

## Experimental Results in Range-Only Localization with Radio

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### Abstract

*We present an early experimental result toward solving the localization problem with range-only sensors. We perform an experiment in which a mobile robot localizes using dead reckoning and range measurements to stationary radio-frequency beacons in its environment, incorporating the range measurements into the position estimate using a Kalman filter. This data set involves over 20,000 range readings to surveyed beacons while a robot moved continuously over a path for nearly 1 hour. Careful groundtruth accurate to a few centimeters was recorded during this motion. We show the improvement of the robot's position estimate over dead reckoning even when the range readings are very noisy. We extend this approach to the problem of simultaneous localization and mapping (SLAM), localizing both the robot and tag positions from noisy initial estimates. Finally, we discuss how our methods will be extended in future research.*

### 1 Introduction

The ability to solve the problem of robot localization efficiently will have a tremendous impact on the ways in which robots can be integrated with daily living. Many tasks for which robots are seemingly well-suited require a high level of precision in localization before such application can occur in the field. For example, a robot delivering mail in an office building, moving plants in a greenhouse, or mapping an underground mine needs to maintain an accurate estimate of its location. One solution to the problem of localization is to obtain absolute position coordinates via the Global Positioning System (GPS), which uses the location of satellites orbiting Earth to triangulate longitude and latitude. This approach is limited, however, to environments in which a clear line of sight to the satellites is available. Robots navigating inside buildings or underground cannot receive GPS data, and even in outdoor environments structures and even foliage can affect the ability to communicate with GPS satellites.

Another common localization technique is deduced reckoning (dead reckoning), in which the robot's posi-

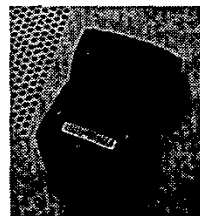


Fig. 1: A radio tag, approximately 12 x 9 cm in size, with which our robot can communicate to obtain range data. Such tags can be placed throughout the robot's environment.

tion is estimated based on measurements of distance travelled and orientation taken from wheel encoders and gyros. Since the dead reckoning position estimate accumulates error over time, a robot must correct position error based on data collected from exteroceptive sensors – for example, landmarks can be visually identified with a camera or detected using sonar or laser scanning. A problem that frequently arises in these forms of landmark identification is that of data association: sensed data must be associated with the correct landmark, even though multiple landmarks may have similar features. Additionally, in many settings it is not possible to guarantee line of sight to the landmarks.

The method of sensing we choose involves an infrastructure of low-cost, low-power, radio frequency tags (Fig. 1, referred to as RF tags or beacons in this paper) placed throughout the workspace. Originally intended as a means to track assets and people in an environment equipped with special RF transponders [13], we invert the paradigm by fixing the tags in the environment and moving a transponder with a robot. In this paradigm, as the robot moves, it periodically sends out a query, and any tags within range respond by sending a reply. The robot can then estimate the distance to each responding tag by determining the time lapsed between sending the query and receiving the response. The advantage of such a method is that it does not require line of sight between tags and the mobile robot, making it useful in many environmental conditions that fail optical methods. Note that, since each tag transmits

a unique ID number, distance readings are automatically associated with the appropriate tags, so the data association problem is solved trivially.

We would like to send a mobile robot into an environment containing these tags at known locations and have it navigate successfully while maintaining a reliable estimate of its location at all times. To achieve this, we combine range measurements with dead reckoning data via a Kalman filter [6, 14] to estimate the robot's position.

In this paper, we discuss one experiment, consisting of two data sets, in its entirety. With a standard deviation of 1.55 meters in the range measurement error, we achieve an average localization error of less than 0.35 meters over an 18 minute traverse and 0.38 meters over a 33 minute traverse, travelling a total of over 2.3 km.

Data collection for our experiment is discussed in Section 3, and a characterization of the errors is given in Section 4. Section 5 discusses how we process the data with Kalman filtering and characterize the error in the range data, and Section 6 explains how we extend this method to the SLAM problem given noisy initial estimates of the beacon locations. We give results in Section 7 and discuss future work in Section 8.

