Manifold Learning for Detection and Localization in Sensor Networks

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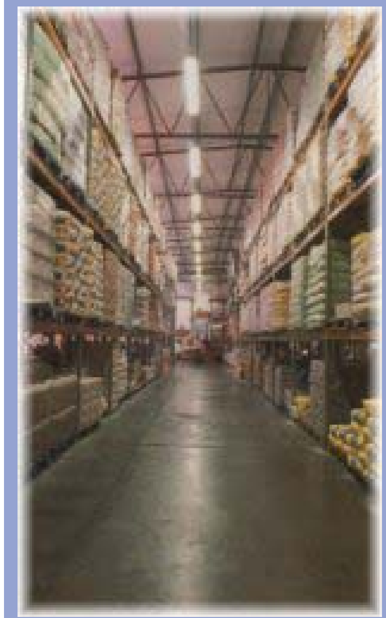
- Sensor networks for geolocation and tracking
- The sensor self localization problem
- Manifold learning algorithms for sensor geolocalization
- Application to anomaly detection in Abilene

Wireless Sensor Applications



- Inventory Management
- Logistics
- Environmental Monitoring

SN Collaborators and Students

- N. Patwari, UMich
- D. Blatt, UMich
- J. Costa, CalTech
- C. Kreucher, GD-AIS
- K. Kastella, GD-AIS
- S. Kyperountas, Motorola
- N. Correal, Motorola
- R. Moses, OSU
- J. Ash, OSU
- R. Nowak, UWisc
- M. Rabat, UWisc

Main Issues

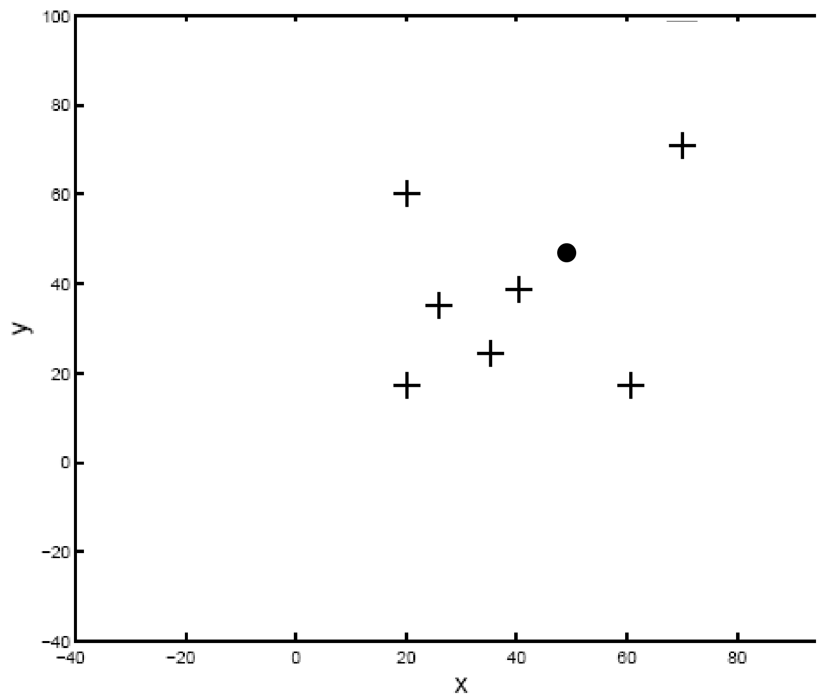
- Stress points for this talk:
  - Accurate self-localization essential for SN applications
  - Algorithms robust to unknown channel characteristics
  - Principled approach required for performance assessment and uncertainty management
    - Distributed numerical optimization algorithms
    - Information theoretic measures of performance
    - Adaptation by active sensing and manifold learning
- Non-stress points for this talk
  - Communications issues
    - MAC
    - Multi-user interference
    - Multi-hop network routing
  - Mathematical details of algorithms and bounds (refs)

Sensor Network Source Localization

- Network Geometry

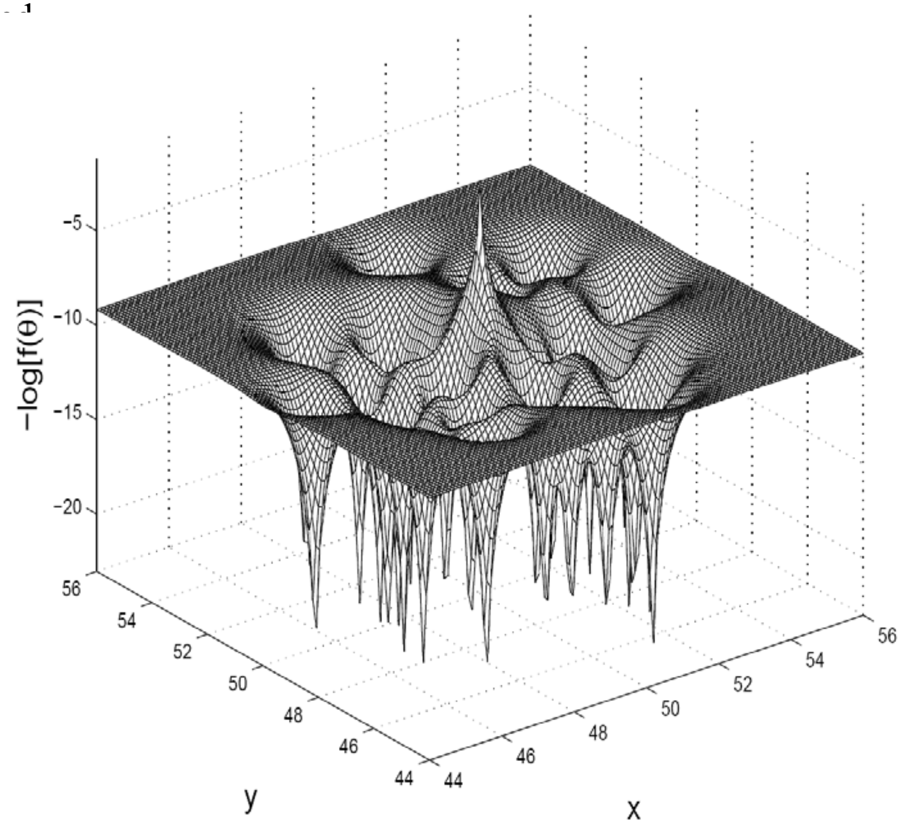
Environmental monitoring: common statistics measu…

Source location: information captured by range measur…



$$y_l = \frac{A}{||r_l - \theta^*||^2} + v_l, \quad l = 1, \ldots, L$$

- Loglikelihood surface



$$f(\theta) = \sum_{l=1}^{L} f_l(\theta)$$

Blatt&Hero:TSP05

Network Source Localization: G and IG recursions

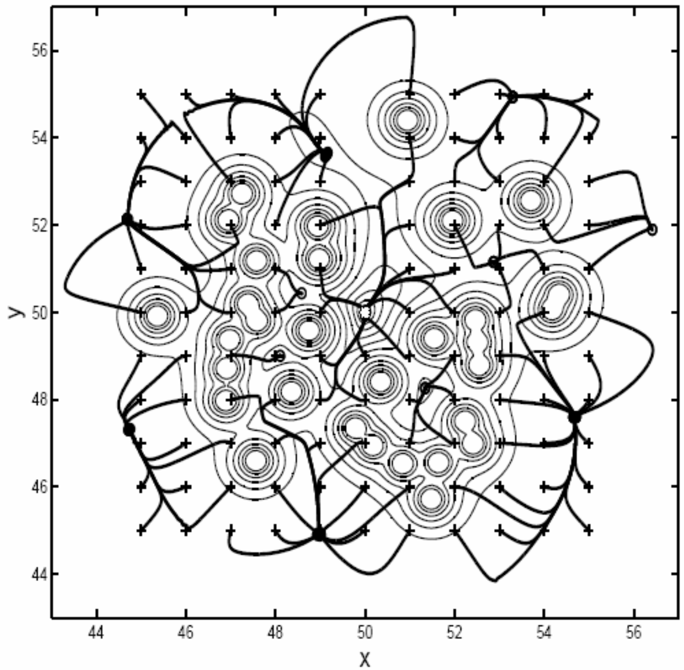


Fig. 3. Paths taken by the steepest descent method.

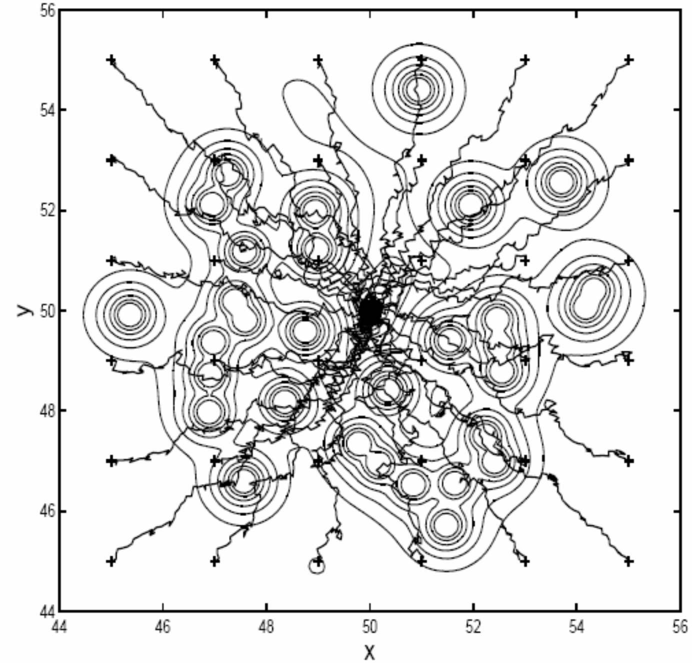


Fig. 5. Paths taken by the normalized IG method.

