Mobile Computing (CS23400/1)
Lab 2 - Report

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1 Task and Challenges

The goal of this lab is to identify the location of a Wi-Fi device by analyzing Received Signal Strength (RSS) data recorded by a Wi-Fi receiver mounted on a moving car. The main challenge in this lab is mitigating RSS noise. Another challenge is that while collecting data, our car would often turn on its own, which would make it difficult to determine the car's position from its starting point, stopping point, and speed. We do not address this last limitation in this lab.

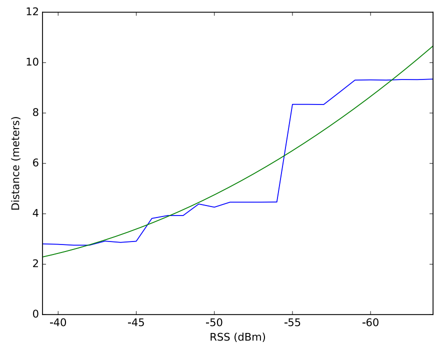


Figure 1: RSS-Distance relationship

2 Proposed Approach

For each RSS reading, we estimate the distance from the car to the Wi-Fi device and thus create a circular locus of possible locations around the car. The relationship between RSS and distance from the transmitter is modeled using a second order polynomial function. We fit this function to the data for which the distance from the transmitter is known (shown in Fig. 1).

As we collect multiple RSS readings from the moving car, we can create multiple loci whose intersection locates the position of the Wi-Fi device. By using the RSS and distance relationship we can draw a radius in which we know that the device location lies somewhere along that radius. In an ideal situation, we would only need 3 RSS readings from 3 different locations to localize a device. However, because of how noisy our data is, it is very hard to pinpoint the exact location of a device by looking for a single intersection from the RSS values. In order to get around this issue we propose using a simple particle filter to find regions that would most likely contain the device. We can begin by overlaying a grid over the space that the car has traveled and where the device could potentially be. The granularity of this grid can be altered to have each area represent centimeters or even meters. Fig. 2 shows how we intersect multiple RSS readings relative to the same device on the 2D discretized representation of the environment. The blue heat-map shows the current probability distribution over locations for a specific WiFi device. The red circle indicates the current measurement, it is centered on the car's position, and its radius corresponds to the estimated distance from the transmitter.

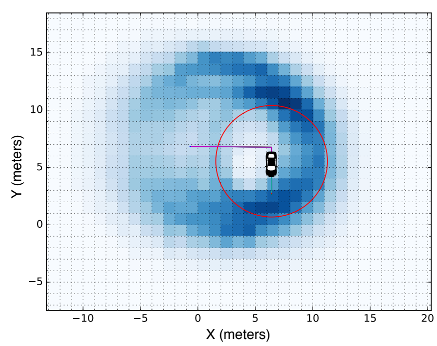


Figure 2: Heat map resulting from the intersection of multiple RSS readings

We discretized the environment using a grid with resolution of 1.0 meter. We based this decision on results from empirical experiments run on the two WiFi devices for which the ground-truth location is known. Fig. 3 shows the localization error for the both devices and for four different grid resolutions.

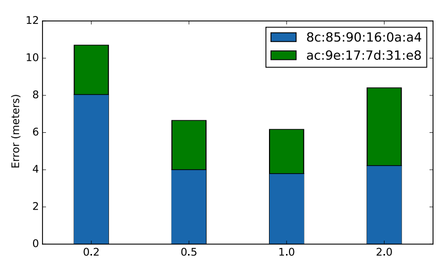
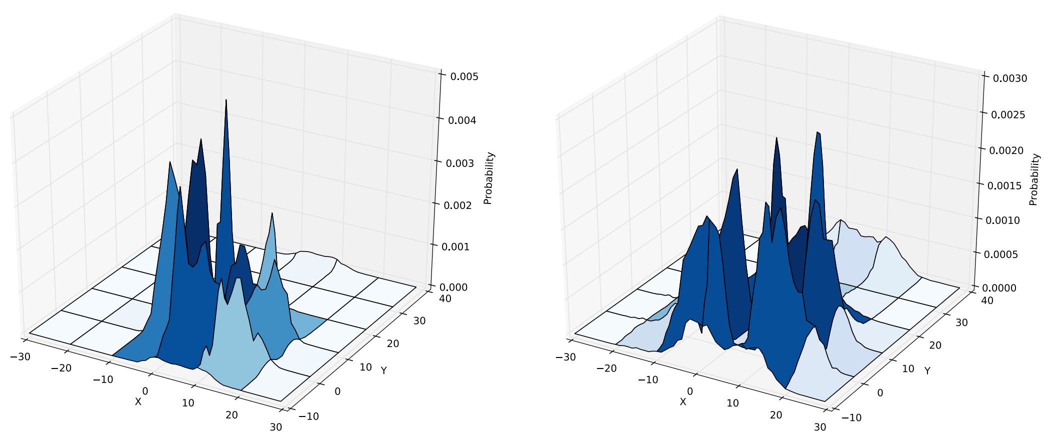


Figure 3: Localization error for different grid resolutions

At the end of this process, we look at the grid squares that had the most intersections and estimate that to be where the device is located. Since we are collecting hundreds of RSS readings each second, the truthful datapoints will



(a) Device with MAC d8:c4:6a:50:e3:b1

(b) Device with MAC f8:cf:c5:97:e0:9e

Figure 4: Probability distributions over locations for the two devices with unknown locations

converge to the correct location, while the noisy datapoints will not converge to a single location as much to outweigh that correct answer. It is worth noting that the center of the darkest cell in the heat-map of Fig. 2 (cell with highest probability) has coordinates $(7.5, 10.5)$, which corresponds to the location predicted by our model for the device 8c:85:90:16:0a:a4 (shown later in Table 1). We believe this to be an appropriate solution, and it will be shown later that it can detect the location of two test Wi-Fi devices of which we know the location with a relatively small error.

3 Results

We tested our approach on two WiFi camera for which we know the true location. Our model predicted the location of the two cameras with 3.77 and 2.37 meters error respectively. Table 1 shows the predicted location along with the prediction error for the cameras for which the true location is known and the predicted locations for the hidden cameras. Fig. 4 shows the final probability distributions over locations for the devices for which the ground-truth location is unknown.

MAC	Predicted location (meters)	True location (meters)	Error (meters)
8c:85:90:16:0a:a4	$(7.5, 10.5)$	$(6.8, 6.8)$	3.77
ac:9e:17:7d:31:e8	$(1.5, 9.5)$	$(0.87, 9.45)$	2.37
d8:c4:6a:50:e3:b1	$(0.5, 14.5)$	–	–
f8:cf:c5:97:e0:9e	$(9.5, 16.5)$	–	–

Table 1: Predicted location and prediction error for four distinct WiFi devices

4 Conclusion

Our approach proved to be able to estimate the location of a WiFi device simply based on noisy observations of the RSS indicator with an average accuracy of 3.07 meters. During our experiments, we noticed that our approach produce better estimations when a high number of readings is available. In particular, Fig. 3 shows that regardless of the grid resolution we choose, the estimation error is always smaller for the device with MAC address ac:9e:17:7d:31:e8 for which we have about $171k$ readings, compared to the device with MAC address 8c:85:90:16:0a:a4 for which we have only $43k$ readings.