RF signal strength models and new localization algorithms for wireless sensor networks

XuanLong Nguyen and Tye Rattentbury

May 12, 2003

Motivation: What benefit is a sensor if its readings are not correlated with the real world?

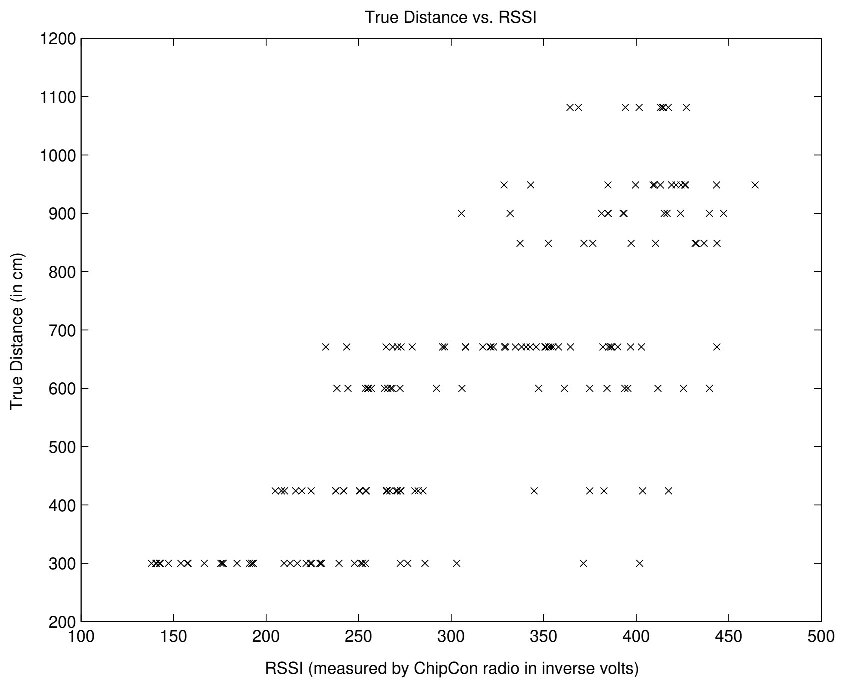
- Ad-hoc sensor networks represent a future branch of computer architecture research
- Important issue is connecting sensor data with context
- Localization addresses this issue

Talk outline

- Problem introduction:
  - Calibration step: Convert RSSI to distance estimates
  - Localization step: Use distance estimate to estimate true positions
- Calibration technique:
  - Modelling distance in terms of RF signal strength
  - Possible solutions
- Localization technique:
  - Previous algorithms (assumptions they make)
  - Our algorithms
- Experiment and Simulation Results
  - Non-distorted networks and Distorted networks

Calibration: Turn RSSI into Distance

- Issues: both macro-node (multilateration, environmental interference) and micro-node (radio peculiarities, physical antenna orientation, node power regulation)



