Low-Cost Localization of Mobile Robots Through Probabilistic Sensor Fusion

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Abstract

Efforts to achieve mobile robotic localization have relied on probabilistic techniques such as Kalman filtering or Monte Carlo localization (Thrun, et al.). These techniques often rely on the use of expensive lasers to provide accurate input data. While they provide accurate sensing, the lasers can cost in the range of thousands. In this paper, a method of wifi based localization for the purpose of inexpensive mobile robotic localization is presented.

1 Introduction

Recently, there have been many efforts to utilize large scale wi-fi network signals for the purpose of localization. Rather than achieving localization for select few robots through odometry and expensive laser rangefinders, this paper seeks to show whether low cost localization is feasible for any robotic application where laser information is not available.

The process of localization is divided into three phases. In the first, the robot simultaneously maps the environment and captures wireless data points from nearby access points. The readings include the access point's MAC ID, SSID, signal strength, and noise strength. This step utilizes the laser sensors to create an accurate map of the environment and the robot's pose in that map. The first step can be performed by any robot with an available laser sensor and is not required for the actual wifi-based localization.

Next, nearest neighbor lookups are utilized to provide likely poses based on the distance from capture points. For a given estimated pose, the lookup map provides the closest sensor reading location and provides a likelihood of the point belonging to that location based on the sensor model chosen.

Lastly, the robot is run once again in the same environment. While the motion model remains the same, the sensor model will come purely from wifi readings. At each predetermined time/motion step, the incoming wireless scans match against the lookup map and update the motion model poses according to the Monte Carlo particle filter update.

2 Theoretical Justification

2.1 Models

The heart of the state and measurement models come from the probabilistic evolution of the Bayesian network. At each time step: t, the current state/pose of the robot: x_t, only depends on the current input: u_t, and previous position: x_{t-1}. In addition, the current pose outputs a sensor reading: z_t. The final Bayes filter, presented by Thrun et. al, follows:

$$\mathrm{p}(x_t) = \eta p(z_t|x_t) \int p(x_t|x_{t-1}, u_{t-1}) p(x_{t-1}) dx_{t-1}$$

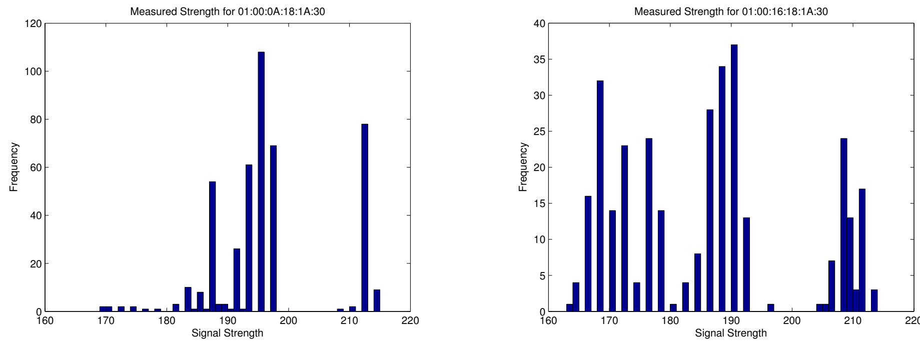

Figure 1: Signal Stength Frequency

Motion Model: $p(x_t|x_{t-1})$ The motion model is distributed according to a normal distribution with the robot error characteristics incorporated into the variances.

Sensor Model : It is common practice in literature to approximate the wireless signal intensities as normal distributions. By assuming a normal distribution for the difference in signal intensity for each access point, the signal's probability of being at a certain point can be approximated by a Gaussian with mean 0 and variance in signal strength (measured in dB), σ^2.

During training, however, the signal strengths often followed bimodal curves and sometimes even multimodal distributions as shown in figure 1. As such, the non-normal prior factored into both data capturing and testing. The signals were fitted to an augmented Normal distribution, P(z) = $\alpha e^{\frac{-d^2}{\sigma^2}}$, where d is the measured difference in signal strength, and α and σ^2 are chosen by experimental evaluation. To test for efficacy of different distributions, the signals were also fit to a normalized Laplacian distribution, Z $\sim \mathcal{L}(0, \beta)$, where β is also chosen experimentally.

3 Testing

The Videre Erratic mobile robot platform is used throughout this experiment. The robot's attached SICK LMS200 laser rangefinder scans at a high frequency with less than 5mm of (sigma) statistical error. While wifi-based localization can be shown to run in underpowered computing environments, the non-parametric nature of nearest neighbor lookup creates a linear dependency on the size of the dataset. While larger datasets increase accuracy, they also require greater computing power.

The wireless card used for these experiments is based off a Realtek 8187L chipset with support for a/b/g network standards.

The William Gates basement was chosen as the environment for testing. Wide availability of accesspoints, broad network thoroughput, and presence of large areas and narrow corriders proved ideal for testing the performance of localization. Testing was performed over a total distance of more than 50 meters at a speed of $.3m/s$.