## 2 Related Work

Most landmark-based localization systems use sensors that measure relative bearing or in some cases both range and bearing to distinct features in the environment. In the case that the location of these landmarks is unknown, the problem is more difficult and is generally called Simultaneous Localization and Mapping (SLAM) [9, 3]. Here we report on localization results with a modality in which only range to known landmarks (RF tags) is measured. Some other researchers have used range to estimate position. In most cases, instead of using range, signal strength from a known transmitter is used to produce a "pseudorange" that is then used for triangulation.

For instance, the Cricket System [10] uses fixed ultrasound emitters and embedded receivers in the object being located. Radio frequency signals are used to synchronize time measurements and to reject multipath readings. The localization technique is based on triangulation relative to the beacons. The RADAR system [1] uses 802.11b wireless networking for localization. This system uses the signal strength of each packet to localize a laptop. RADAR uses nearest neighbor heuristics to achieve localization accuracy of about 3 meters. The SpotOn system [5], uses radio signal attenuation to estimate distance between tags. The system localizes wireless devices relative to one another, rather than to fixed base stations, allowing for ad-hoc localization. Note that GPS also works by triangulating ranges to multiple satellites. In some cases, GPS localization is augmented with inertial measurement and/or

dead reckoning. In almost all such systems, GPS triangulation generally develops an estimate of position as well as uncertainty that is merged with a position estimate from dead reckoning. Other methods choose to train on patterns of signal strength to localize. For example, Ladd et al propose a Bayesian formulation to localize based on signal strength patterns from fixed receivers [8].

In contrast, we use a single filter to combine range measurements with dead reckoning and inertial measurements. While the range measurements are noisy and exhibit biases, we find that treatment by an extended Kalman filter—necessary because the underlying system is non-linear—after preprocessing to remove outliers and to remove systematic biases, suffices.

Originally introduced in 1960, the Kalman filter assumes a multivariate Gaussian distribution [6]. The Kalman filter has the advantage that the representation of the distribution is compact; a Gaussian distribution can be represented by a mean and a covariance matrix. Consequently, several robot localization systems have been based on Kalman filtering [9]. The robot's pose estimation is maintained as a Gaussian distribution and sensor data from dead reckoning and landmark observations is fused to obtain a new position distribution.

Recent extensions of Kalman filtering allow for non-Gaussian, multimodal probability distributions through multiple hypothesis tracking. The result is a more versatile estimation technique that still preserves many of the computational advantages of the Kalman filter. Monte Carlo localization, or particle filtering, provides a method of representing multimodal distributions for position estimation [4, 12], with the advantage that the computational requirements can be scaled. The main advantage of these methods is their ability to recover robustly from a poor initial condition.

We chose the Kalman filter as a first implementation of range-only localization specifically with the intention of extending this method to approach the SLAM problem. (For results from this extension, see Sections 6 and 7.) Previously, we reported a suite of algorithms to perform localization from range measurements and showed an extension that is able to deal with the case where the beacons are uncertain to start [7, 11]. Here we extend the results reported from simulation for an omnidirectional vehicle to the case of a conventionally steered vehicle, with data collected from a real vehicle.

## 3 Data Collection

Data for this experiment was collected by an instrumented autonomous robot with highly accurate (2 cm) positioning for ground truth using RTK GPS receivers as well as a fiber optic gyro and wheel encoders. Position is updated at 100 Hz. We model the error in the wheel encoders and gyro as zero mean, Gaussian

error with a standard deviation of  $\sigma_{encoder} = 0.001$  meters/meter travelled and  $\sigma_{gyro} = 1e-7$  radians/second.

We equipped this robot with antennae pointing in four directions and a computer to control the tag queries and process responses. For each tag response, the system produces a time-stamped integer estimate of the distance (in feet) to the responding tag, along with the unique ID number for that tag. For experimentation, the RF tags are placed on the ground on polystyrene cups about four inches high to avoid signal attenuation from the Earth.