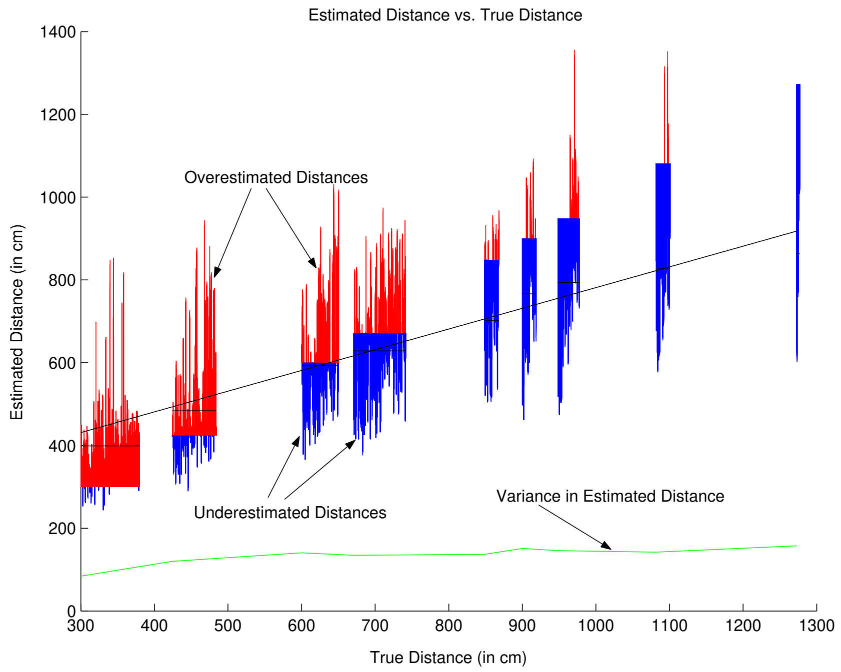
- No accurate model exists

Calibration(cont'd): RSSI-to-Distance Models

- Antenna Theory Model:
  - $\frac{1}{RSSI_{i \to j}} \propto PT_i \cdot d_{ij}^n$
  - geometric average normalized error around 40%.
- Revised Model:
  - $RSSI_{i \to j} \propto PT_i \cdot d_{ij}^n$
  - geometric average normalized error around 17%.

Calibration(cont'd): Model Error

- Error follows a pattern: overestimate short distances, underestimate long distances



- This systematic error can be exploited by algorithms
- We will refer to data following this pattern as *Distorted*

Localization problem

- Given a sensor network consists of n nodes $X_1, \ldots, X_n$
- Distance estimates d_{ij} of a subset of edges $E_o \subseteq E$ are given
- Positions of some anchor nodes are known
- Problem: Recover the positions of all $X_1, \ldots, X_n$
- Why this is very hard problem:
  - Inaccurate distance estimates
  - Sparse graph
  - Small number of anchors
  - Distorted distance measurements

3 key features in existing localization algorithms in literature

- Initialization (if algorithm is iterative)
- Objective function to minimizes
  - All try to minimize square of error in some sense
  - Not clear what are the exact objective equations
  - Usually not discuss implicit assumptions involved
- What is the optimization procedure?
  - Centralized or distributed
  - Use of network topology

Initialization

- Bounding Box
  - Enforcing constraints:

$$
\begin{aligned}
X_{j1} - d_{ij} &\leq X_{i1} \leq X_{j1} + d_{ij} \\
X_{j2} - d_{ij} &\leq X_{i2} \leq X_{j2} + d_{ij}
\end{aligned}
$$

  - Let X_i be the center of "bounding box"
- Convex optimization approach
  - Enforcing constraints: If X_i is connected to X_j, then

$$
||X_i - X_j|| \leq R
$$

    for some R
  - Useful only when R is small enough (not true!)

Maximum-likelihood formulation

- Assume d_{ij} is Gaussian with mean $||X_i - X_j||$ with variance σ_{ij}
- Assume d_{ij} are statistically independent
  - Both these assumptions are not true (recall the Calibration step).
- Maximize log likelihood $\equiv$ minimize sum of square error:

$$L_{E_o}(X) := \sum_{(i,j)\in E_o} \frac{1}{\sigma_{ij}}(d_{ij} - ||X_i - X_j||)^2.$$

Our approach (Intuitions)

- Try to minimize the a different sum of square error:

$$\begin{aligned} L(X) &:= L_{E_o} + L_{E_h} \\ &= \sum_{(i,j)\in E_o} \frac{1}{\sigma_{ij}} (d_{ij} - ||X_i - X_j||)^2 + \\ &\quad \sum_{(i,j)\in E_h} \frac{1}{\sigma_{ij}} (d_{ij} - ||X_i - X_j||)^2 \end{aligned}$$

- Call L_{E_o} the *observed error*, and L_{E_h} the *hidden error*
- Perform gradient descent on $\partial L(X)/\partial dX_i$
  - The problem: We can't compute the hidden error
  - Need to learn the behavior of the hidden error