Ref: Rabat&Nowak:ICASSP04

$$\theta^{k+1} = \theta^k - \mu^k \nabla f(\theta^k)$$

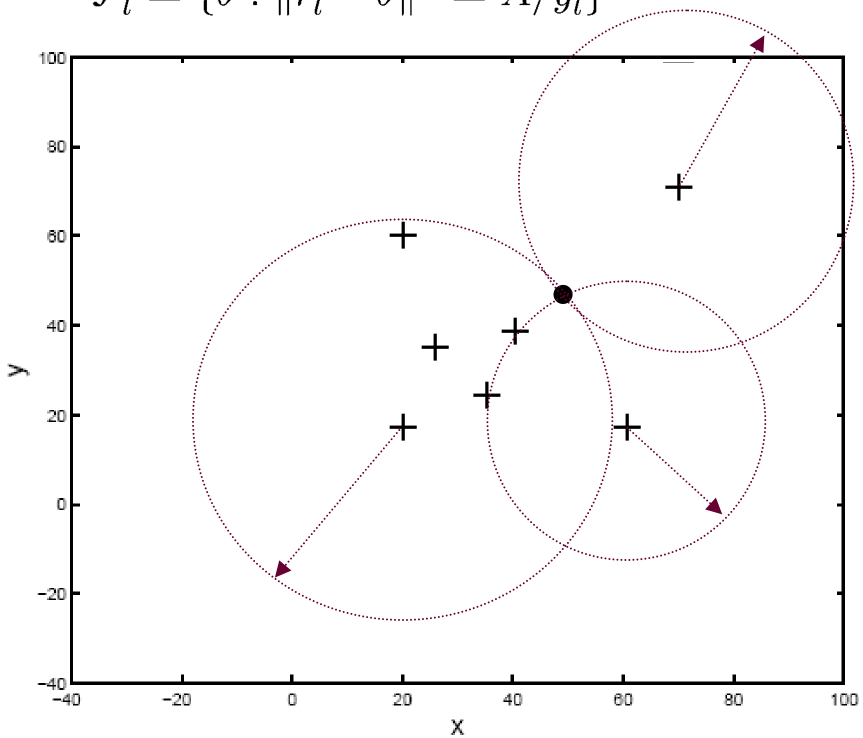
$$\theta^{k+1} = \theta^k - \mu^k \nabla f_{\kappa(k)}(\theta^k)$$

Acceleration: POCS

Network Geometry

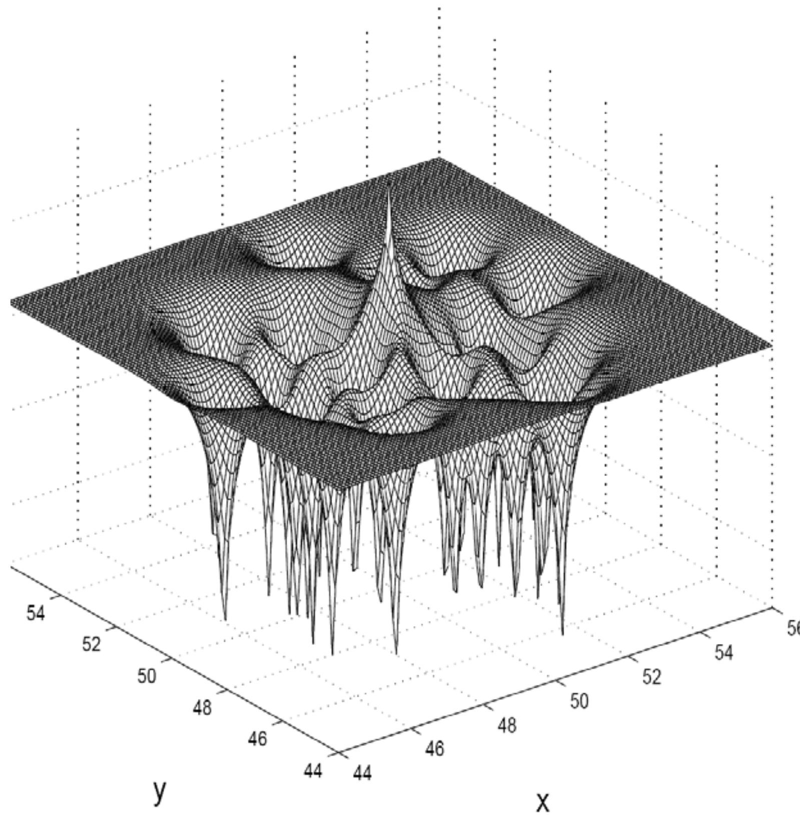
•Each likelihood component is annular Gaussian with ridge along circular feasible region

$$\mathcal{F}_l = \{\theta : \|r_l - \theta\|^2 = A/y_l\}$$



$$y_l = \frac{A}{\|r_l - \theta^*\|^2} + v_l, \quad l = 1, \ldots, L$$

Loglikelihood surface



$$f(\theta) = \sum_{l=1}^{L} f_l(\theta)$$

Blatt&Hero:TSP05

POCS Method (Blatt&Hero:TSP2005)

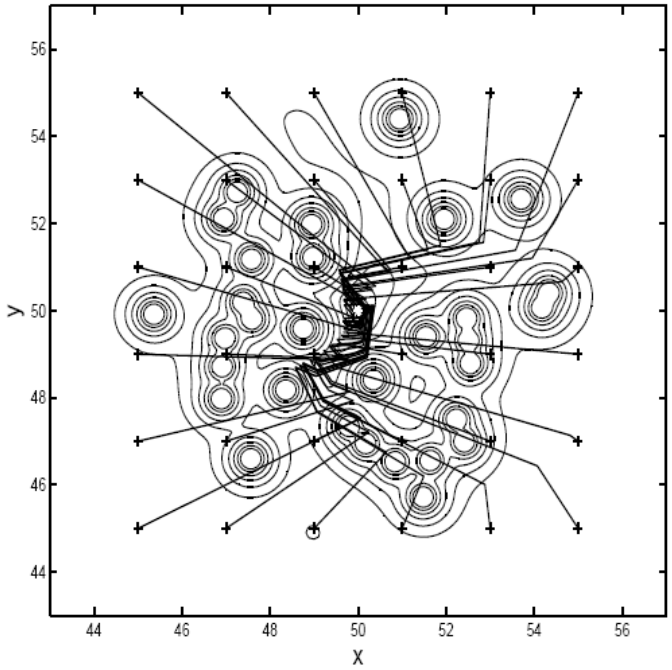


Fig. 7. Paths taken by the POCS method. Ref: Blatt&Hero:TSP05

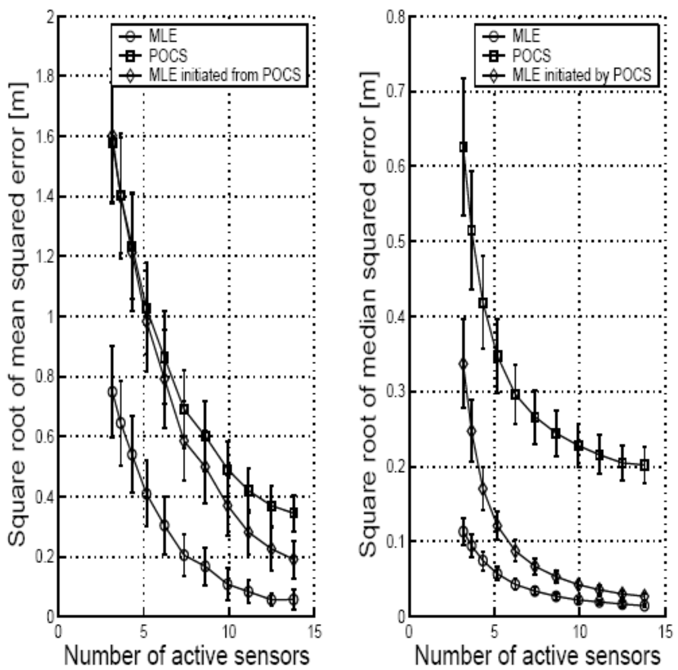


Fig. 9. Local performance: POCS vs. MLE, mean (left) and median (right).

$$\theta^{k+1} = \theta^k + \lambda^k \left[\mathcal{P}_{D_{\kappa(k)}}(\theta^k) - \theta^k \right]$$

Acceleration: Incremental Aggregated Gradient (IAG)

- Standard POCS/IG require vanishing step size for convergence: this leads to slow convergence, e.g. for IG:

$$\theta^{k+1} = \theta^k - \mu^k \nabla f_{\kappa(k)}(\theta^k), \quad \lim_{k\to\infty} \mu^k = 0, \quad \sum_{k=l}^{\infty} |\mu^k| = \infty$$

- Simple solution: Incremental Aggregated Gradient (IAG) (Blatt&Hero&Gauchman:SIOPT05)

$$\theta^{k+1} = \theta^k - \mu \frac{1}{L} \sum_{l=0}^{L-1} \nabla f_{\kappa(k-l)}(\theta^{k-l})$$

- Properties
  - Faster convergence for large class of Lipshitz functions
  - Network-implementable with distributed updates, like IG, POCS
  - Applicable to many different problems
    - Distributed source localization in sensor networks – SIOPT05
    - Distributed boosting of weak classifiers (Logitboost) – SIOPT05
    - Accelerated iterative image reconstruction algos for CT - TMI05

Example: source localization

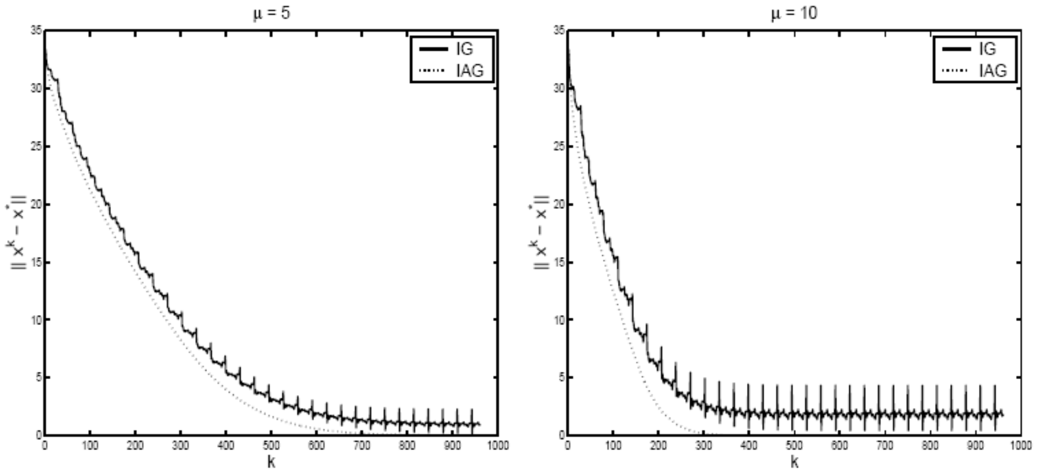


FIG. 4.3. *Distance of IG and IAG iterates to the optimal solution x^* for source localization problem.*