The localization experiment was conducted on a flat, grassy area about 30 meters by 40 meters in size. We placed 13 RF tags at surveyed locations throughout the area, then programmed the robot to drive in a repeating path among the tags. The tag positions and robot path from ground truth (GPS + INS) are shown in Figure 5a; four of the thirteen RF tags inexplicably gave no measurements throughout the duration of our experiments, so they are ignored. With this setup, we collected three kinds of data: (1) the ground truth path of the robot from GPS and inertial sensors, (2) the dead reckoning estimated path of the robot from inertial sensors only, and (3) the range measurements to the RF tags. We ran two tests, one for 18.73 minutes (referred to here as Test 1) and a second for 33.31 minutes (Test 2); in both tests the robot traverses the same repeating path, continuously collecting data.

Because of the errors in odometry, the dead reckoning path estimate tends to drift away from the true path over time (Fig. 5b). By applying a Kalman filter, we will use distance readings from the RF tags, whose error does not drift over time, to improve this dead reckoning estimate.

#### 4 Range Noise Characterization

Our results with Kalman filtering require an understanding of the characteristics of the noise present in ranges reported by the radio tags. We gain this by looking at the probability distribution functions for each tag measurement.

We obtain the PDFs as follows: for every reported measurement, we find the true range to the robot when that distance was reported using the ground truth position data. We then compile all the true distances corresponding to a particular measurement value and store the mean and variance of this list. We use data from both experimental runs to compile the PDFs. Since we assume that the error in the tags is Gaussian, storing the mean and variance equates to storing the PDF for each measurement (Figure 2).

Figures 3 and 4 plot the mean and variance, respectively, for each measurement as a function of the measured ranges. Figure 3 shows that the means associated with measurements below 10 ft and above 70 ft vary erratically, when, if the readings were more accurate, they

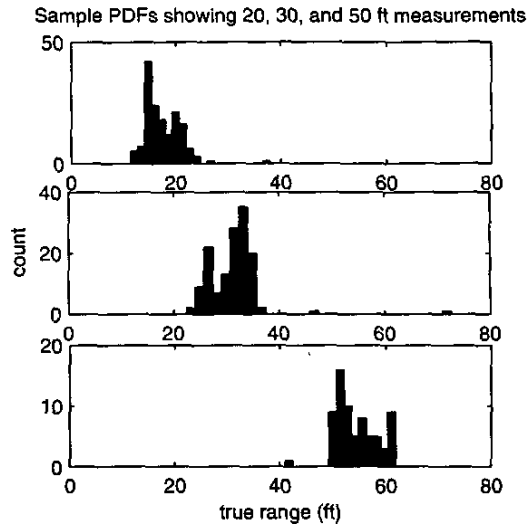


Fig. 2: Sample PDFs showing the true ranges associated with 20, 30, and 50 ft measured ranges. Under the Gaussian noise assumption, it is sufficient to store only the mean and variance of each distribution for use in the Kalman filter.

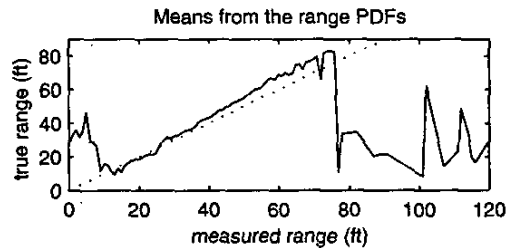


Fig. 3: The mean true distances to RF tags vs. measured distances

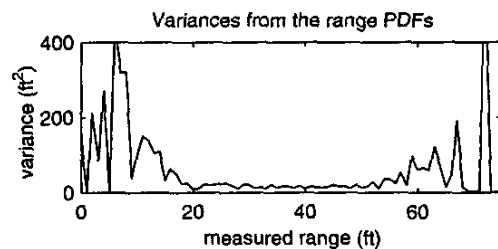


Fig. 4: The variance in true distances to RF tags vs. measured distances

would be following an upward trend on the line  $y = x$ . Similarly, Figure 4 shows that the variance values for measurements below 10 and above 70 ft are either very large or unbelievably small. These observations lead us to distrust tag measurements less than 10 ft or greater than 70 ft, so we can improve the localization results by simply ignoring such readings. The average standard deviation of measurements between 10 and 70 ft is 5.4 ft.