4 Results

4.1 General

The optimal σ value, corresponding to the standard dev. of the dB drop in signal strength was chosen by setting all other variables constant and measuring the average error over a test run. As seen in figure 2, values that were too small limited the bandwidth of the wifi measurment update and thus its effectiveness. Large values had the opposite effect in that the filter included too many false positive readings.

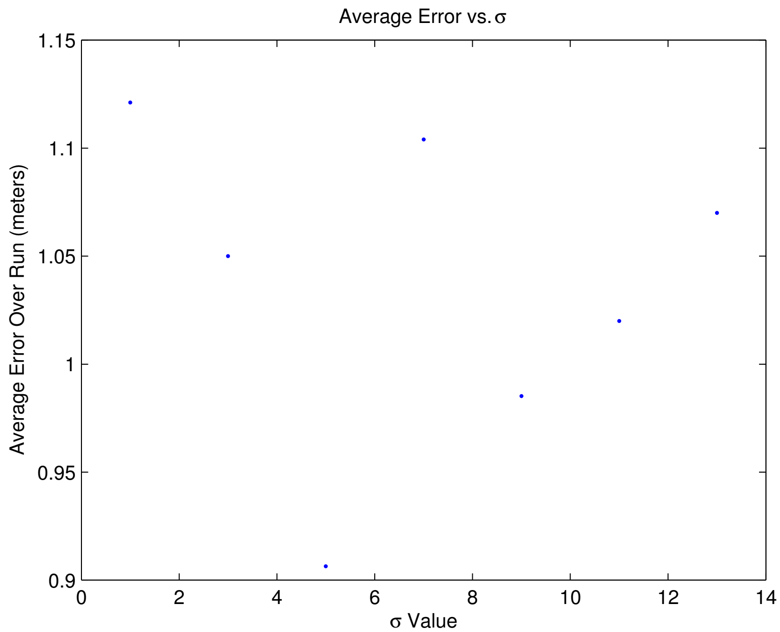

Figure 2: Comparison of σ value

Gaussian Model $\sigma = 5$		Laplacian Model	
α	Mean Error (meters)	β	Mean Error (meters)
.6	1.2464	1.0	1.0287
.4	1.0816	.7	.9562
.3	1.0072	.3	.9417
.1	.9064	.1	1.0300

Table 1: Mean Error

In order to determine an optimal model for the sensor measurements, tests were run comparing the mean error vs. coefficients for both Gaussian and Laplacian distributions, given an initial position estimate. As a matter of comparison, the mean error over the entire run for a motion model of the odometry was 1.3208 meters. In general, the Laplacian fitting performed consistently with Gaussian fittings. In addition, as shown in figure 3, the wifi-based localization performed remarkably well for both the Laplacian and Gauussian models. Locations where the error increased are most likely due to sampling from a different mode of the sensor distribution than the central mode.

4.2 Dataset Performance

Naturally, the use of nearest neighbor lookups implies greater localization accuracy with larger data sets. This generally held true in comparison. Smaller datasets with greater error meant that there were a general lack of data points around the vicinty. On the other hand, larger data sets with greater errors meant that the set contained incorrect readings for some of the sampled points. Therefore, the size of the data set did not matter as much as the uniformity of the captured locations and the mode of distribution with which the signals were chosen from.

