Relative Bearing Estimation from Commodity Radios

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Abstract-Relative bearing between robots is important in applications like pursuit-evasion [11] and SLAM [7]. This is also true in in sensor networks, where the bearing of one sensor node relative to another has been used for localization [5], [17], [20] and topology control [13], [22], [6]. Most systems use dedicated sensors like an IR array or a camera to obtain relative bearing. We study the use of radio signal strength (RSS) in commodity radios for obtaining relative bearing. We show that by using the robot's mobility, commodity radios can be used to obtain coarse relative bearing. This measurement can be used for a suite of applications that do not require very precise bearing measurement. We analyze signal strength variations in simulation and experiment. We also show an algorithm that uses this coarse bearing computation in a practical setting.

I. INTRODUCTION

Along with ranging, *relative bearing* is useful for solving a variety of problems in robotics like pursuitevasion[11], formation control[18], localization[5] [17], SLAM[7], and navigation[3]. Similarly in wireless sensor networks the bearing of one node relative to another has been used for localization[20] [4] [21] and topology control [13] [22]. Most of these systems use dedicated sensors for calculating bearing (typically IR, laser rangefinders or cameras). In this work we attempt to do away with the requirement of having a specialized sensor for bearing calculation; instead we use commodity radios and exploit robot mobility for computing relative bearing. We advocate our method for coarse bearing estimation (on the order of 20°) and show experimental results that substantiate this claim.

II. RELATED WORK

Bearing has been used on a variety of platforms ([16], [19], [24]) for a suite of applications. The common sensors used for bearing estimation are vision, IR and sonar. Each of these sensors has its own advantages and disadvantages. Numerous robotic algorithms use vision to compute bearing. [10] solves the problem of pose estimation cast as a estimation problem that estimates the translation and rotation relationship between two coordinate frames given a rigid body motion of the

sensor, the object, or both. The point data is an input from either a laser scanner or a camera. The proposed solution is a globally convergent iterative technique. [1] propose a linear set of solutions for both points and lines.

In sensor networks, many sensor nodes have been equipped with special sensors that could be used to estimate bearing. The Medusa nodes [27] and cricket nodes [24] have ultrasonic arrays that are mainly used for ranging but can also be used to compute relative bearing. Bearing has been used in wireless networking literature for localization [20] and topology control [13], [22].

Large-scale fading effects of radios have been used in various other applications. [14] attempt to use local movements to position the robot at the best reception position by sampling the signal strength locally. They also give lower bounds on the number of samples to be collected and some traversals to obtain the samples.

Signal strength has been used for localization in a variety of settings. The RADAR system [2] uses signal strength information to locate users in the building using access points in the environment. [29] use a signal strength map and a model of WiFi signal strength to localize a robot with a standard Monte-Carlo algorithm. [9] use Gaussian processes to generate a likelihood model for signal strength measurements and use the model for localization. [8] uses a Gaussian process-latent variable model to label unlabeled signal strength data and use a motion dynamics model with it to determine the topological graph and efficient localization.

III. COMPUTING RELATIVE BEARING ANGLE

Our objective is to use commodity radios and robot mobility to compute coarse relative bearing. We experimentally study two radios - 802.11b (WiFi) and 802.15.4 (Zigbee). Both operate on 2.4 GHz.

A. Radio Fundamentals

Radio signal fading can be attributed to three mutually independent phenomena. We briefly list these phenomena for better understanding of our method. For further details, the reader is referred to [28].

• **Multipath propagation** is a *small-scale effect* when the distance scales involved are on order of a wavelength. Multipath is caused by interference of the main(line of sight) and reflected component.

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The interference has either a constructive or destructive effect on the main component depending on whether it arrives in phase or out of phase. By making very minor variations (order of wavelength) between transmitter and receiver, this property can be used to understand the positioning of the two radios. This property is also called *Fast fading*.

• **Path loss** is the *large-scale effect* of propagation in any medium (like air or water). This is mainly because of the way the radio energy is transmitted in the medium of propagation and how much loss it endures. This property is also called *Slow fading*.

There are numerous radio propagation models that have been proposed in literature based on the models of fading they account for. We consider three popular models from literature. The free space loss is an idealistic loss model that considers the loss of signal strength resulting from line of sight transmission in free space. The Log-distance model and the ITU indoor model are more realistic and model multipath effects that occur in buildings and other similar dense areas.

Free space loss models the received power as the 3D spread.

$$Loss_{dB} = P_t - P_r = 20\log_{10}(d) + 20\log_{10}(f) + 32.44$$
(1)

where P_r is the received power, P_t is the transmit power, f is the frequency of transmission in MH_z and d is the distance between the transmitter and receiver in km. This model does not consider the medium of transmission or obstacles in the environment.