Since erroneous measurements can still occur among the measurements in the 10-70 ft range, we also imple-

ment a measurement validation gate. The further the robot has travelled without receiving an absolute measurement from the RF tags, the more likely it will be to accept a measurement that seems erroneous. However, if an absolute measurement has recently been incorporated into the state estimate, the gate will disallow a wild measurement. Using a method described in [2], we compute the normalized innovation squared for each measurement and reject the measurement if this value is outside the gating values, which are looked up from a chi-square distribution table.

## 5 Localization Algorithm

The dynamics of the wheeled robot used in this experiment are well-modeled by the following set of nonlinear equations:

$$q(k+1) = \begin{bmatrix} x_k + \Delta D_k \cos(\theta_k) \\ y_k + \Delta D_k \sin(\theta_k) \\ \theta_k + \Delta \theta_k \end{bmatrix} + v(k) \triangleq f(q) + v(k)$$

with measurements modeled by:

$$y(k) = \begin{bmatrix} \sqrt{(x_b - x_k)^2 + (y_b - y_k)^2} \\ \theta_k - \theta_{k-1} \end{bmatrix} + w(k) \\ = \begin{bmatrix} r_k \\ \Delta D_k \\ \Delta \theta_k \end{bmatrix} + w(k) \\ \triangleq h(q) + w(k)$$

where,

- $q(k)$  = the robot state at time  $k = [x_k, y_k, \theta_k]^T$
- $x_k, y_k,$  and  $\theta_k$  are the robot's position and orientation at time  $k$ ,
- $\Delta D_k$  is the odometric distance travelled,  $\Delta \theta_k$  is the change in heading,  $r_k$  is the range measurement received at time  $k$ , and
- $(x_b, y_b)$  is the location of the beacon from which a measurement is received.

To apply the extended Kalman filtering algorithm, we linearize these equations about the current state estimate discrete time system of the form:

$$q(k+1) = A(k)q(k) + v(k) \quad (1)$$

$$y(k) = H(k)q(k) + w(k) \quad (2)$$

where,

$$A(k) = \frac{\partial f}{\partial q_k} \Big|_{q=\hat{q}} \quad (3)$$

and

$$H(k) = \frac{\partial h}{\partial q_k} \Big|_{q=\hat{q}} \quad (4)$$

We now apply standard extended Kalman filtering to fuse the measurements and predict the state and covariance of the system at each timestep. We begin the algorithm with the robot's initial position 7.8 m away from the true position and the initial heading off by 45 degrees, illustrating the Kalman filter's ability to recover from initial errors within certain bounds. Since the robot receives nonlinear range measurements which must be linearized, the filter *will* diverge if the initial condition is not relatively close to true; fortunately, having a fairly good initial estimate is a reasonable assumption for many real-world applications.

## 6 SLAM

The Kalman filter approach described in Section 5 can be reformulated for the SLAM problem. To perform SLAM, we include position estimates for each tag in the state, producing a state vector of the form:

$$q(k) = [x_k, y_k, \theta_k, x_{b_1}, y_{b_1}, \dots, x_{b_n}, y_{b_n}]^T,$$

where  $n$  is the number of beacons.

For experimentation, we initialize the beacon locations by adding noise with a 3m standard deviation to the true tag locations and use the variance of that noise for the initial diagonal terms of the covariance matrix, which describes the uncertainty and correlation of the terms in the state estimate. As measurements are obtained, the tag locations converge to their true locations, just as the robot poses are updated (Fig. 7). Results from performing SLAM in this manner are given in Section 7.