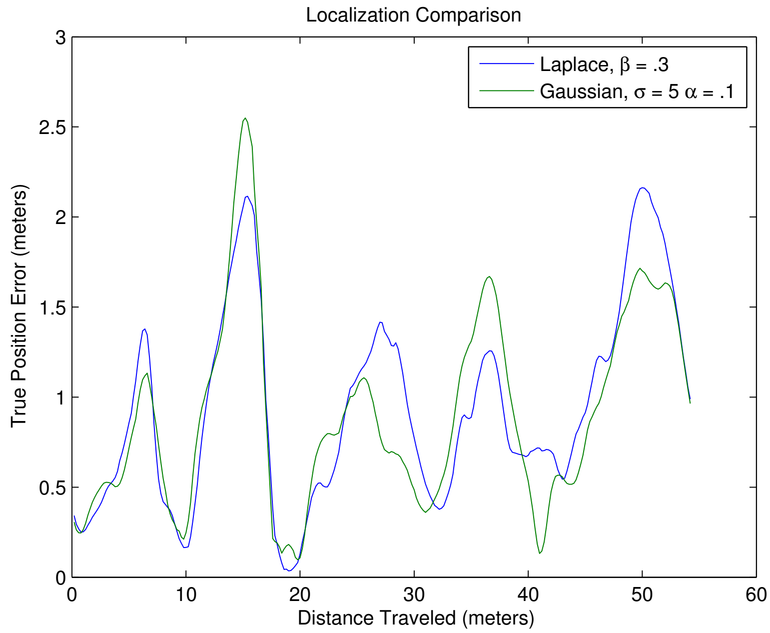

Figure 3: Error over distance given initial pose estimation

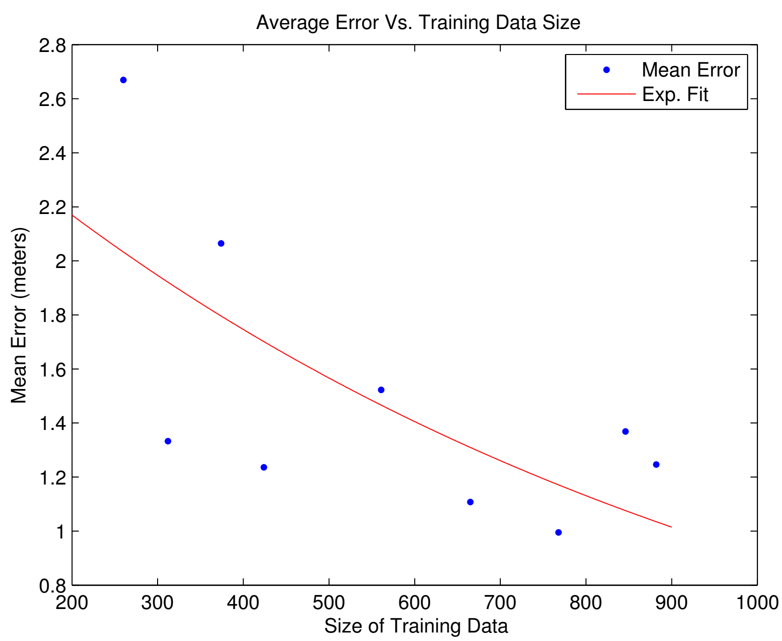

Figure 4: Gaussian Accuracy for Data Set Size, with $\alpha = .1$, and $\sigma = 5$

4.3 Global Localization

The strength of the wi-fi particle filter update comes into play during global localization. In experiments run with no prior estimation of the robot pose, the nearest neighbor filter was able to bring the robot

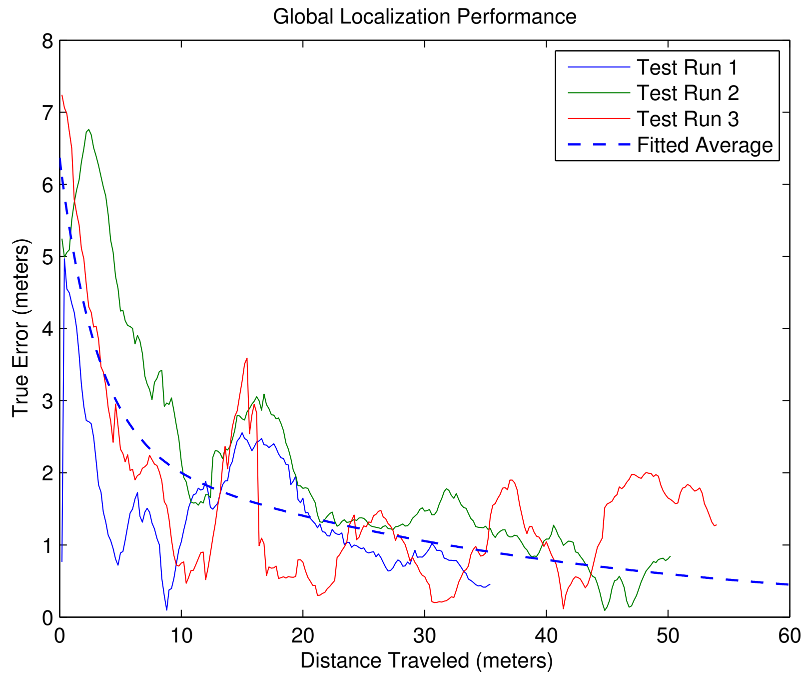

Figure 5: Global localization with Gaussian distribution, with $\alpha = .1, \sigma = 5$

to within an average of 1 meter away from the true robot position.

5 Conclusion

Wifi based localization is an effective method of tracking within an average of around 1 meter over a 50 meter run. The greatest asset is its ability to localize quickly in the case of global localization. It is pertinent to note that unlike laser localization, wifi lookup maps inherently cannot provide theta estimation. Future improvements would be to utilize LOWESS methods or gaussian processes in the sensor measurement update. Overall, for applications requiring meter-scale precision, wifi-based localization is an ideal low cost alternative to laser-based options.

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References

[1] S. Thrun, W. Burgard, D. Fox *Probabilistic Robotics* 2005: MIT Press.

[2] M. Quigley, D. Stavens, A. Coates, S. Thrun *Sub-Meter Indoor Localization in Unmodified Environments with Inexpensive Sensors* 2010: IROS.