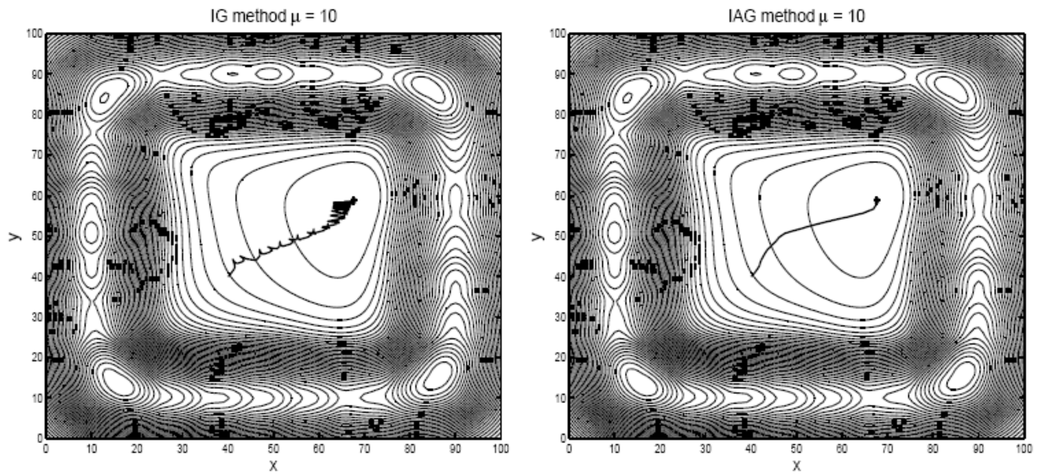
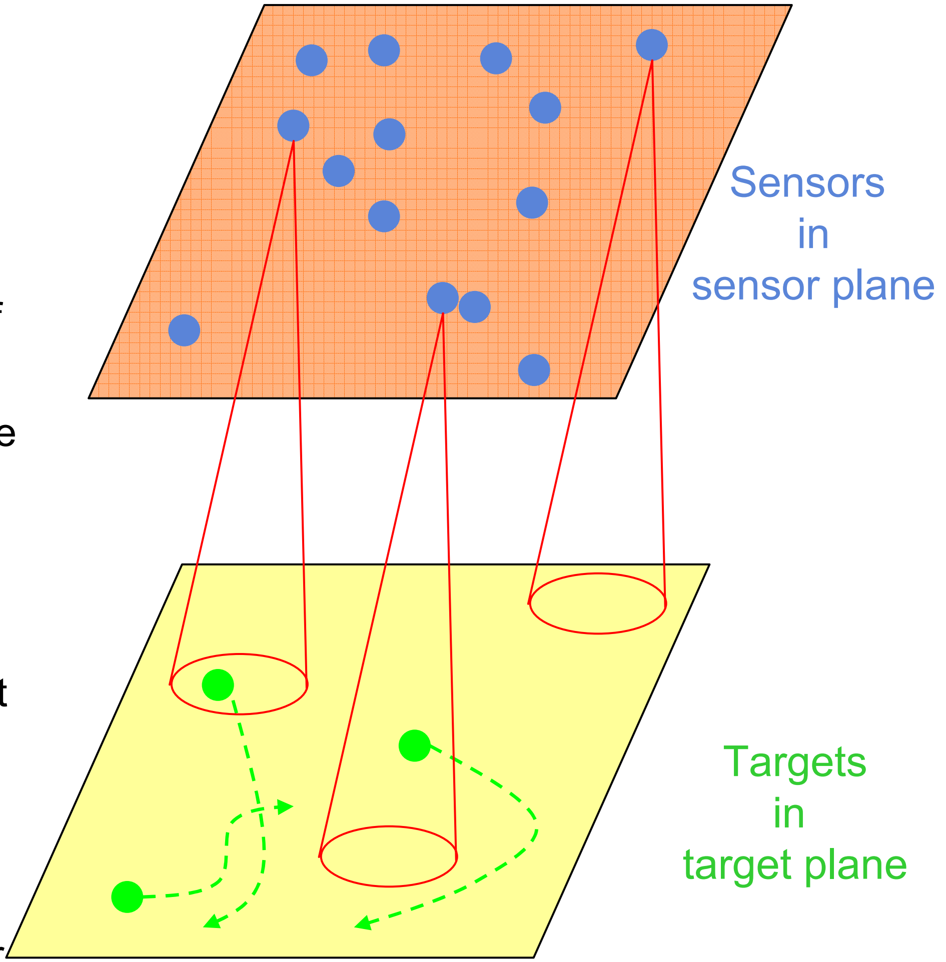


FIG. 4.4. *Path taken by the IG and IAG methods for source localization problem.*

Source Tracking with Sensor Swarms

- **Available: large number (100's or 1000's) of (cheap, low performance) sensors**
- Model problem:
  - An unknown number of moving ground targets
  - Sensors are to determine the number of targets and states of each (position and velocity) through repeated interrogation of the ground
  - Sensors "hover" at a fixed height and stare directly down
    - Sensor detects targets w/ probability Pd
    - The sensor (falsely) detects targets in empty regions with probability Pf
  - The sensor management problem in this setting is to recursively determine the best motion for each sensor (so as to change the ground patch it views)
  - Main ingredients of solution:
    - Bayesian with particle filtering
    - Information theoretic path planning
    - Must tradeoff tracking existing targets for maintaining adequate coverage to detect new targets.



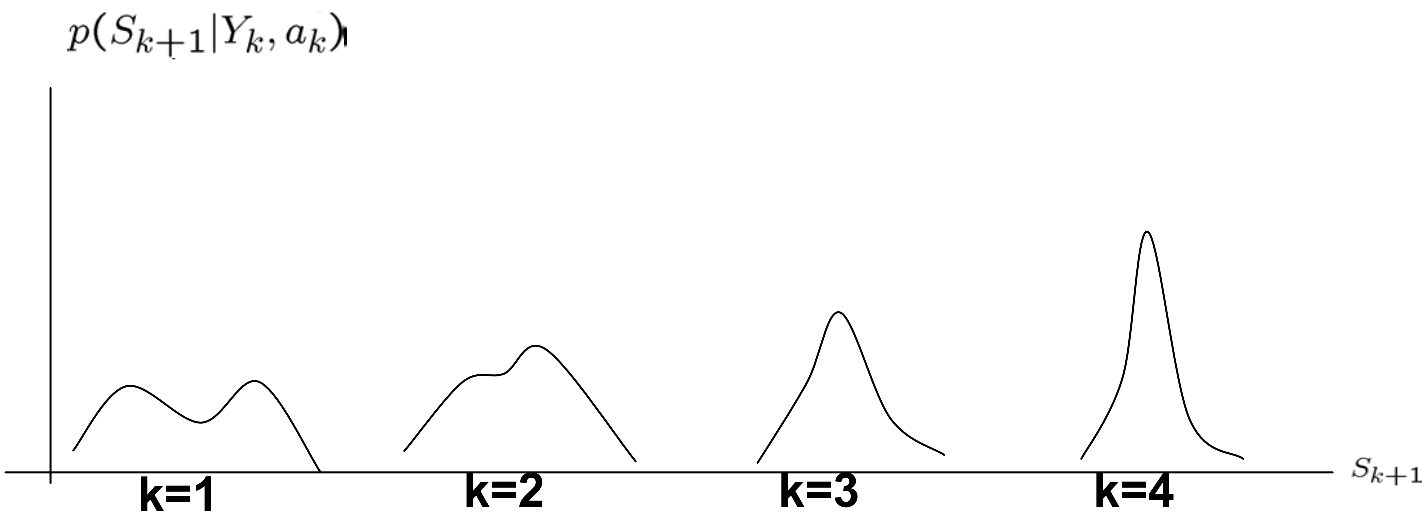
Kreucher&Kastella&Hero:SPIE05

Information Gain Criterion

- "Information state" determines variance of predicted reward

$$E[r(S_{k+1},a)|Y_k,a] = \int r(S_{k+1},a)p(S_{k+1}|Y_k,a)dS_{k+1}$$

- IG policy: choose actions that improve information state



$$D(f\|g) = \frac{1}{\alpha-1}\log\int f(s)\left(\frac{g(s)}{f(s)}\right)^{\alpha}ds$$

- Information gain captures concentration of info state

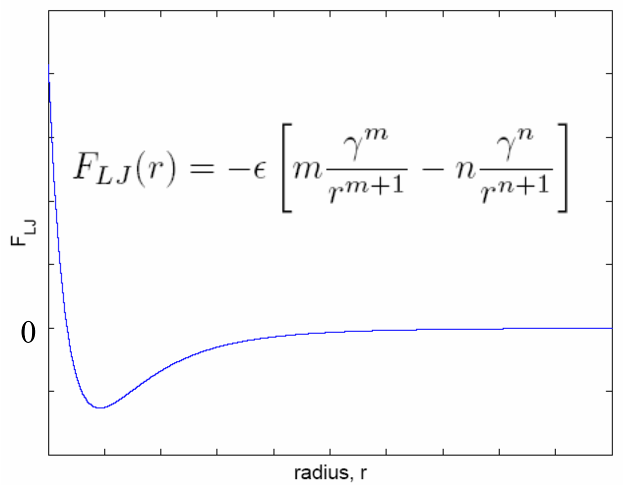
Molecular Fluid Path Planning Model

Objectives

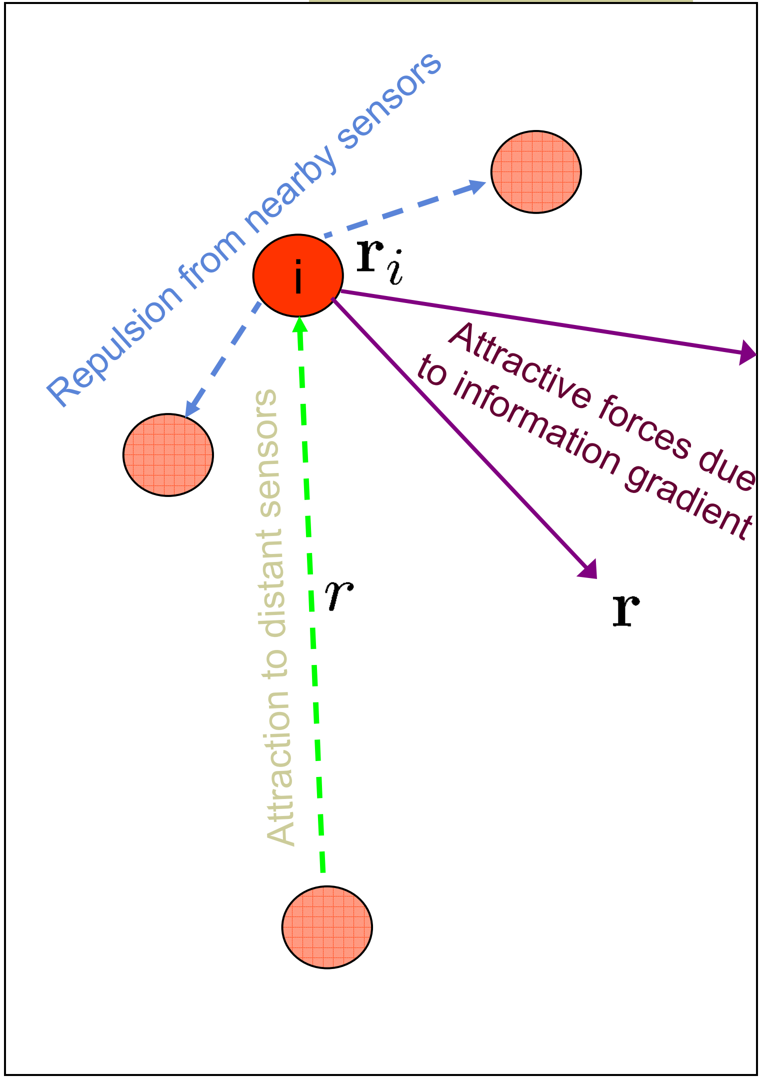
- Accurately detect and track targets
- Maintain coverage of surveillance area
- Focus resources on target locations