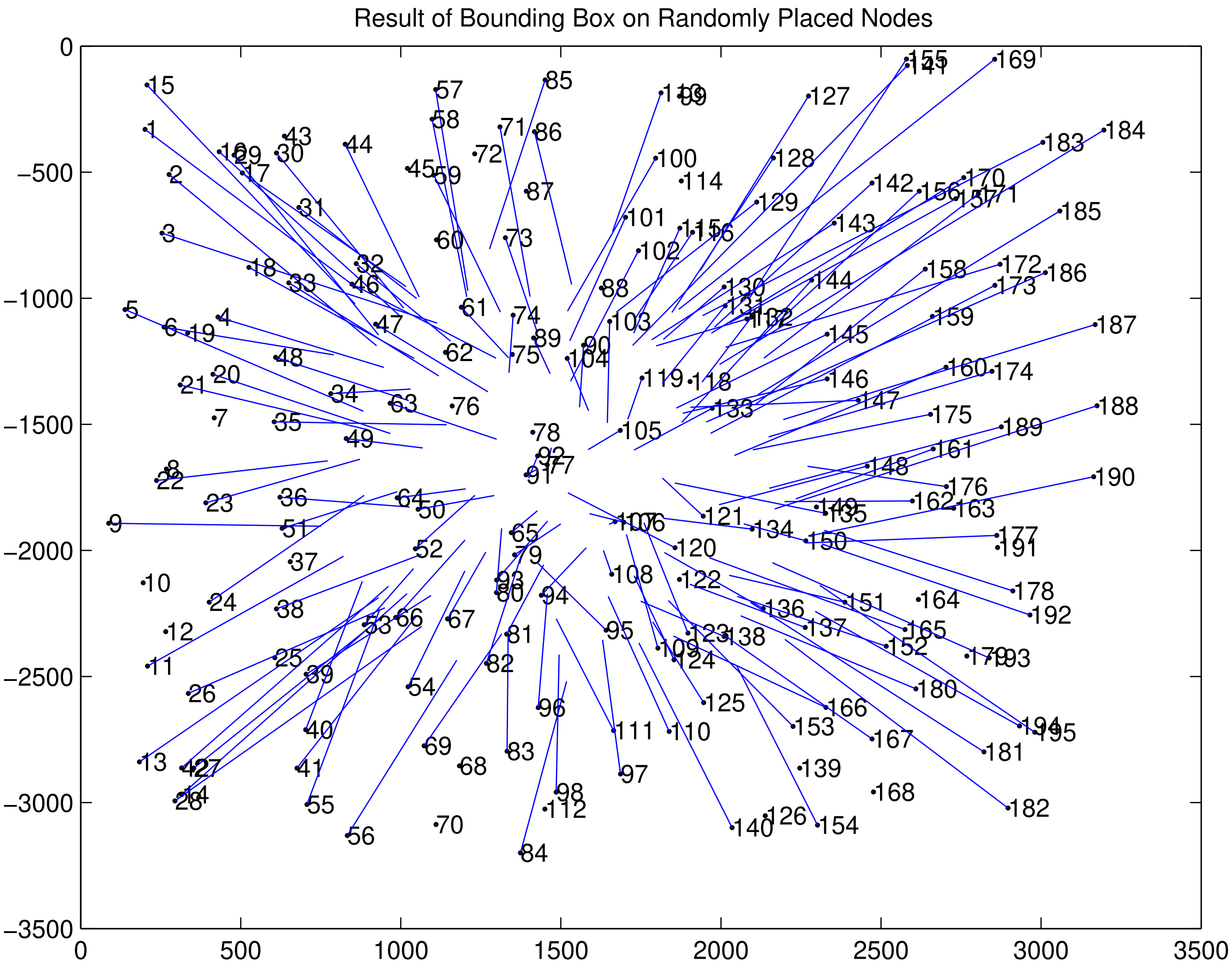


Figure 1: Pulled-to-center effect of Bounding Box algorithm.

A regularized approach

- New objective function:

$$L_\lambda(X) = \sum_{(i,j)\in E_o} \frac{1}{\sigma_{ij}}(d_{ij} - ||X_i - X_j||)^2 - \lambda \sum_{i=1}^{n} ||X_i - C||^2,$$

- λ is a regularization parameter between 0 and 1.
- The second term in RHS aims to minimize hidden error.
- Our iterative algorithm performs gradient-descent on this function.

Algorithm for non-distorted network

- 1. Initialize $X = \text{BoundingBox}(d_{ij}, i, j = 1, \ldots, n)$.

  2. Let $C = \frac{1}{n}(X_1 + \ldots + X_n)$.

  3. Repeat until L_{E_o} stops decreasing, in which case go to 5.

  4. For each node $i = 1, \ldots, n$ update X_i according to equation

  $$\begin{aligned} X_{i1} &= \frac{1}{\text{deg}(i)} \left(\sum_{j:(i,j) \in E_o} X_{j1} + d_{ij} \frac{X_{i1} - X_{j1}}{||X_i - X_j||} \right) + \lambda(X_{i1} - C_1) \\ X_{i2} &= \frac{1}{\text{deg}(i)} \left(\sum_{j:(i,j) \in E_o} X_{j2} + d_{ij} \frac{X_{i2} - X_{j2}}{||X_i - X_j||} \right) + \lambda(X_{i2} - C_2) \end{aligned}$$

     where $\text{deg}(i)$ denotes degree of node j.

