Robotics-Based Location Sensing using Wireless Ethernet

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Motivation

- Location awareness
- Wireless security
- Mobile robotics

Standard approaches

- GPS (doesn’t work inside)
- Install beacons around the space (expensive to install)
  - Infrared
  - Sonar
  - Computer vision targets
  - Specialized attenas

Wifi-based localization

- Pluses
  - Cheap
  - Available
  - Already deployed
  - Can locate an attacker
- Minuses
  - Extremely noisy signals
  - Heavy discretization (about 5 bit of range)
  - Require a lot of training
  - Sensitive to the environment conditions

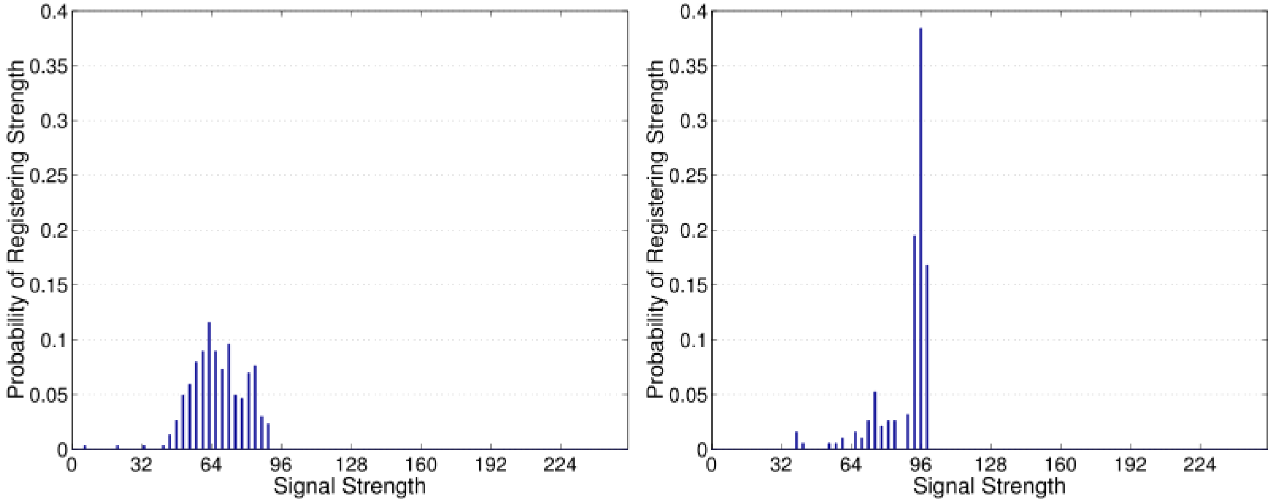


Figure 2: Samples of signal strength taken at the same positions facing opposite directions