Non-linear fluid dynamics approach:

- Sensors exert attractive and repulsive forces on each other following a molecular BM model



1. Candidate target locations extert attractive forces in proportion to gradient of IG



$$F_I(\mathbf{r}) = -\beta \nabla_{\mathbf{r}} \phi(\mathbf{r})$$

LJ + IG Fluid Dynamical Model

- Total attractive force on *i*-th sensor at time *t*

$$f_i(t) = \int (F_{LJ}(r,t) + F_I(r,t))d\mathbf{r}$$

- The acceleration of a unit mass object obeys the Langevin equation

$$\ddot{\mathbf{r}}_i(t) = -\frac{1}{\tau}\dot{\mathbf{r}}_i(t) + \mathbf{f}_i(t) + d\beta_i(t)$$

- Can integrate this to determine the sensor position versus time – however in general no closed form solution exists

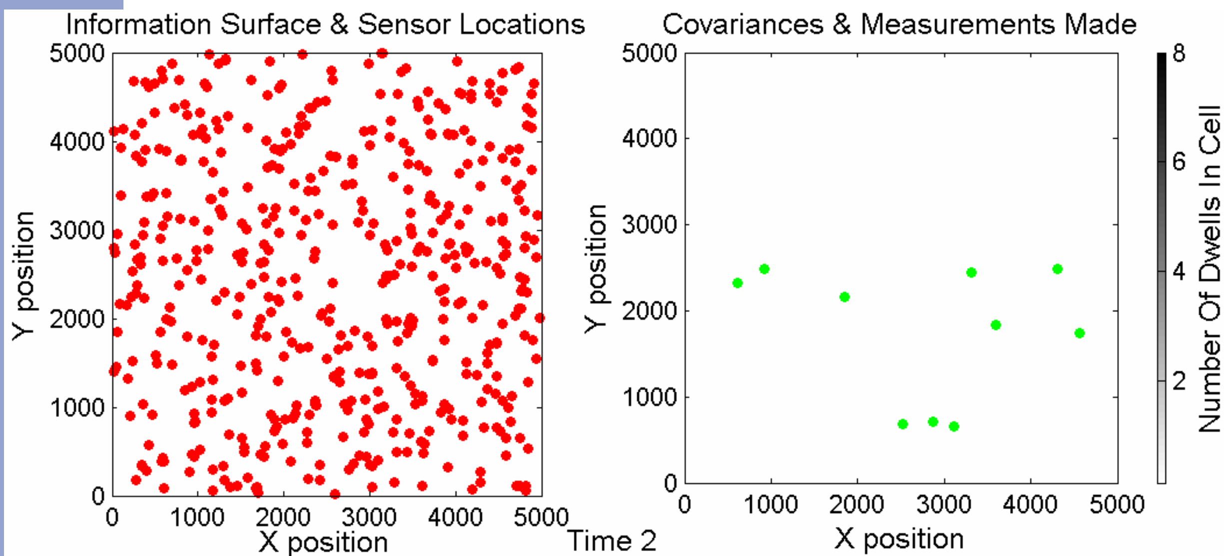
- Discretization via Verlet BM algorithm yields an update to the position and velocity of sensor *i* given by

$$\mathbf{r}_i^{k+1} = \mathbf{r}_i^k + c_1\kappa\dot{\mathbf{r}}_i^k + c_2\kappa^2\mathbf{f}_i^k + \delta\mathbf{r}_i^k$$

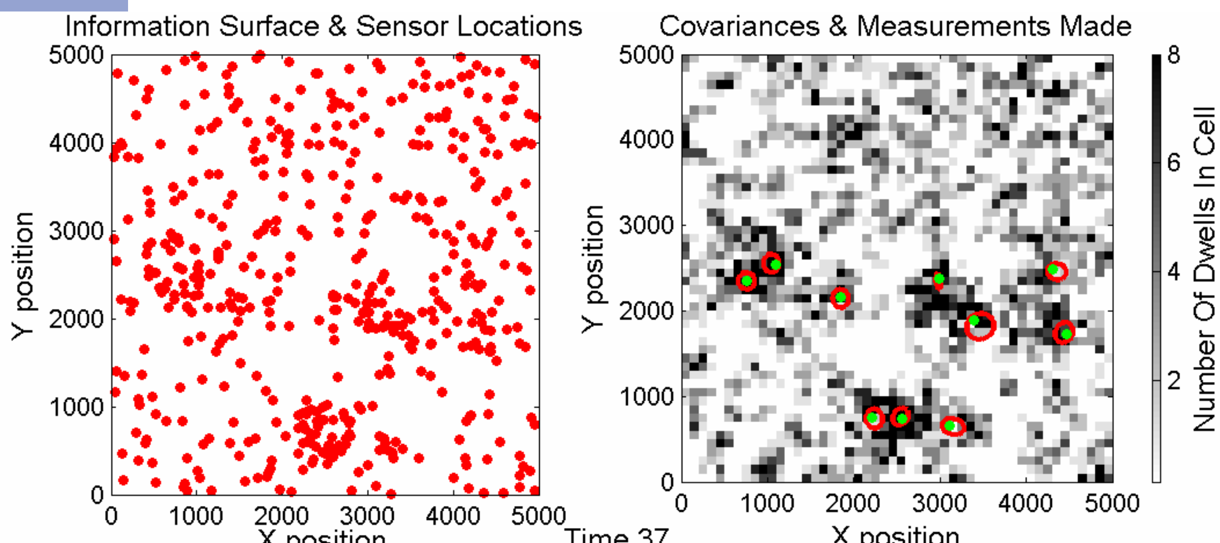
$$\dot{\mathbf{r}}_i^{k+1} = c_0\dot{\mathbf{r}}_i^k + (c_1 - c_2)\kappa\mathbf{f}_i^k + c_2\kappa\mathbf{f}_i^{k+1} + \delta\dot{\mathbf{r}}_i^{k+1}$$

Kreucher&Kastella&Hero:SPIE05

Simulation

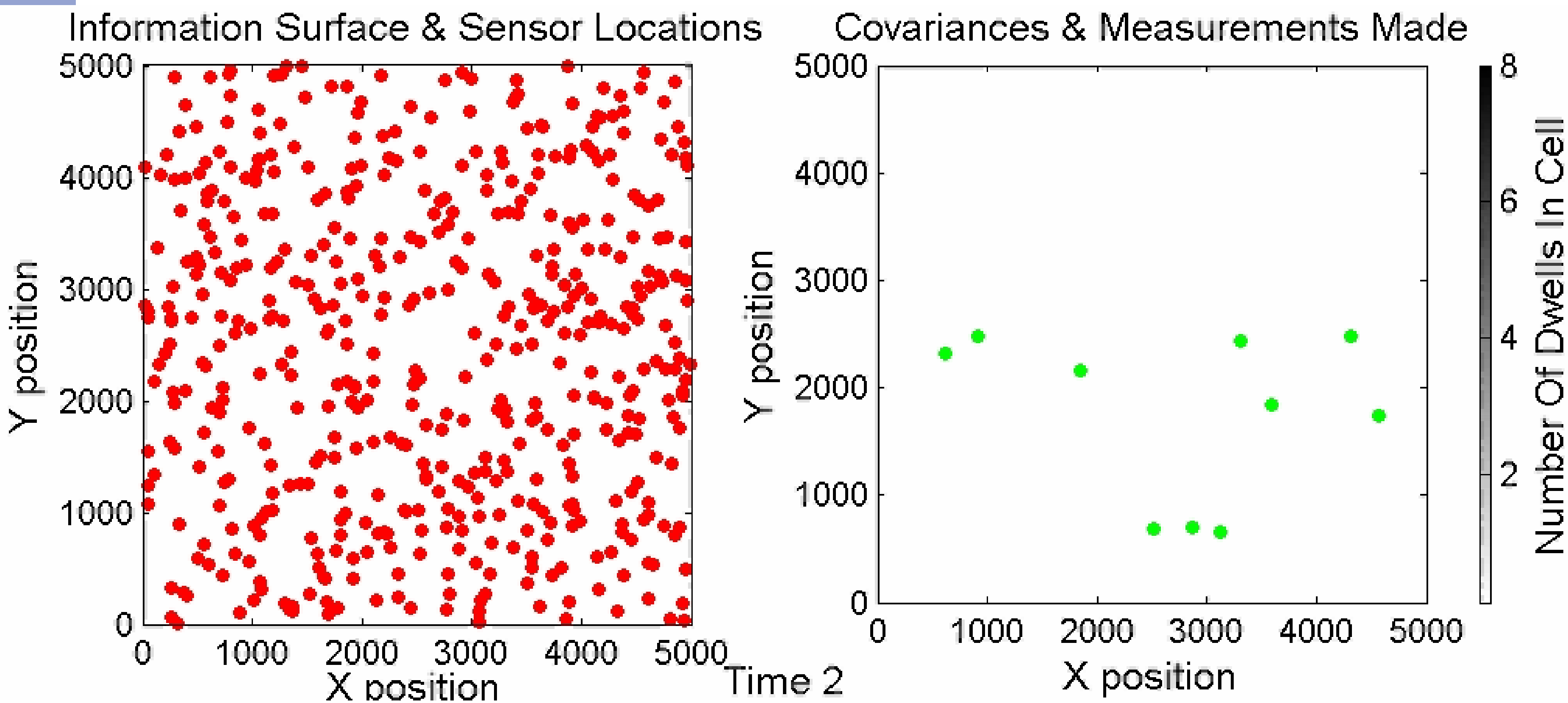


At initialization, the information surface is uniform (lots of uncertainty) and so sensor behavior is dictated by the Lennard-Jones forces : The sensors spread out uniformly through the region