However, when the same initial noisy tag locations are used with Test 2, our SLAM technique fails to converge. Since the Kalman filter uses a linearization of the nonlinear range measurements, if the linearized estimate is too far away from the truth, the filter may be unable to recover and will diverge. The fact that this occurs in one of our experiments motivates the use of nonlinear techniques such as a Variable Dimension Filter, since these techniques do not require such a good initial estimate. We discuss the potential of the VDF in Section 8.

## 7 Results

For both of the tests mentioned in Section 3, we filtered the tag data for outliers as described in Section 4 and processed the remaining data with the Kalman filter. The resulting path for Test 1 is plotted in Figure 5c, with ground truth and dead reckoning also plotted for comparison.

Numerically, we can evaluate the performance of the dead reckoning and Kalman filter localization methods by considering the cross-track error (XTE). That is, for each pose we measure how far left or right of the true position our estimation is, orthogonal to the true

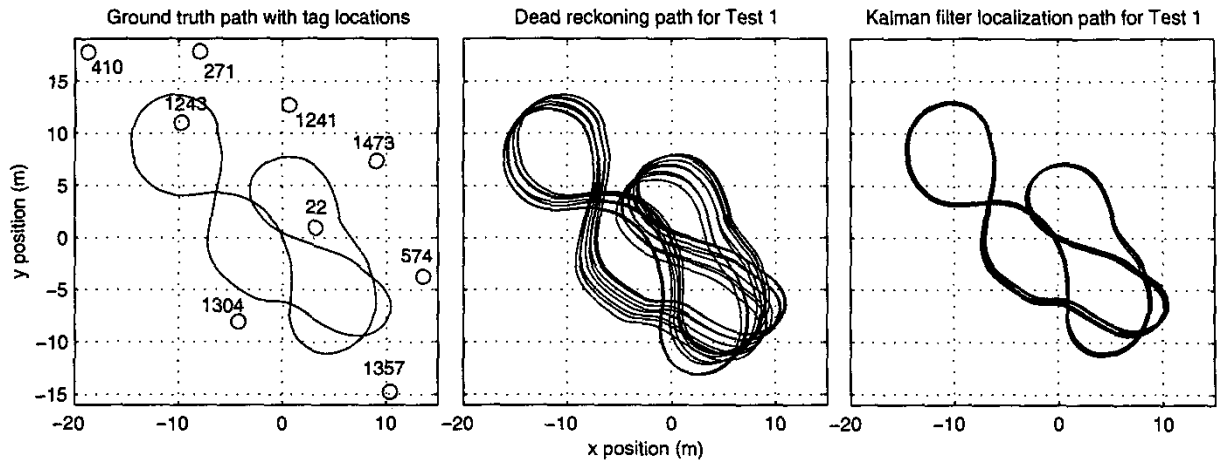


Fig. 5: (1) The ground truth path with tags indicated by circles. The numbers indicate how many range measurements were received from each tag over the duration of Test 1. (2) The path estimate from dead reckoning alone. (3) The path estimate from localization using a Kalman filter. The filter fuses data from odometry and a gyro with absolute measurements from RF tags to produce this path estimate. Numerical results are given in Table 1.

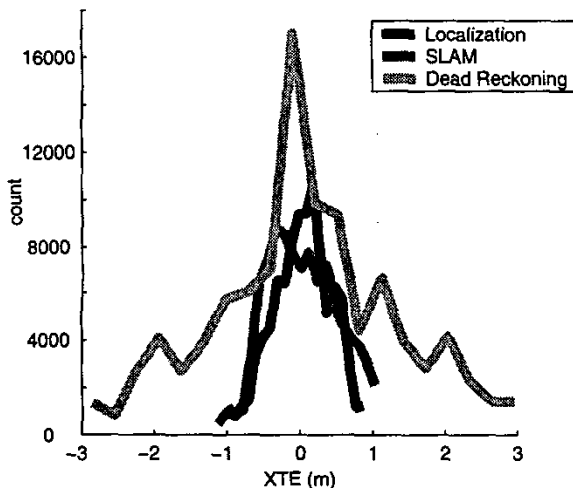


Fig. 6: This plot compares the histograms of cross-track error in the dead reckoning, localization, and SLAM path estimates for Test 1.

heading. We compile these errors for every point along the path, then find the maximum value along with the mean and standard deviation of the errors to produce the evaluative statistics in Table 1.