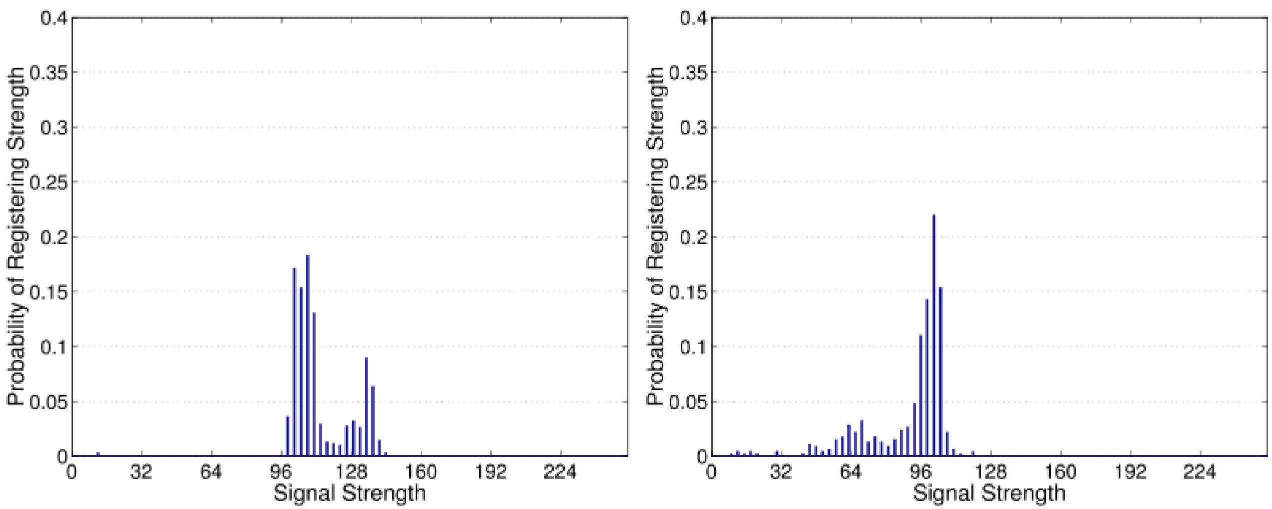


Figure 3: Examples of signal strength distributions of two different base stations, measured simultaneously from one location

RF Signal Propagation

- Interference
- Reflections
- Refractions
- Scatterings
- Absorptions (water, including people)

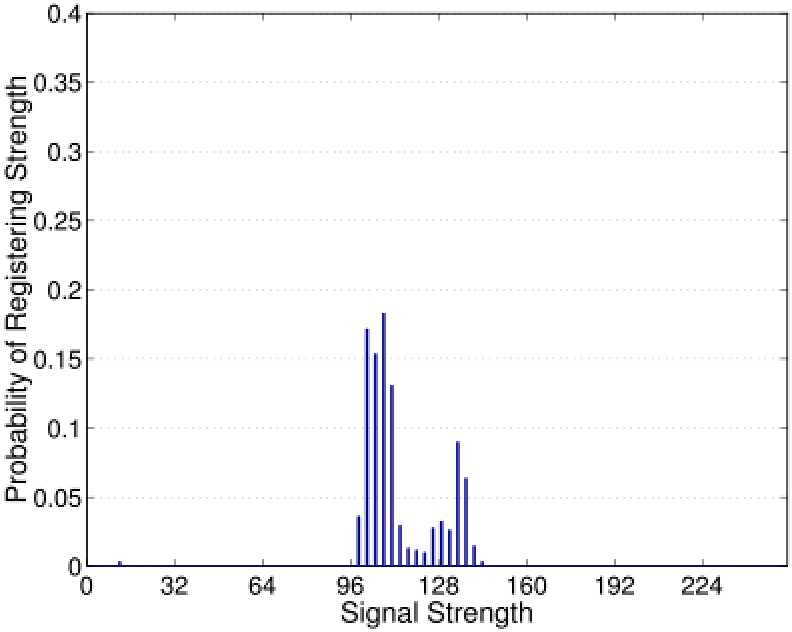
- = House of mirror effect

Models of propagation

- Orientation matters
- Related to distance to base station
  (though not necessarily correlated!)
- No other effect was tractable
  (to us, and to Nescovic et al.)

- Sample the distribution at many locations (5 feet)
- Assume:
  - smooth transitions between location
  - smooth transitions between signals strengths
  - small probability of outliers