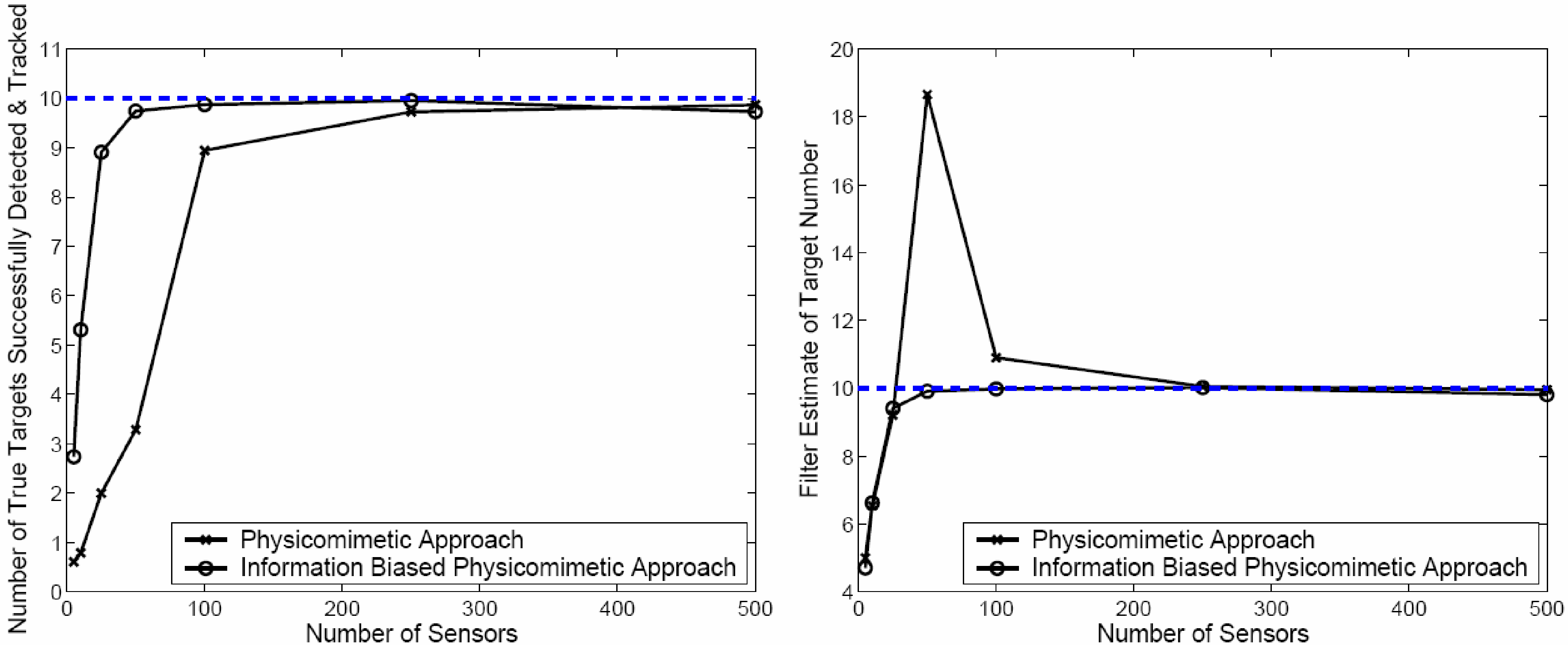
After some time, targets are detected and sensors tend to clump over target locations; however, the Lennard-Jones force ensures sensors still cover the region to address the possibility of new target arrival

Demo



Kreucher&Kastella&Hero:Birkhauser05

Monte Carlo Results

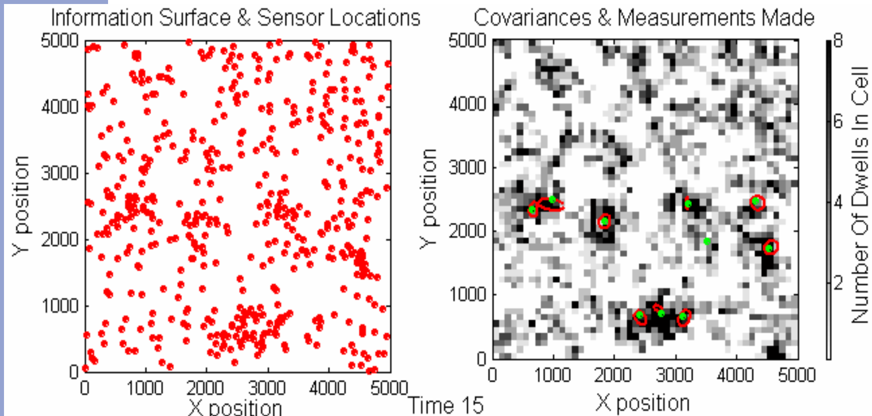


- This plot shows the performance of the Info-based AP method (compared to a purely AP method) at detecting and tracking 10 targets
- Two ways of comparing : The number of true targets successfully detected and the filter estimate of target number
- Coupling to information surface results in factor of 5 to 10 improvement in number of sensors required to meet a performance criteria

