiments. For this set of experiments, we consider a square shaped localization arena of size $20\,\text{m} \times 20\,\text{m}$. The localization area is subdivided into a $n \times n$ equal size grids while the center of each grid represents a distinct symbol in the LOCO model. For each location of the robot, the RSSI values are collected using four stations ($m = 4$) located at a distance of $1.41\,\text{m}$ diagonally away from each of the four corners of the localization space S. The transmitting powers (P_t) are 7dBm where the path loss at the reference distance $d_0 = 1\text{m}$ is -42dBm. These values are chosen based on our insights from real world experiments, briefly presented in Section 5.3. The path loss exponent, η, is taken to be 2.2 (which is the traditional value of path loss exponent for outdoor environments). With this setup, we compare the channel performance in terms of effective bits per symbol (refer to Eqn. 8) for varying the grid granularity i.e., n, with two different values of noise variance ($\sigma_r^2 = \{5, 10\}$). The evaluation results are presented in Figure 4. Figure 4 indicates that for a given noise variance there exists a threshold of granularity beyond which a denser constellation hinders performance due to the noise. Based on our preliminary analysis, the actual value of this optimal granularity changes with the noise variance, bits per symbol, and the source/channel coding schemes. A detailed theoretical analysis of such optimal configuration is left as a future work. Figure 4 also indicates that doubling the noise variance, σ_r^2, results in a significant reduction ($\approx 30\%$) reduction in the maximum effective bits per symbol.

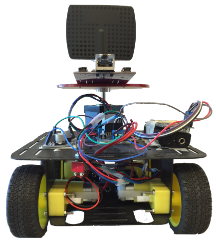

Figure 5: Robot Used For Data Collection

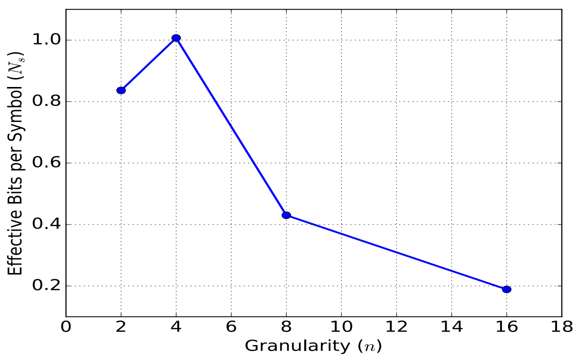

Figure 6: Channel Performance for RSSI Based Location Signaling Using Parity Bit Channel Coding and Real Measurements

5.3 RSSI Based Localization Emulation

In the previous section, we presented a simulation based analysis of a passive RF localization schemes. However, most common architecture in RF localization are based on active radio transmission from the robot. To explore another part of the RF based localization spectrum, in this section, we present an example of LOCO channel where we assume that the robot has a beacon module dedicated to localization only. Now, the channel formulation will be mostly same as the formulation in Section 5.2 with the Eqn. 10 modified as

$$P_r^i|_{\text{dBm}} = P_t^i|_{\text{dBm}} + K|_{\text{dB}} - 10\eta \log_{10}\left[\frac{d_i}{d_0}\right] + W_i|_{\text{dB}} \qquad (11)$$

To analyze the performance, we perform a set of emulations that incorporate RSSI traces collected from an indoor environment. We used a a generic robot, illustrated in Figure 5 with an OpenMote [8] placed on top of it and a standalone OpenMote for the data collection purpose. We statically place the devices at $d \in \mathcal{D} = \{0.5\text{m}, 1\text{m}, 1.5\text{m}, 2\text{m}, 2.5\text{m}, 3\text{m}, 4\text{m}, 5\text{m}, 6\text{m}\}$ distance apart to collect 1000 sets of RSSI samples in an indoor environment. To estimate the RSSI for a random distance $d \in \mathbb{R}^+$, first, we find the distance $d_{near} \in \mathcal{D}$ such that $d_{near} = \arg\min_{d_i \in \mathcal{D}} |d_i - d|$. Next, we randomly select one sample, say r^s, from the set of 1000 samples for d_{near} to interpolate the RSSI as follows.

$$r^e|_{\text{dBm}} = r^s|_{\text{dBm}} - 10 \times \eta \times \log_{10}(d/d_{near}) + W|_{\text{dB}} \qquad (12)$$

where r^e is the interpolated RSSI value for configuration $\mathcal{C}$.

The measured value of the path loss exponent is this context is 1.8076. Note that, we add an extra noise of variance $\sigma_r^2 = 2$, on top of the noisy samples (with $\sigma_r^2 \approx 5$). We use this RSSI interpolation method to generate the RSSI values observed by each of the stations, for each possible location of the robot. For this set of experiments, we consider a $6\text{m} \times 6\text{m}$ localization arena. The grid formulation as well as the access point placements are kept same as discussed in Section 5.2. With this setup, we compare the channel performance in terms of effective bits per symbol (refer to Eqn. 8) for varying the grid granularity (n). The evaluation results, illustrated in Figure 6, shows similar results as in Section 5.2, i.e., there exists a threshold of granularity beyond which a denser constellation hinders performance due to the noise.

6 Conclusion

In this paper, we proposed a novel communication scheme, LOCO, for robots to communicate with a remote control station. We investigated its feasibility using existing localization schemes, and demonstrated the channel performance based on simulation and emulation experiments with real world data. While this work provides a proof of concept, further investigations are required, firstly, to characterize the channel performance under general settings, for instance by including the movement patterns and constraints imposed by terrains into our communication model; secondly, to perform a set of real-world experiments to analyze the effect of the robots movement constraints such as speed on the throughput.

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