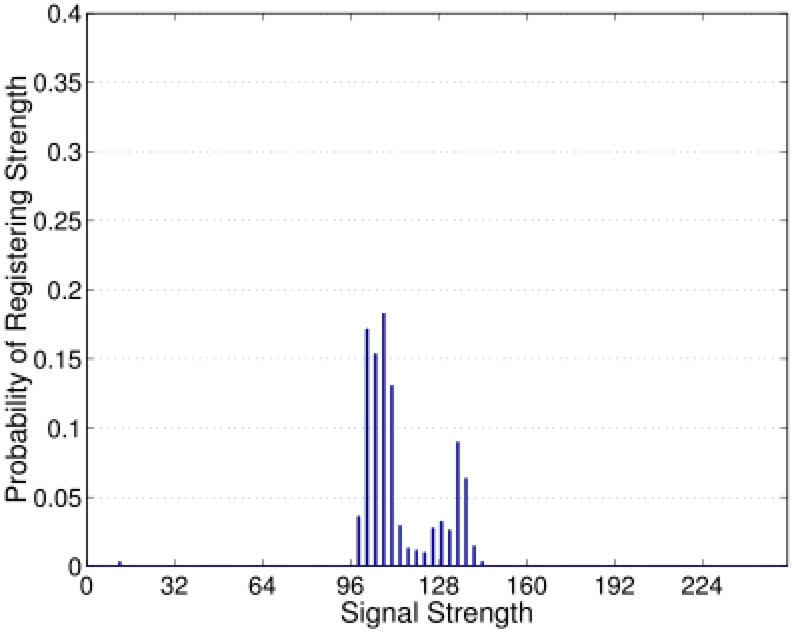
Localization Example



X

96 db
100 db
130 db

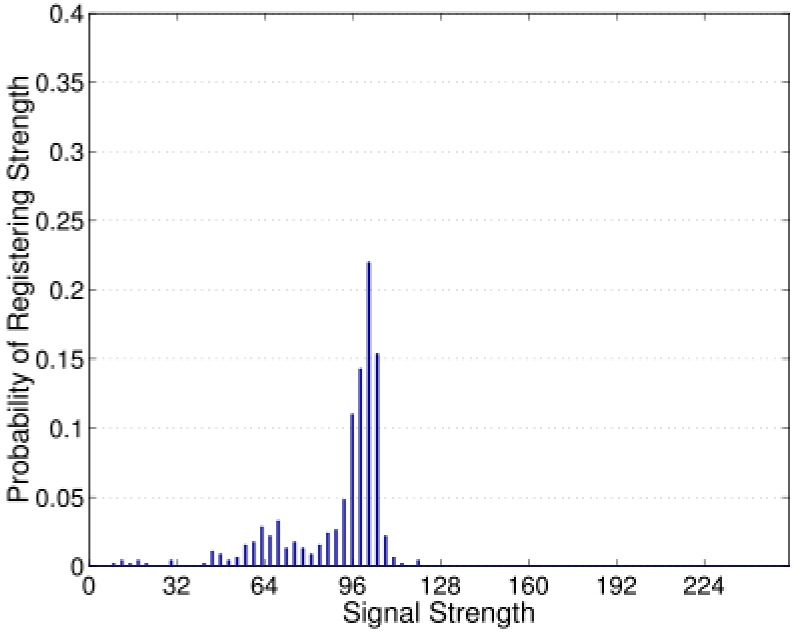
Localization Example



X

96 db	103 db
100 db	110 db
130 db	64 db

Localization Example



X

96 db	103 db
100 db	110 db
130 db	64 db

Details - Training

- Send a base station probe packet
- Receive up to 4 probe packet replies per base station
- Build tables with:

  $Pr(fi = a \mid s_i)$ the probability that the reply count from **j**th base station is equal to **a** at state $\mathbf{s_i}$

  $Pr(L_j \mid b_j, s_i)$ the probability that the base station **j** has signal strength $\mathbf{L_i}$ at state $\mathbf{s_i}$

Details – Localizing – Step 1

- Send a base station probe packet, get replies
- Calculate

$$\text{sum}_j[\Pr(fi = a \mid s_i)] \quad x \quad \text{sum}_j[\Pr(L_j \mid b_j, s_i)]$$

Details – Localizing – Step 2

- Return the maximum probability as the current location

- Move the person randomly

Results – Not moving

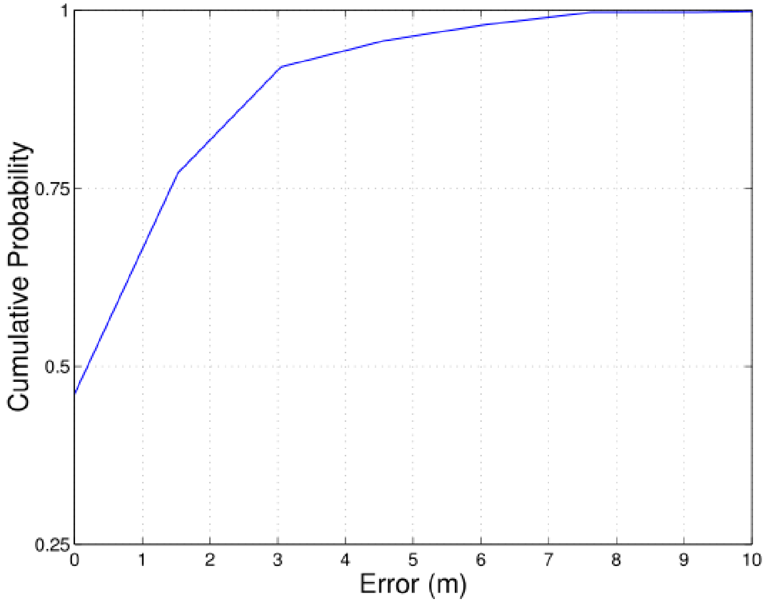


Figure 4: Bulk cumulative error distribution for 1307 packets over 22 poses in a hallway localized using the position of maximum probability as calculated by direct application of Bayes' rule.