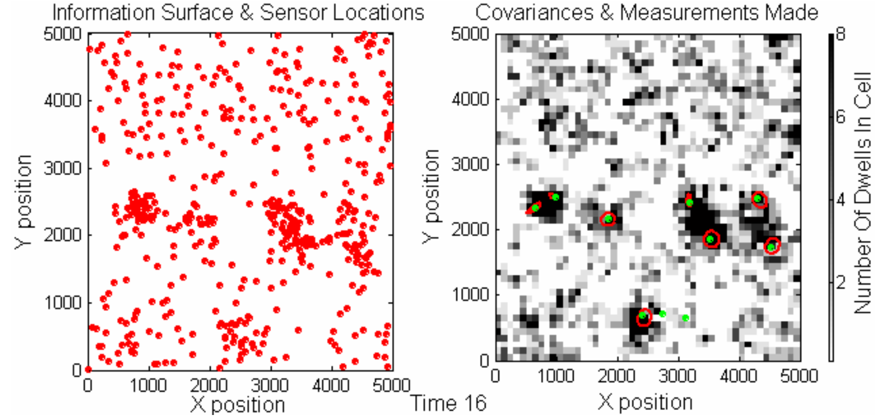
Kreucher&Kastella&Hero:Birkhauser05

On the Choice of β, the Mixing Parameter

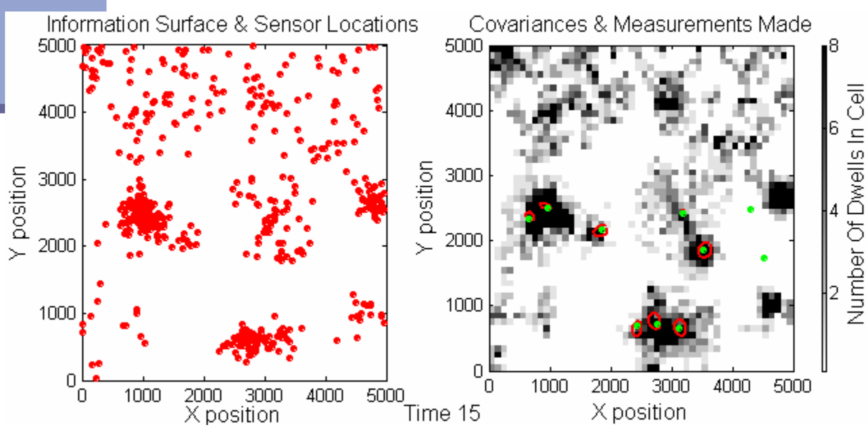
β=.01



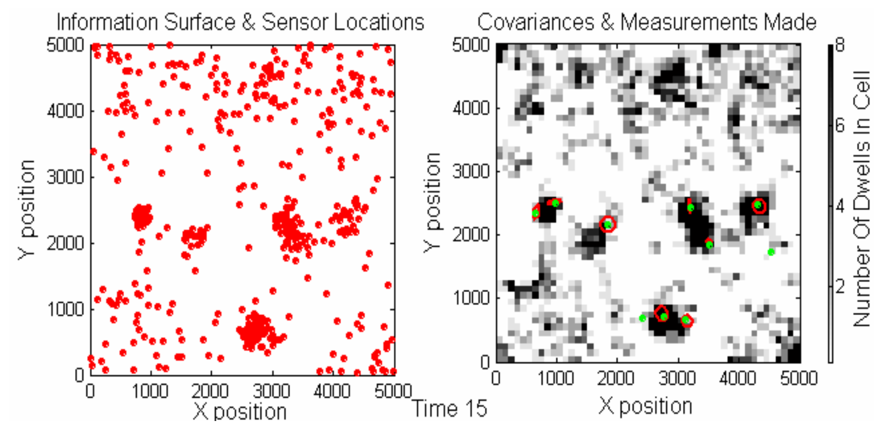
β=.02



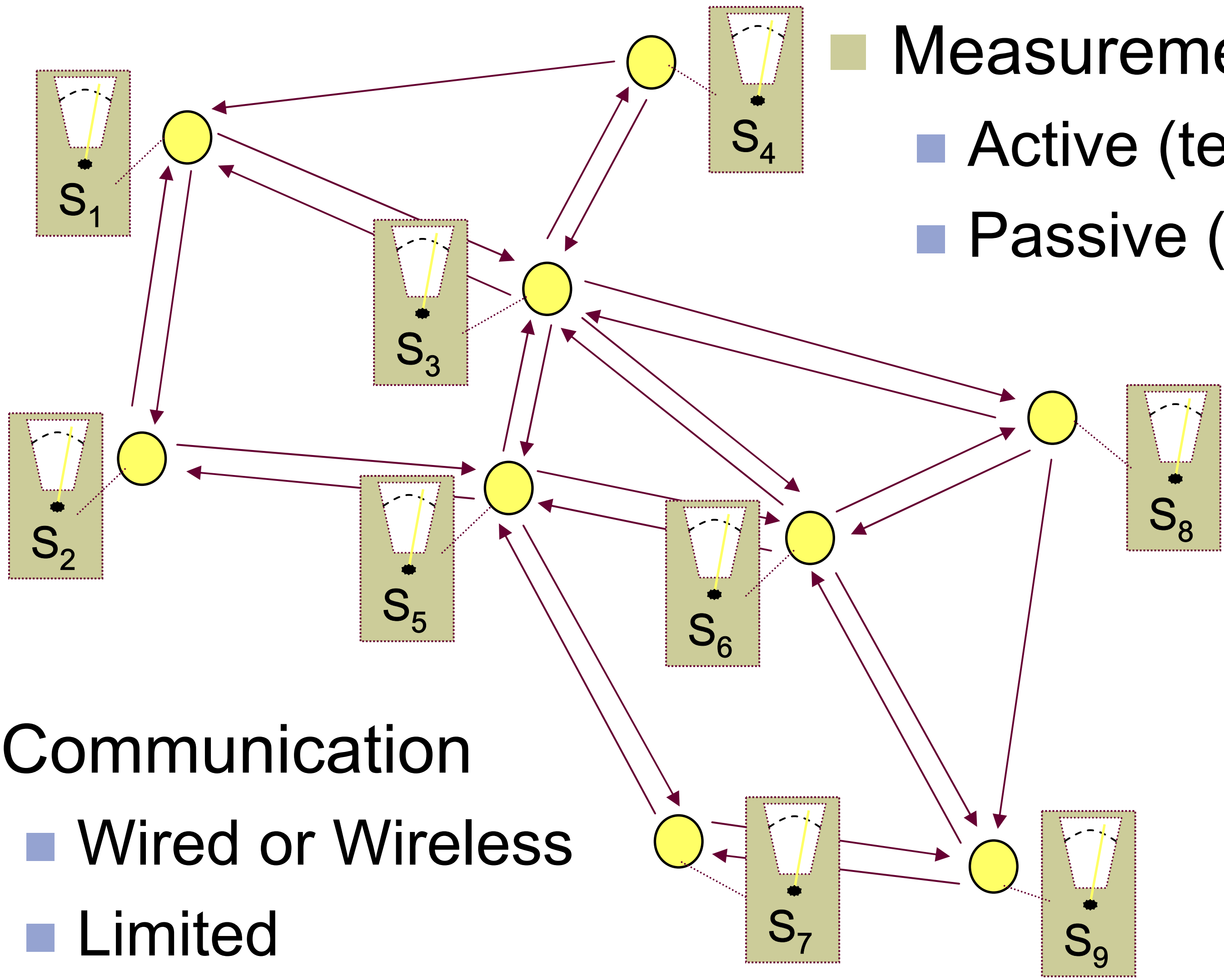
β=.04



β=.08



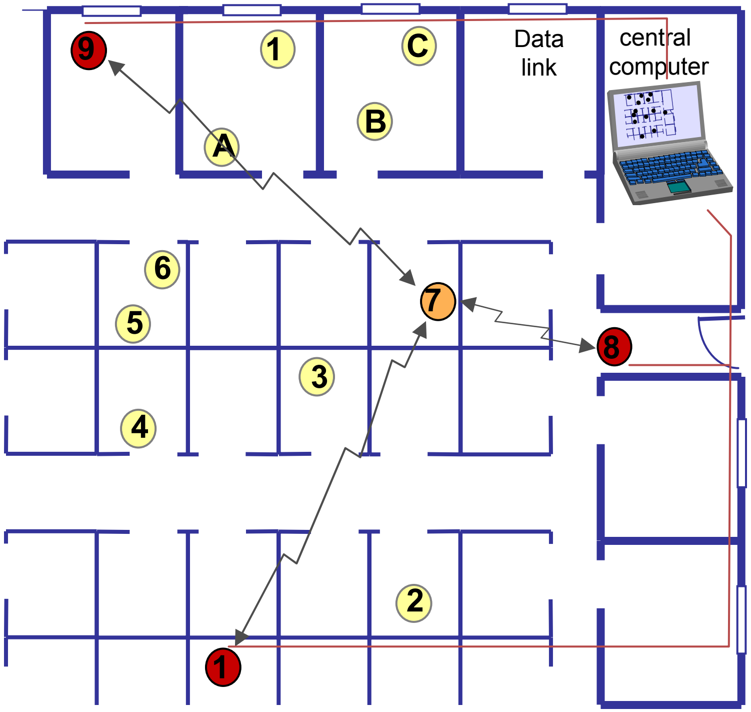
Sensor self-localization problem

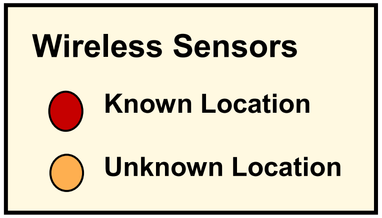


- Measurement
  - Active (telemetry)
  - Passive (correlation)
- Communication
  - Wired or Wireless
  - Limited

GPS / LPS Won't Fill Needs

- LPS: Local Positioning Systems
  - Triangulation / Trilateration

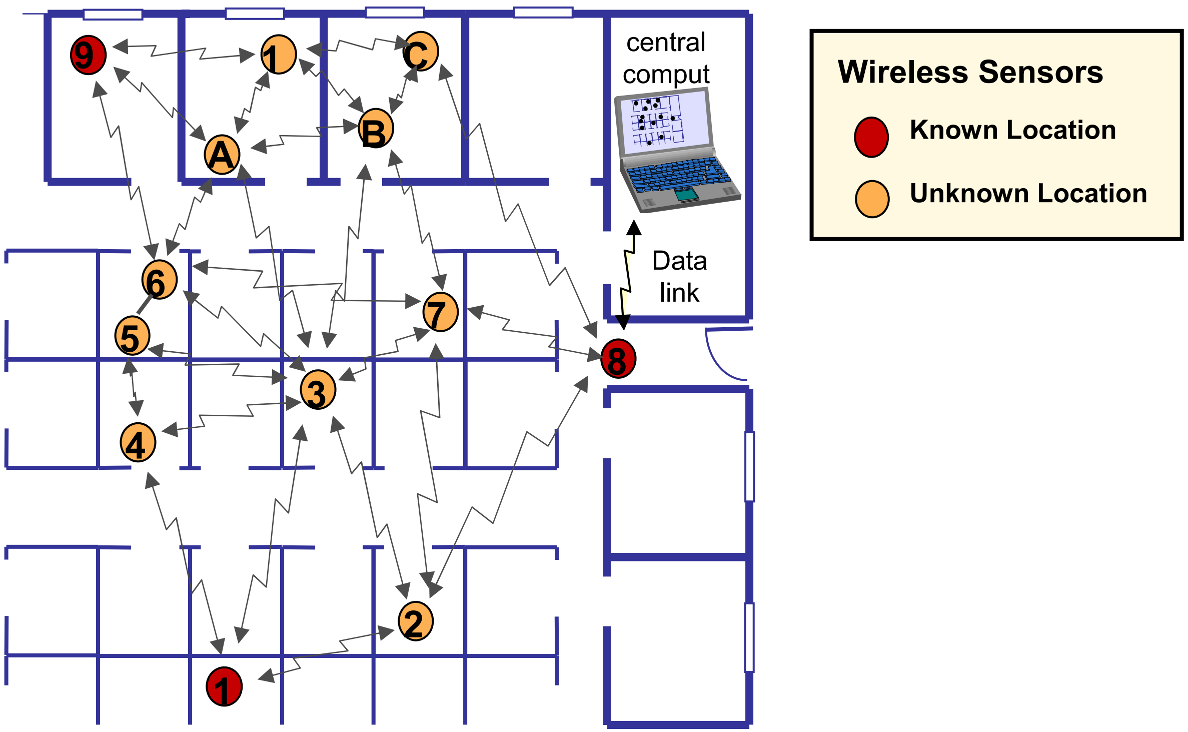




- Cons: Sensors need long-range TX

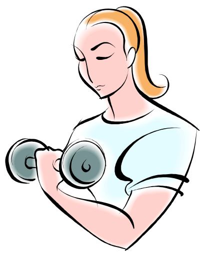
Cooperative Localization

- *Additionally*, use measurements made between pairs of unknown-location devices

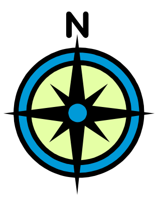


What Pair-wise Measurements?

- Time-of-Arrival (TOA)



- Received Signal Strength (RSS)
  - Connectivity (Proximity)
  - Quantized RSS (QRSS)



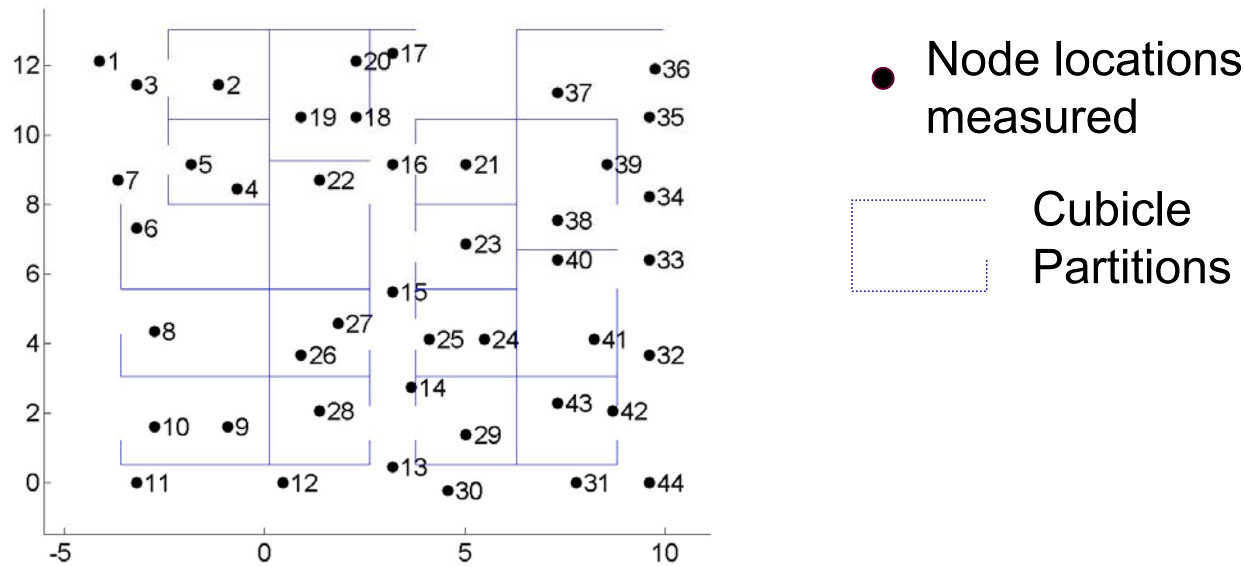
- Angle-of-Arrival (AOA)

- Media: RF / Light / Acoustic

TOA and RSS Localization Experiments

Credit to collaborators at Motorola Labs, Plantation, FL: Matt Perkins, Neiyer Correal, Yanwei Wang

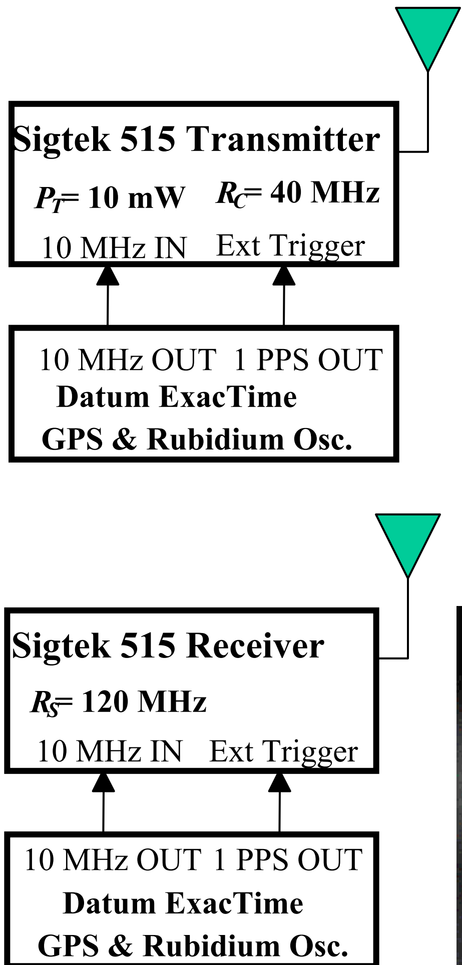
Measurement Exp II: Environment



- Typical (Dilbert) office environment
- 13 by 15 m area, and 44 devices (0.2 / m^2)
- Multipoint-to-multipoint: 44 x 43 x 5 = 9460 measurements
- Data set available online:

  http://www.eecs.umich.edu/~hero/localize

Measurement Exp II: Equipment



Block Diagram of Measurement System

- Wideband Measurement System
  - DS-SS Tx and Rx, f_C = 2443 MHz
  - Sleeve Dipole Antennas, Height 1 m
  - Power Delay Profiles (PDP)
  - TOA estimated (template-matching)
  - RSS estimated (sum multipath powers)

SigTek Receiver

- Averaging
  - Time
  - Reciprocal Channel

Model for Received Signal Strength

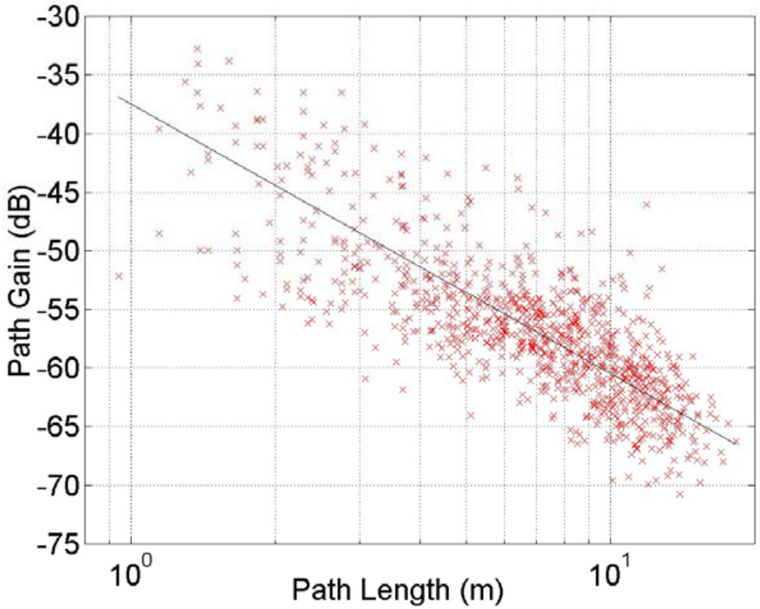


Figure 2.8: Measured Path Gain vs Path Length.