Indoor propagation is better modeled using the **log-distance path** loss model.

$$L = L_0 + 10\gamma \log_{10}(d/d_0) + X_g$$
(2)

where L_0 is the path loss at the distance d_0 and X_g is a Gaussian random variable with zero mean and standard deviation σ that stands for shadow/slow fading.

Another popular model to represent indoor radio transmission is the **ITU Indoor model**.

$$L_{dB} = 20\log_{10} f + N\log_{10} d + Lf(n) - 28 \qquad (3)$$

where L_{dB} is the total path loss in dB, f is the frequency of transmission in MHz, d is the distance between transmitter and receiver in m, N is the power loss coefficient and Lf(n) is the floor penetration factor. The constants N and Lf(n) are modeled in detail in [28]. We use suitable values from [28] for our simulations and analysis.

B. Algorithm

Our objective is for a robot to find the relative bearing of its neighbors. The principle is to sample the signal strength in the local neighborhood of the robot and identify the signal strength *gradient*. The robot that wants to



Fig. 1: Pattern of signal strength sampling

compute relative bearing starts by sending a message to all its neighbors to start transmitting. On receiving this message, all its neighbors start sending beacon messages periodically (every 10ms). The robot then travels a small distance (the step size of our algorithm) and samples the received signal strength a given number of times (100 in our experiments). The robot returns to its original position by reversing. It then turns in place 45° anticlockwise and repeats. It does this eight times until it returns to the original spot. The sampling is done according to the pattern shown in Fig. 1.

Principal component analysis (PCA) is then performed on this sampled data. PCA is a linear transform that transforms the data to align the greatest variance along the first coordinate, the second greatest variance along the second coordinate and so on. If we assume monotonicity and symmetry of signal strength decay from the transmitter, the first coordinate of the PCA (the direction of greatest variance) is the relative bearing of the source. This is the value we seek to estimate.

C. Step distance

One of the main parameters in the above description is the step size that the robot moves. This is an important parameter since the signal strength decay is subject to the environment the robots are in. If there is not enough signal strength difference between three collinear sampled points, our bearing calculation can be arbitrarily poor.

Let us consider the Log-Distance model. Using values from our sample data collection indoors, $d_0 = 3.1$, $L_0 =$ 9dB, L = 20dB, $\sigma = 3$ and inverting for step distance that causes a 20dB drop (*L*) we obtain a step size of approximately 2*m*. Similarly, outdoors we get a step size of approximately 5*m*. These results are for WiFi radios. We also collected data from 802.15.4 radios. Inverting them resulted in similar step sizes - 1.5 *m* indoors and approximately 3 *m* outdoors.



Fig. 2: Sample robot configuration

IV. SIMULATION

A. Simulation Setup

We studied the three radio fading models for a variety of step distance sizes and different noise variances to understand how the the estimated bearing error varies. Presented below are the results from the simulations. We performed hundred trials for each setting. Each trial places the two robots randomly within a square area of side 20 m.

Figures 2, 3, 4 show a sample trial in simulation.Fig. 2 shows the initial robot placement and the sampling pattern that the robot will follow.Fig. 3 shows the RF field according to the log-distance model. Fig. 4 shows the bearing computation in this case and the actual bearing. For this particular trial the computation is off by about 21.31° .

In Figs. 5(a),5(b),5(c) we vary the step distance from 1 *m* to 20 *m* with the standard deviation of error 5 *dB* and taking hundred samples at each point. As we would expect, increase in step distance decreases the bearing error. The error variance tapers off close to 5 *m* in most cases agreeing with our analysis above. Figs. 6(a),6(b),6(c) show the effect of number of samples collected at each point on the bearing error. The number of samples is varied from 10 to 1000 with standard deviation of error 5 *dB* and step distance 5 *m*. It can be seen that increase in number of samples reduces bearing error. From simulation results, we conclude that 100 is a reasonable number for the number of samples to be collected at each point. This is the number used in all



Fig. 3: Signal strength contours and sampling pattern



Fig. 4: Computed bearing for the sample case



Fig. 5: Effect of step distance

Fig. 6: Effect of number of samples

our experiments.

In Figs. 7(a),7(b),7(c) The standard deviation is varied from 1 to 10 *dB* keeping the number of samples at 100 and the step distance at 5 *m*. As would be expected, increase in error increases the bearing error. However, we note that in practice the observed error standard deviation at a given point is around 5 *dB*. For such error in signal strength, the bearing error is is under 10° . Thus our predictions from simulation are promising.