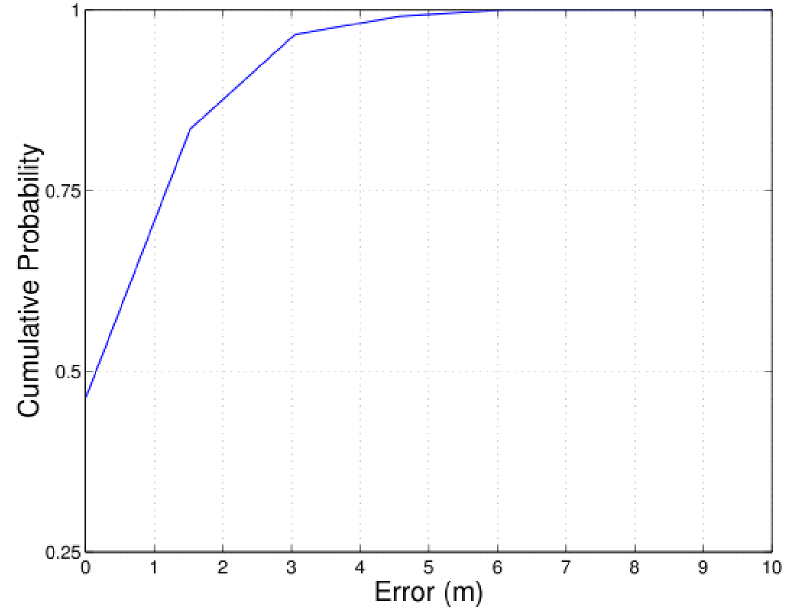


Figure 5: Bulk cumulative error distribution for 1465 packets over 22 poses in a hallway localized using the position of maximum probability as calculated by merging distributions over a one second window.