  5. Return.

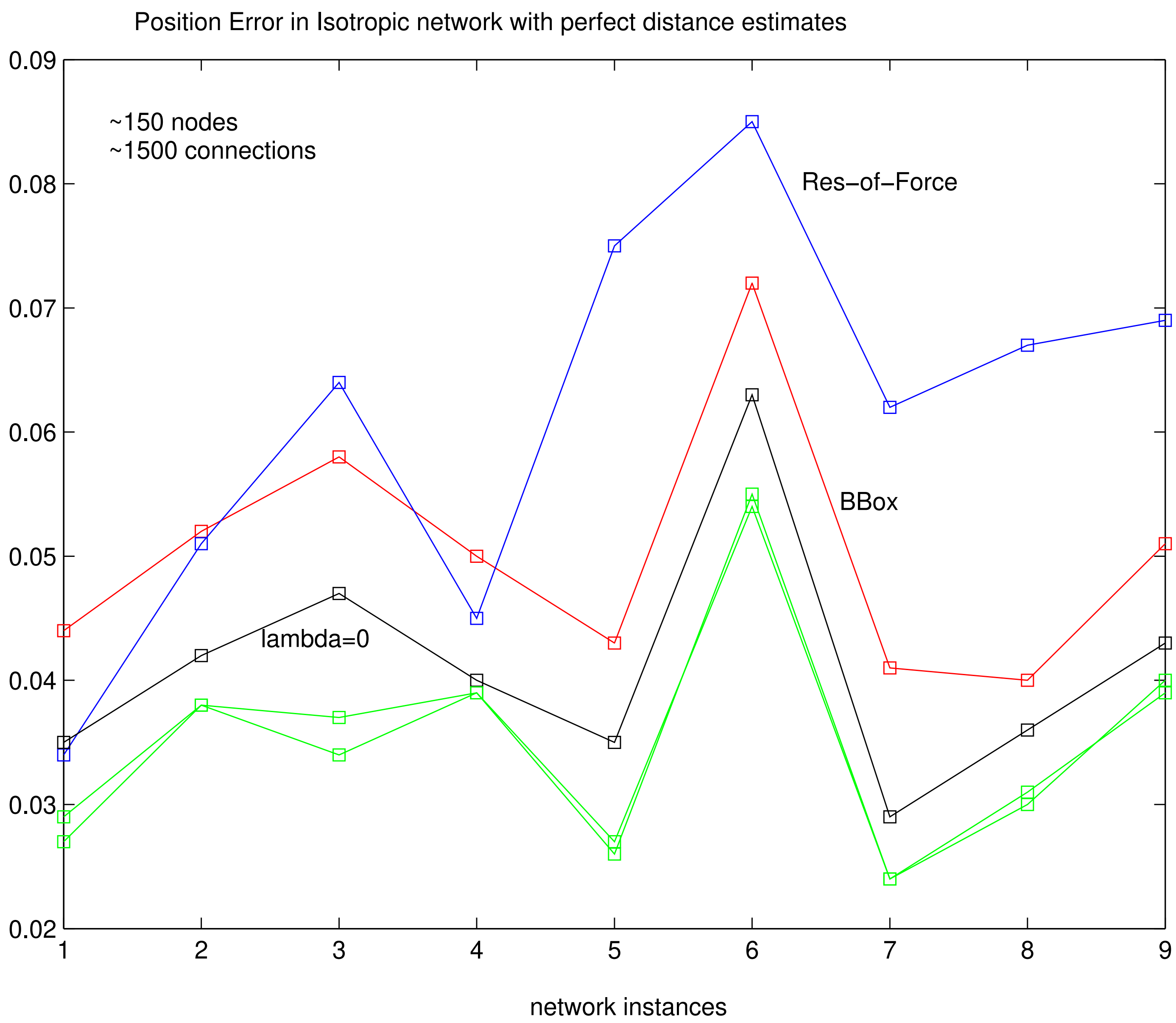


Figure 2: Position Errors in Non-distorted Networks with perfect distance estimates.