X **Measured Power,** $P_{i,j}$

— $\bar{P}(d)$ with n_p = 2.30

- Log-log RSS residual, $P_{i,j} - \bar{P}\left(\|\mathbf{z}_i - \mathbf{z}_j\|\right)$, is approximately Gaussian with σ_{dB} = 3.9 dB

Model for Time-of-Arrival

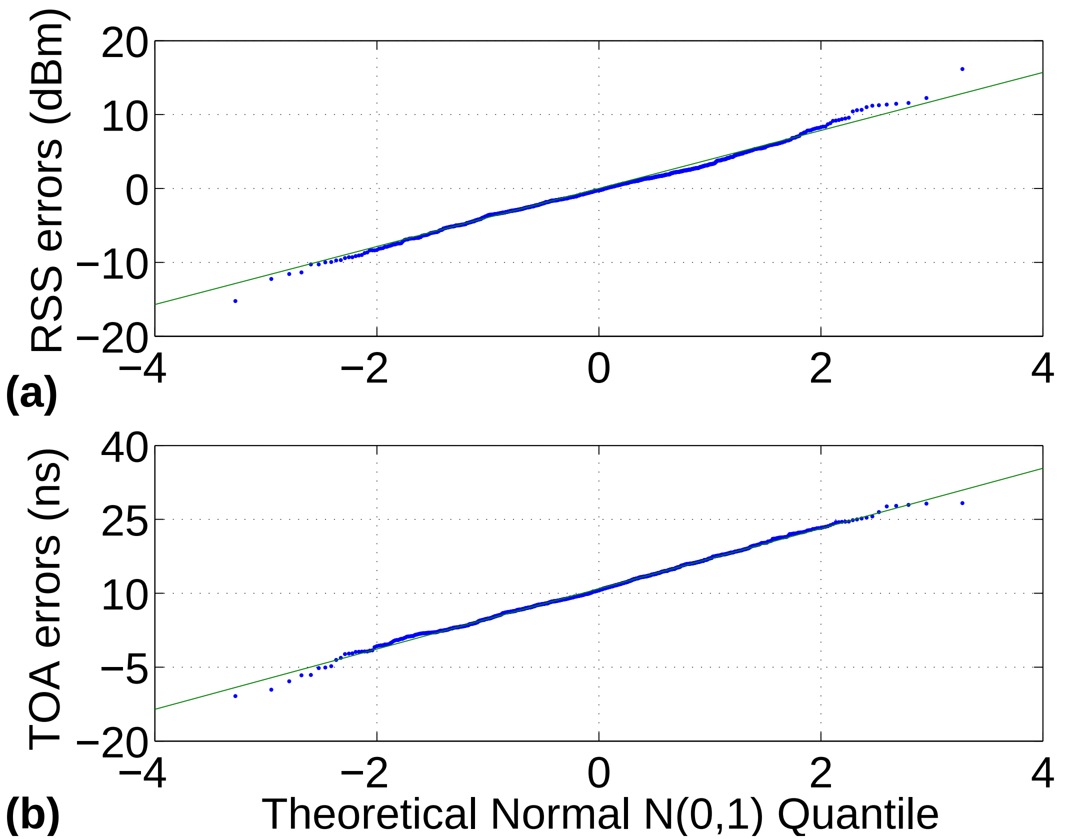
- Positive bias due to multipath
  - Resulting TOA statistic is Gaussian with positive mean:

$$\mathcal{N}(\mu + \|\mathbf{z}_i - \mathbf{z}_j\|/v_p, \sigma_T^2)$$

    - Measurements: μ = 10.9 ns, σ_T = 6.1 ns
  - Good model for short path lengths

Distributions of Measured Data

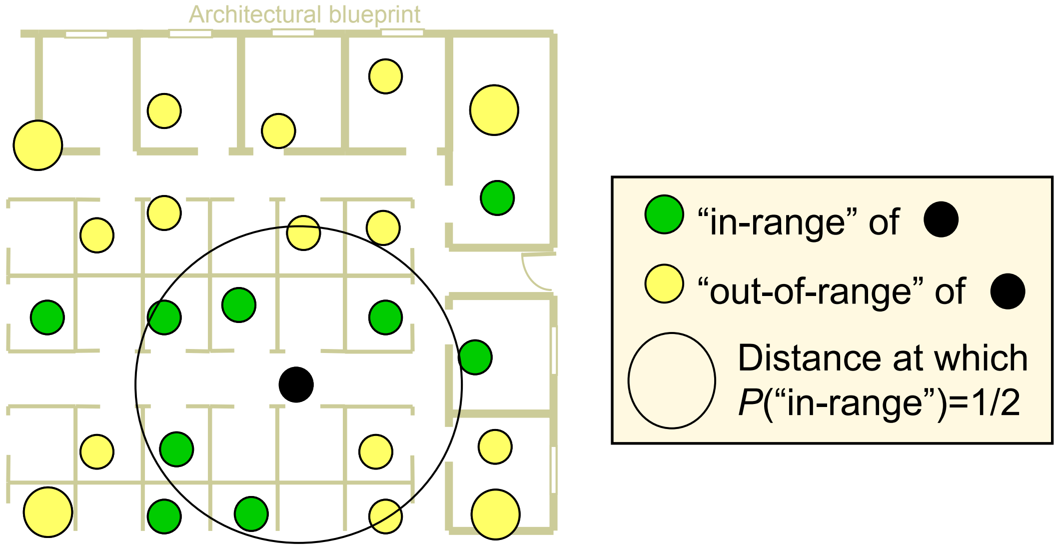
- Quantile-Quantile: compare distributions to Gaussian



- Both TOA and RSS (in dB) are compared to Normal CDF
- Measured data shows heavier tails $\rightarrow$ mixture models?

Connectivity isn't Deterministic

- Devices which can communicate are *connected:*
- Connectivity is *not* solely determined by geometry!



Model for Connectivity: QRSS

- Approximation:
  - RSS > Threshold Power: Devices ‘in-range’
  - RSS < Threshold Power: Devices ‘out-of-range’
- Connectivity is a binary quantization of RSS
- Arbitrary K-level Quantized RSS (QRSS) is possible
  - In reality, RSS must be sampled
  - Automatic Gain Control (AGC) changed in steps
- Considered in [3]

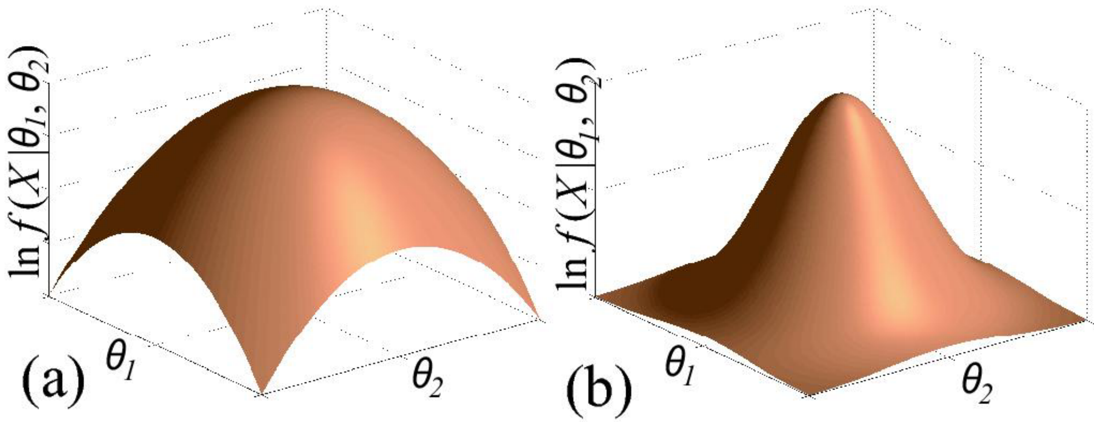
[3] N. Patwari and A.O. Hero, “Using Proximity and Quantized RSS for Sensor Localization in Wireless Networks”, *2nd ACM Wireless Sensor Nets. and Apps. (WSNA)*, San Diego, CA, Sept. 19, 2003.

Benchmarking achievable performance

- Design Questions
  - What measurement method should be used?
  - What is a good density / placement strategy for known-location sensors?
  - How do channel parameters / nuisance parameters impact performance?
  - What configurations of a sensor network provide acceptable performance?
- To answer these questions in an algorithm-independent manner a benchmark is required

Design tool: Information Theory

- Average curvature (FIM) of log-likelihood gives lower bound on variance of any unbiased estimator



- Results for TOA/AOA, RSS, QRSS, connectivity [4,5]
- Rate distortion theory for quantized measurements

[4] R. L. Moses, D. Krishnamurthy, R. Patterson, "An auto-calibration method for unattended ground sensors," ICASSP, May 2002.

[5] N. Patwari, A.O. Hero, M. Perkins, N. S. Correal, R. J. O'Dea, "Relative Location Estimation in Wireless Sensor Networks", IEEE Transactions on Signal Processing, vol. 51, no. 8, Aug. 2003.

[6] R. Gupta, A.O. Hero, "High rate vector quantization for detection", IEEE Transactions on Information Theory, vol. 49, No. 8, pp. 1951-1969, Aug. 2003.