Results – Moving – Hallway #1 – With BS

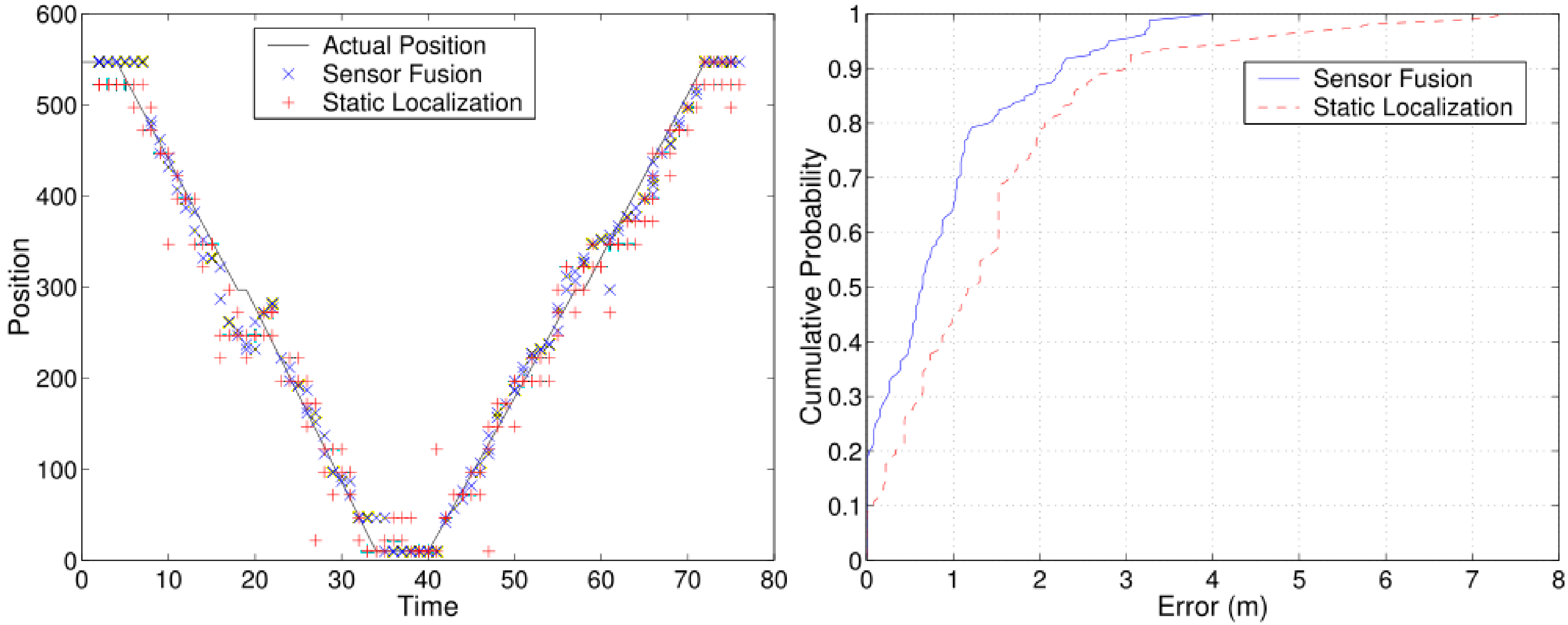


Figure 6: Tracking a round-trip walk of hallway 1 in our test area (see Figure 1 the building map). Measured error for the track, shown on the right graph, is within one meter with probability 0.64, an improvement of 45% over static localization. This improvement is illustrated in the actual tracking performance, shown in the left graph. Position in the left graph is measured in pixels on our map; 50 pixels is approximately equal to 3 meters.