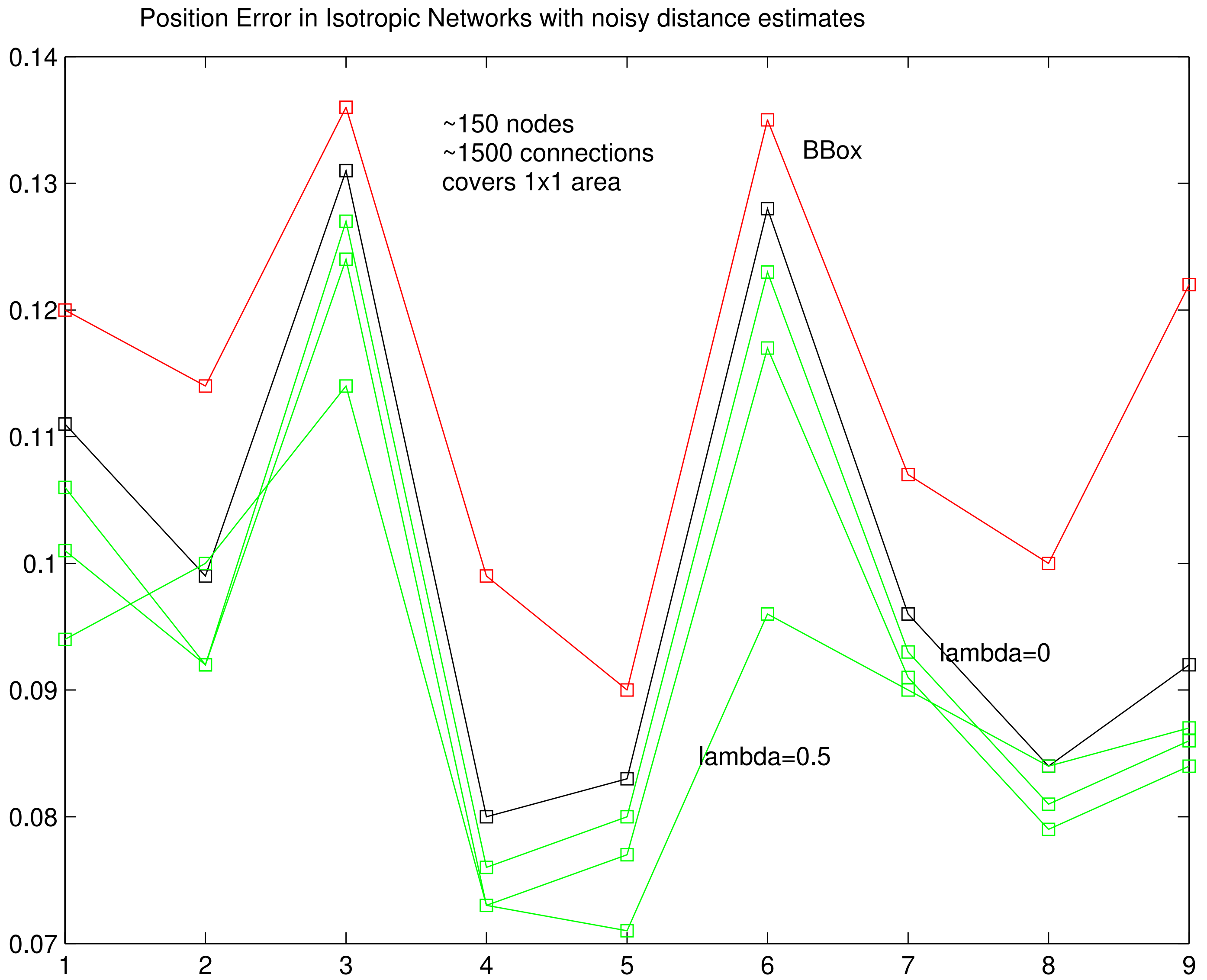


Figure 3: Position Errors in Non-distorted Networks with noisy distance estimates

Distorted Networks

- d_{ij} is Gaussian with mean $(a||X_i - X_j|| + b)$ for some paramters a and b.
- $\Rightarrow$ Doesn't make sense to minimize sum of square error
- Our approach:
  - Learn a and b, first within anchor nodes, then between nodes that have been localized.
  - Updating the given distance estimates by rescaling according to a and b.
  - Now we can use our regularized least square algorithm as before using the non-distorted assumption.
- This approach works well when the graph is sufficiently connected (If not, a and b have to be learned in a separate preprocessing step).