V. EXPERIMENTS

We ran numerous trials outdoors in practice to determine the accuracy of the bearing computation. We collected hundred samples at each sample point. While the focus of this paper is simply on obtaining relative bearing information, in parallel work we have used this information to build biconnected robot networks. As an example of the usage of bearing information we show the biconnectivity algorithm here. The experimental work is done using the Create platform (Fig. 8) from iRobot which is fitted with the e-box 3854, an 800 MHz PC with an EMP-8602 mini PCI 802.11 a/b/g card (WiFi). We raised the antennas as shown in Fig. 8 to alleviate multipath effects from the ground. We also connect a telos mote [23] to the e-box for a 802.15.4 (Zigbee) radio. Our testbed is similar to the MADNeT [25] and SmURV [26] robot testbeds.

Shown in Fig. 9(a) is the effect of step distance on bearing error for both WiFi and Zigbee radios outdoors. We performed three trials with the robots to measure the bearing error and variance. The bearing error is higher than the simulations because the RSS error is not perfectly Gaussian as assumed. The other observation is that the Zigbee radios perform better consistently than the WiFi radios. This is explained by the fact that the Zigbee radios are much simpler than WiFi. Their signal strength gradient is much more pronounced than WiFi. WiFi has many non-linearities in its physical layer and hence its signal strength gradient is not as pronounced or symmetric.

Fig. 9(b) shows the effect of step distance indoors. The behavior is similar to the tests outdoors and increase in step distance results in decrease in bearing error in general. However, at the largest step distance the bearing error goes up. This is because we approach a glass door in one direction. This results in a lot of reflection (and higher receive signal strength) which corrupt the signal strength gradient and consequently the bearing estimate. Such problems can be solved either with *a priori* knowledge of the map of the robot's surroundings or by doing some higher level inferencing by integrating odometry.



(a) Effect of noise in RSS - Free space model









Fig. 7: Effect of ambient noise



Fig. 8: Create fitted with raised antenna

TABLE I: Angles computed for four node network

		Trial 1		Trial 2	
Edge	Actual	Measured	Bearing	Measured	bearing
	angle	angle(T1)	error(T1)	angle(T2)	error(T2)
1	-60°	-45.7°	14.3°	-52.8°	7.2°
2	45°	28.3°	16.7°	58.2°	13.2°
3	135°	162.43°	28.57°	158.93°	23.93°
1^{1}	90°	65.68°	24.32°	109.58°	29.58°

A. Sample application

We show an example application of this bearing estimate in a real setting. In parallel work, [6] we proposed an algorithm to achieve biconnectivity in a robot network starting from a connected network by using relative bearing measurements and mobility. We use the mote radios for the bearing computation for experiments with this algorithm. We performed two sets of two trials each; one with four nodes and another with five nodes. Shown below in Table. I, II are results from the trials. The average bearing error in the four node experiments was 20.97° and 5 node experiments was 18.65° .



(a) Bearing error - outdoors



(b) Bearing error - indoors

Fig. 9: Bearing error in real world

TABLE II: Angles computed for 5-node network

		Trial 1		Trial 2	
Edge	Actual	Measured	Bearing	Measured	bearing
	angle	angle(T1)	error(T1)	angle(T2)	error(T2)
1	120°	103.7°	12.3°	94.9°	25.1°
2	135°	104.8°	30.2°	147.4°	12.4°
3	45°	58.8°	13.8°	49.7°	4.7°
1 ¹	-30°	-11.8°	18.2°	-36.2°	6.2°
4	-150°	-130.7°	19.3°	112.8°	37.2°
41	0°	25.8°	25.8°	-18.6°	18.6°

VI. CONCLUSIONS

We present a way of computing relative bearing from commodity radios that makes use of robot mobility. We systematically study the parameters that affect the accuracy of the bearing estimate in simulation and on a physical testbed with two radios. We also show a sample application of this bearing computation suggesting that our bearing computation can be useful for a class of applications that do not need high precision.

We have used the large-scale fading effects and robot mobility to compute bearing. Radios also exhibit smallscale effects that can be taken advantage of to perform bearing computation. Movements of very small distance in space (order of one wavelength) or in time (frequency shifts) can help us determine the line of sight direction of reception. Such techniques have been used for ranging/localization [15] and tracking of mobile nodes [12]. We intend to explore the use of similar techniques for accurate bearing computation in the future.

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 $^1\mathrm{The}$ repeated edge is for bearing calculated by the other node of the edge

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