Results – Moving – Hallway #2 – without BS

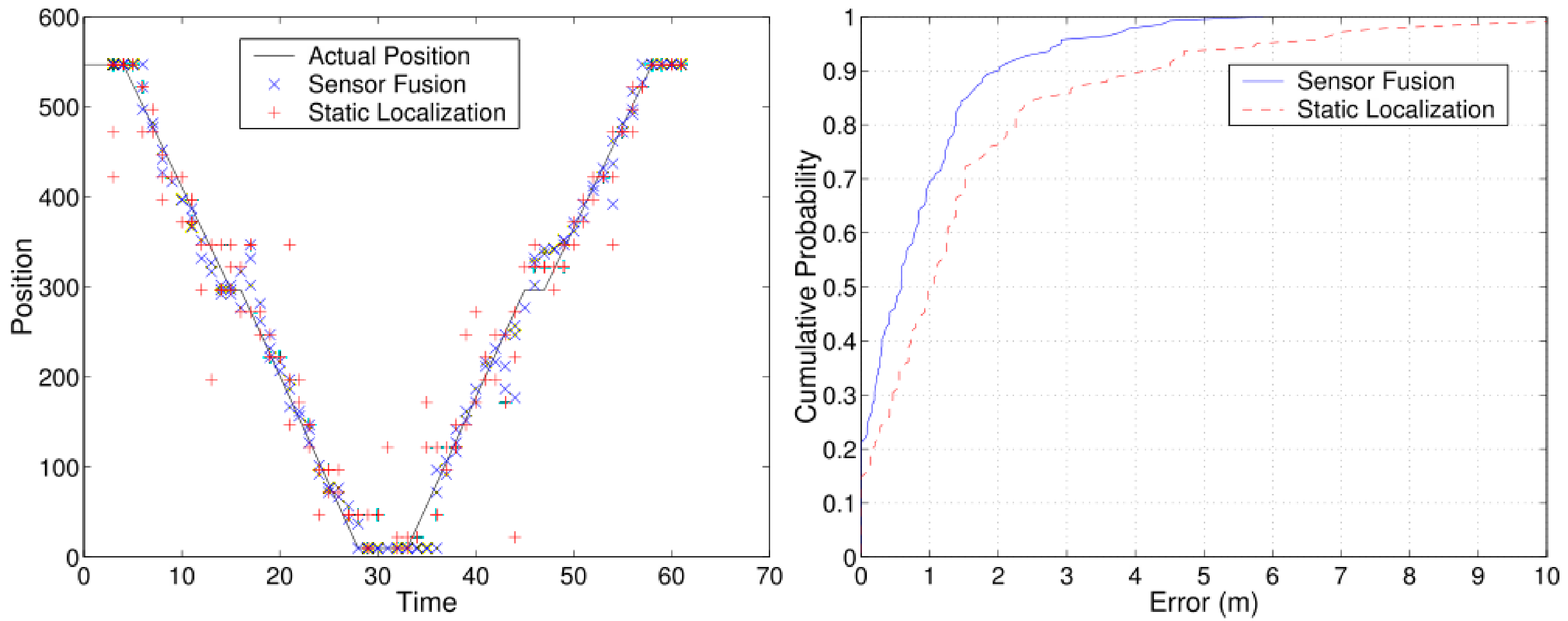


Figure 7: Tracking a round-trip walk of hallway 2 in our test area (see Figure 1 the building map). Measured error for the track, shown on the right graph, is within one meter with probability 0.7, an improvement of 40% over static localization. This improvement is illustrated in the actual tracking performance, shown in the left graph. Position in the left graph is measured in pixels on our map; 50 pixels is approximately equal to 3 meters.

Results – Moving – Hallway #4 – Half-opened

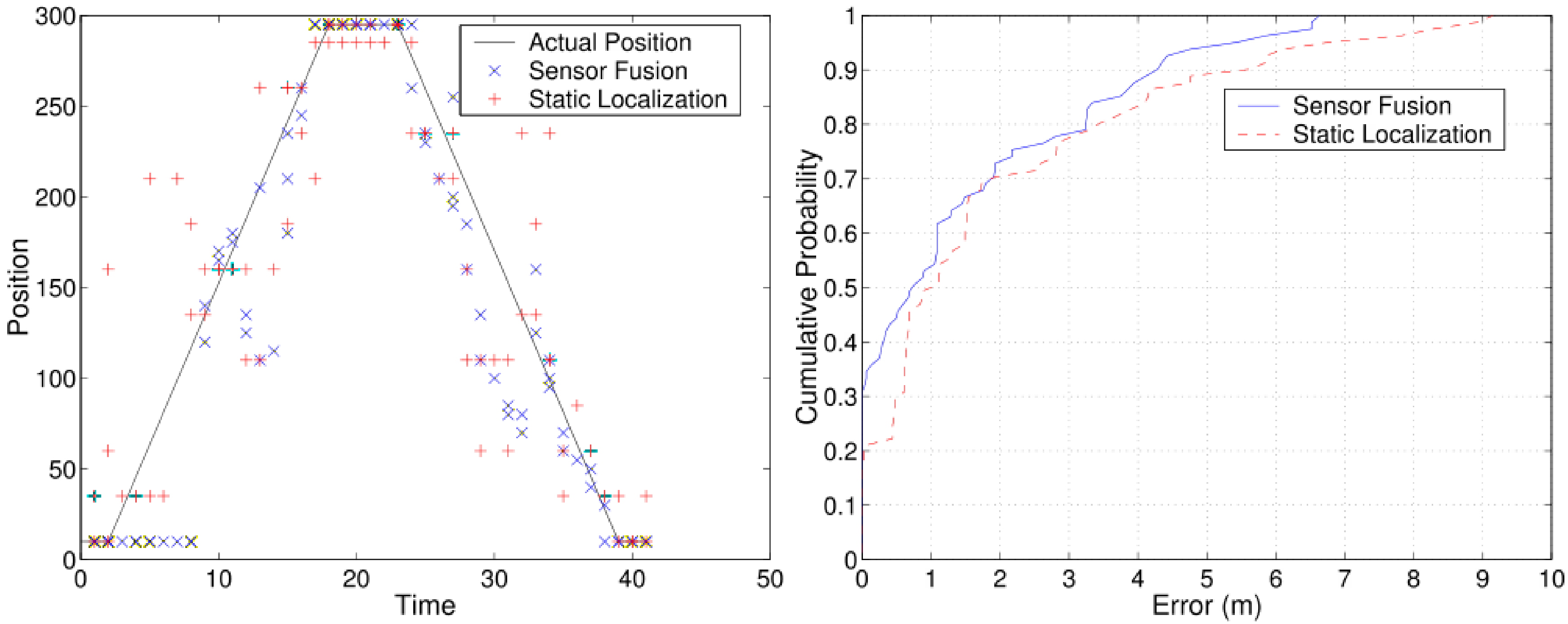


Figure 8: Tracking a round-trip walk of hallway 4 in our test area (see Figure 1 the building map). While sensor fusion provided some improvement, it was not significant. As shown in the left graph, when static localization was significantly off, so was sensor fusion, but when static localization appears to track actual movement, sensor fusion is surprisingly accurate despite the noise. Position in the left graph is measured in pixels on our map; 50 pixels is approximately equal to 3 meters.