Dataset	Estimated Dist. Standard Dev.	Avg. TE (m) Bounding Box	Avg. TE (m) Our algorithm	Avg. TE (m) Force-resolution
1	15	4.061	.1308	2.396
2	30	5.617	.1704	3.948
3	45	6.716	.3696	5.148
4	60	5.579	.8592	3.662
5	75	5.809	.5826	4.843
6	90	4.540	.4867	3.055
7	105	6.530	2.095	5.531
8	120	5.584	.8403	2.785
9	135	4.984	1.713	2.991
10	150	5.402	1.728	3.058

Table 1: Algorithm results on distorted simulation data. Error is in meter. The network covers 30x30 square meter

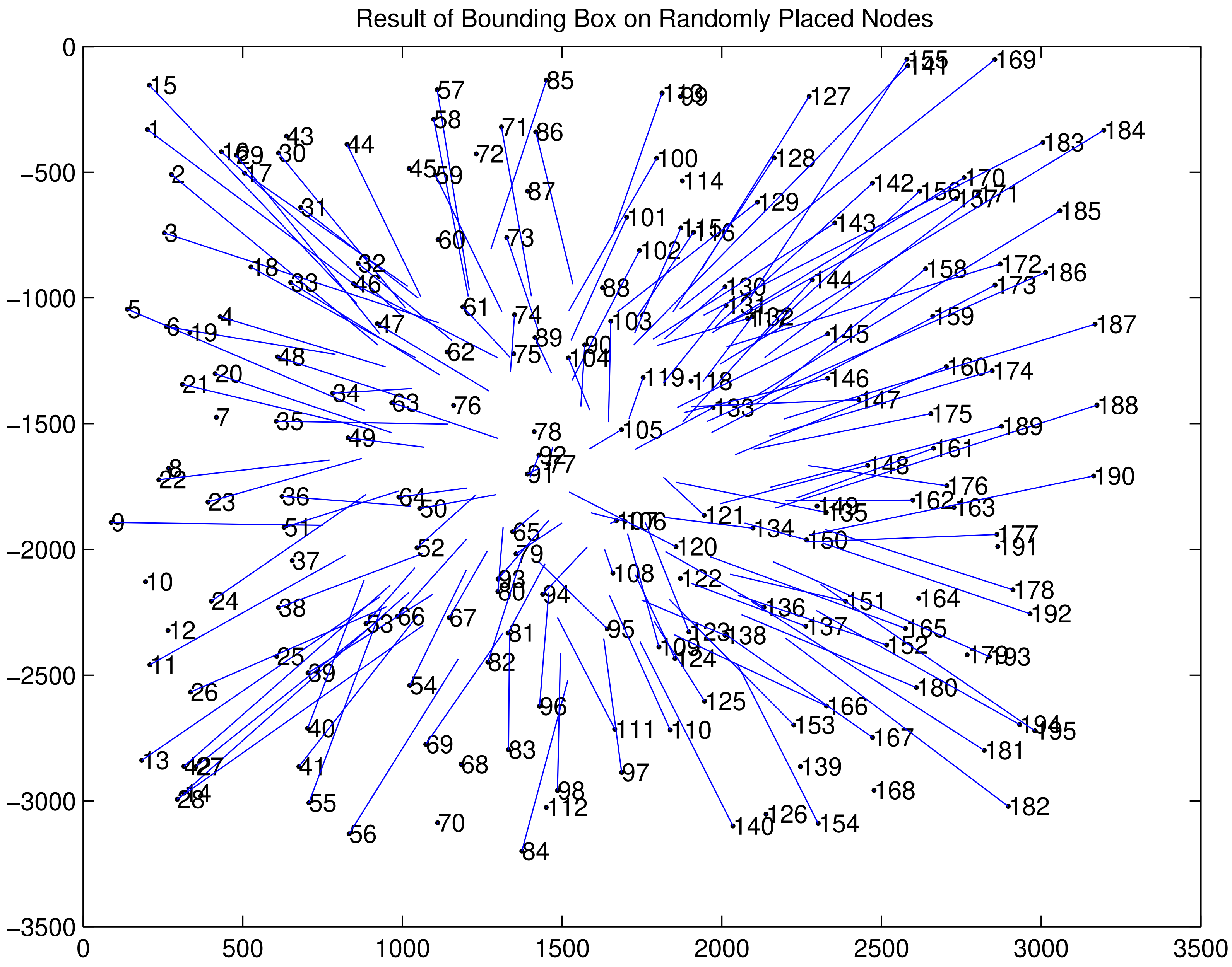


Figure 4: Result of bounding box algorithm.