## 8 Future Work

Through Kalman filtering, we have improved the accuracy of our robot's localization using a low cost artificial infrastructure of radio tags. We have also made a first step toward SLAM with range-only measurements, and we have produced a valuable data set that will be

very useful in testing and comparing future algorithms.

More sophisticated algorithms exist which could improve our localization results, including particle filtering, batch optimization, and variable dimension filtering. We are currently developing a batch localization method, which considers all the data collected by the robot and finds the best path estimate given all the data. Although time consuming computationally, this will produce the theoretically optimal result obtainable from the collected data; we can then evaluate the results of our online localization method by comparing to this optimal solution. Additionally, we will extend the batch method to produce a variable dimension filter, as used by Deans for the case of bearing-only sensors [3], which would consider some window of previous robot states and optimize the position estimates based on the data in that window. We are specifically working toward batch and VDF because we think they provide the most promise for being able to perform robust simultaneous localization and mapping with range-only sensors.

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	XTE Results			
	Dead Reckoning	Localization (Test 1)	SLAM (Test 1)	Localization (Test 2)
Max. error	3.1078 m	1.0520 m	1.1837 m	1.6777 m
Avg. error	0.8618 m	0.3233 m	0.4002 m	0.3712 m
Std. dev.	0.7847 m	0.2345 m	0.2628 m	0.2305 m

Table 1: Cross-track error in path estimates generated using dead reckoning, localization and SLAM techniques.

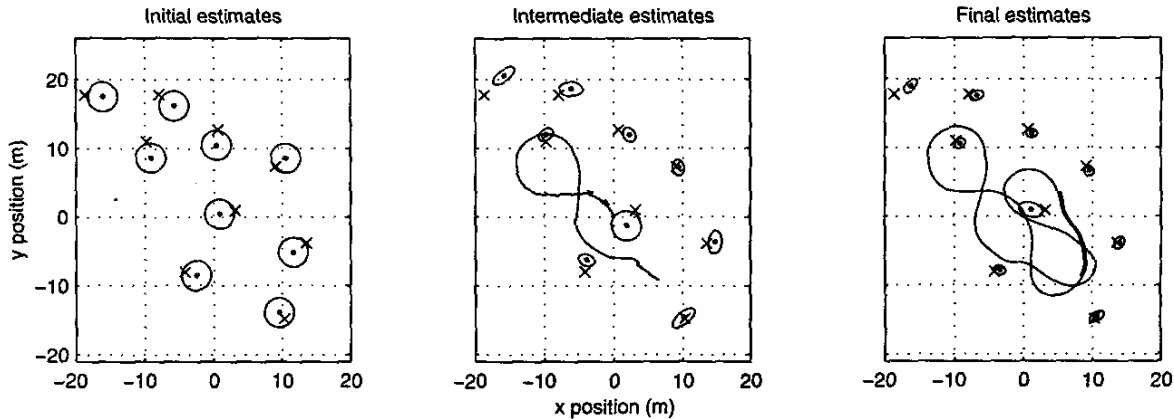


Fig. 7: SLAM on Test 1: The tag position estimates (shown as dots surrounded by uncertainty ellipses) converge toward the true tag positions (marked by x's). The initial placement error is random noise with a standard deviation of 3m. The ellipses indicate a region of 90% certainty in which the tag is believed to lie. They are initially circles, since the initial uncertainty is isotropic (the uncertainty matrix is initially diagonal, with zeros on the off-diagonals); as measurements are incorporated, the uncertainty matrix changes to form elliptical regions of certainty. The tags localize from an initial average Cartesian distance error of 2.06m to an error of 1.01m. The robot's initial position has an error of 1.4m, with a heading error of 23 degrees; compare the jaggedness of the early part of the path (middle) to the smooth path after convergence (right).

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