Results – Moving – Hallway #3 – Opened

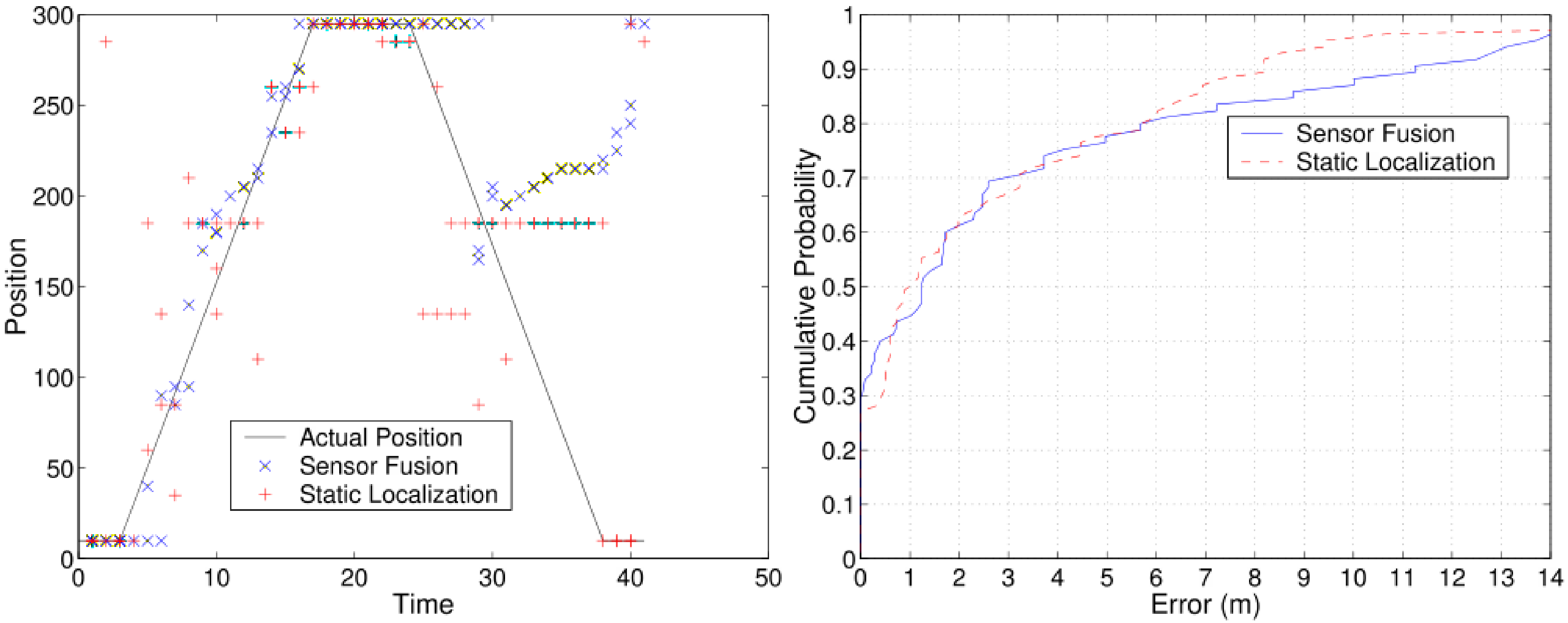


Figure 9: Tracking a round-trip walk of hallway 3 in our test area (see Figure 1 the building map). Sensor fusion did not provide a significant improvement in error, and at times increased error, as shown in the right graph. However, as shown in the left graph, the raw data was already extremely noisy in this case. Position in the left graph is measured in pixels on our map; 50 pixels is approximately equal to 3 meters.

Conclusions

- RF behavior is too complicate to model mathematically, sample it instead.
- Direction matters. Train and solve for direction.
- Amount of people matters too. Train and solve for the amount of people.
- Probabilities are useful for aggregating evidence

Conclusions

- Need better hardware support
- Need better protocol support