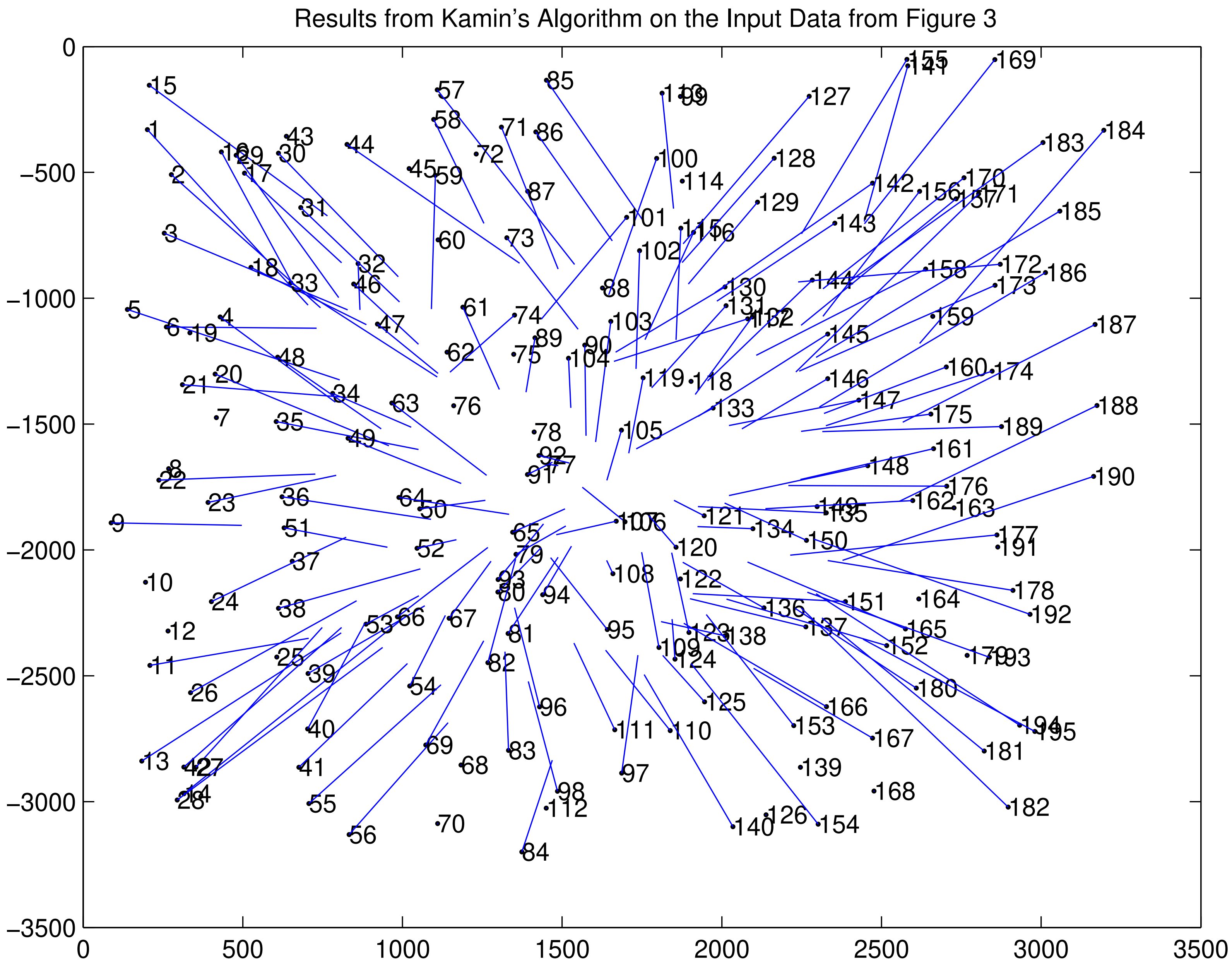


Figure 5: Result of Kamin's force-resolution algorithm, same network.

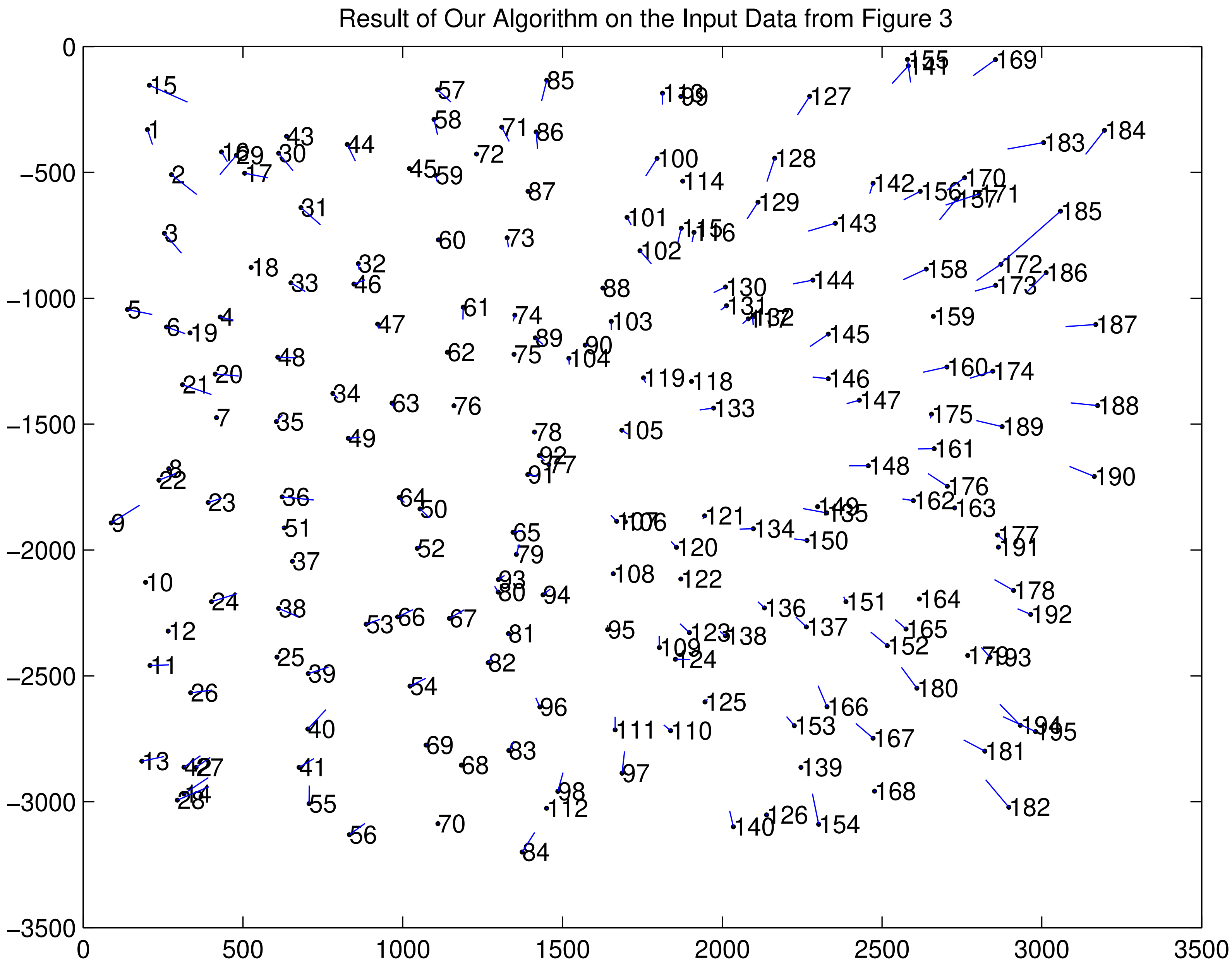


Figure 6: This data is the result of our algorithm, same network

Conclusion and Future Work

- Two contributions:
  - Revealed and analyzed characteristics of RSSI-based distance estimates
  - Proposed a new localization algorithm using regularized, rescaled, least square approach
- Future work:
  - Need more real data to learn RSSI-based distance model
  - Apply our algorithm to this real-world setting
  - Analyze the power effect of the algorithm (and the tuneable parameter λ).