Key Intuition Obtained From CRB

- As we scale the diameter of network
  - TOA bounds remain constant
  - AOA, RSS bounds increase proportionally
- Proportionality to channel parameters
  - TOA variance prop. to $(\sigma_T v_p)^2$
  - AOA variance prop. to σ_α^2
  - RSS, QRSS, Connectivity prop. to $(\sigma_{dB}/n_p)^2$
- Effect of RSS Quantization
  - Connectivity best case: $h_{k,l} \approx 0.64$

CRB GUI

- Localization CRB when measuring RSS, QRSS, Connectivity
- CRB code available online (all modes)
- GUI: Collaboration with J. Ash at OSU [7]

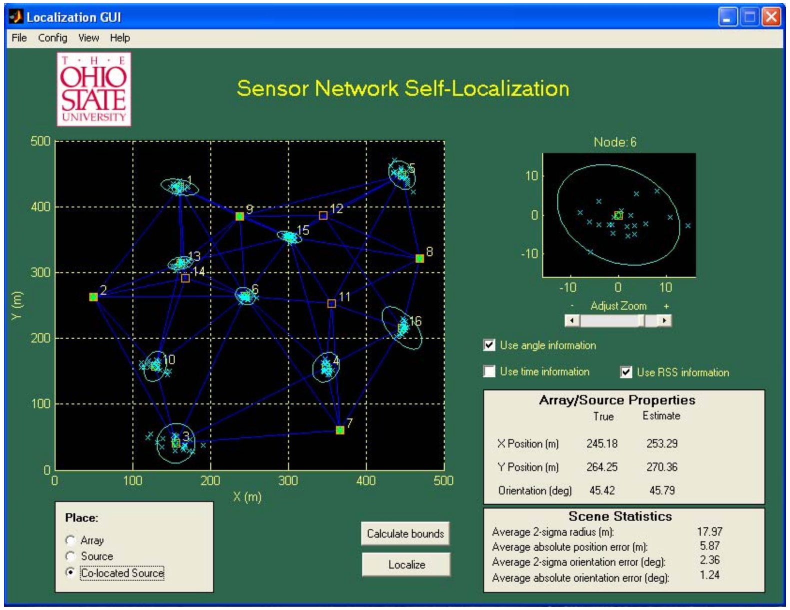


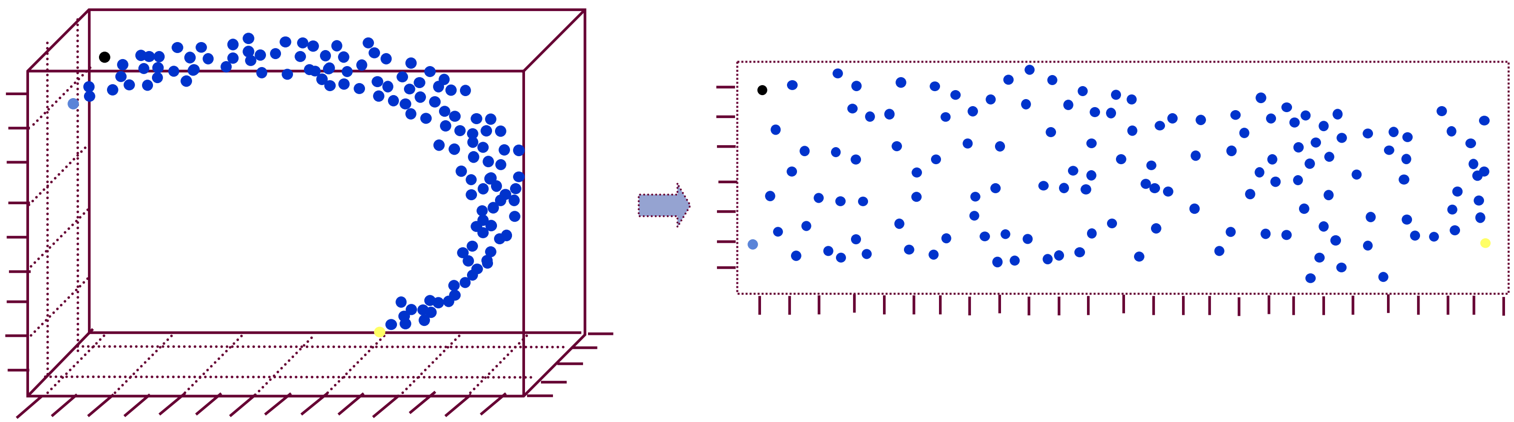
Figure 3.2: *GUI for calculation of cooperative localization CRB and simulation of maximum likelihood estimator (MLE) performance*

- Measurement data available on our website

[7] N. Patwari, J. Ash, S. Kyperountas, A. O. Hero, R. M. Moses, N. S. Correal, “Locating the Nodes”, IEEE Signal Processing, July 2005.

Model Free Approach: Manifold Learning

- Extract low-dim structure from high-dim data
- Data may lie on curved (but locally linear) subspace



[8] J.B. Tenenbaum, V. de Silva, J.C. Langford "A Global Geometric Framework for Nonlinear Dimensionality Reduction" *Science*, 22 Dec 2000.

[9] Sam T. Roweis and Lawrence K. Saul, "Nonlinear dimensionality reduction by local linear embedding," *Science*, Dec 2000.

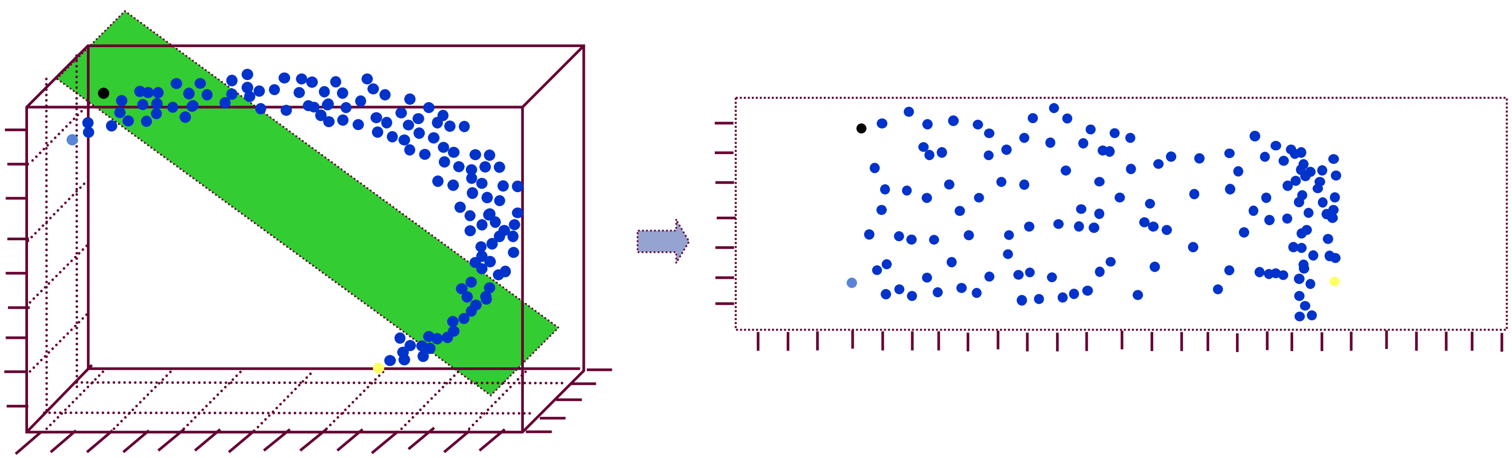
[10] David L. Donoho and Carrie Grimes, "Hessian eigenmaps: New locally linear embedding techniques for highdimensional data," Tech. Rep. TR2003-08, Dept. of Statistics, Stanford University, March 2003.

Simple version: MDS/PCA for TOA

- Key property for geolocation of planar sensor networks
  - Matrix $\mathcal{E}_X = \left(\left(\|x_i - x_j\|\right)\right)_{i,j=1}^{n}$ of pairwise distances is linearly related to sensor locations

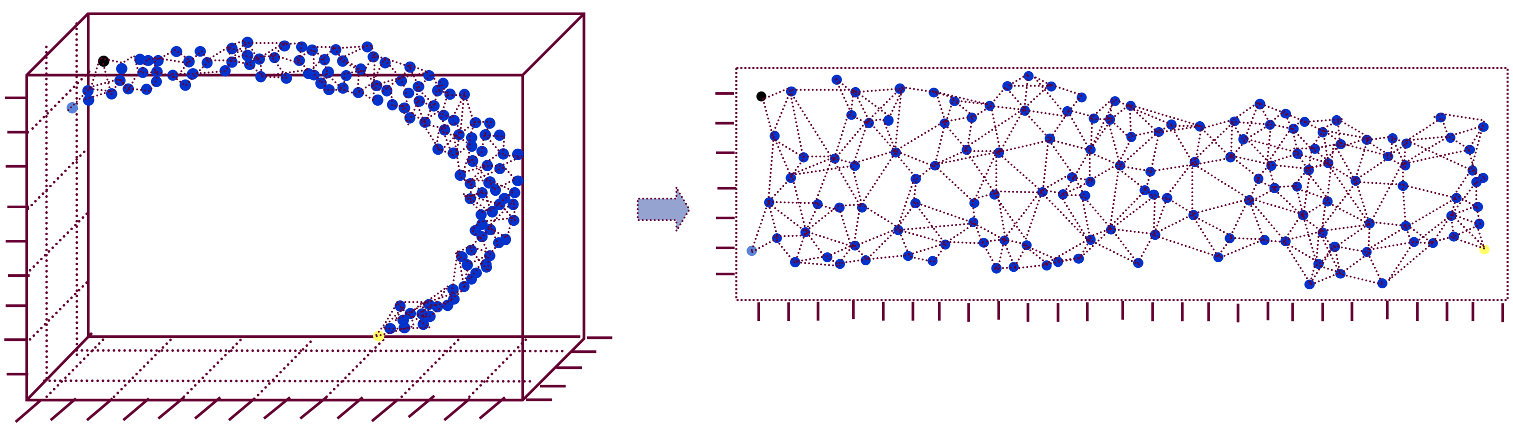
$$X = D^{1/2}_{(1:2,1:2)} U_{(1:2,:)} \qquad [I - \underline{1}\underline{1}^T]\mathcal{E}_X[I - \underline{1}\underline{1}^T] = UDU^T$$

  - Pairwise measurements (TOA, RSS, QRSS) are related to physical geometry
  - In the case of TOA this relation is linear and MDS is applicable
  - In other cases, the relation is non-linear or not known precisely



Manifold Learning: Preserve Neighbors

- Preserve local structure (nearest neighbors)
  - Isomap: Preserve shortest path distances in nearest-neighbor graph
  - Distributed weighted multi-dimensional scaling (dwMDS): Preserve weighted distances (weight = 0 for non-neighbors)
  - Laplacian eigenmaps (LE): Preserve similarity, i.e., inverse distance, which is zero for non-neighbors.
    - Locally Linear Embedding (LLE), Hessian-based LLE



Two Perspectives on one Solution

- Equivalent Problems:
  - Find coordinates for sensor's data
  - Find location of sensor

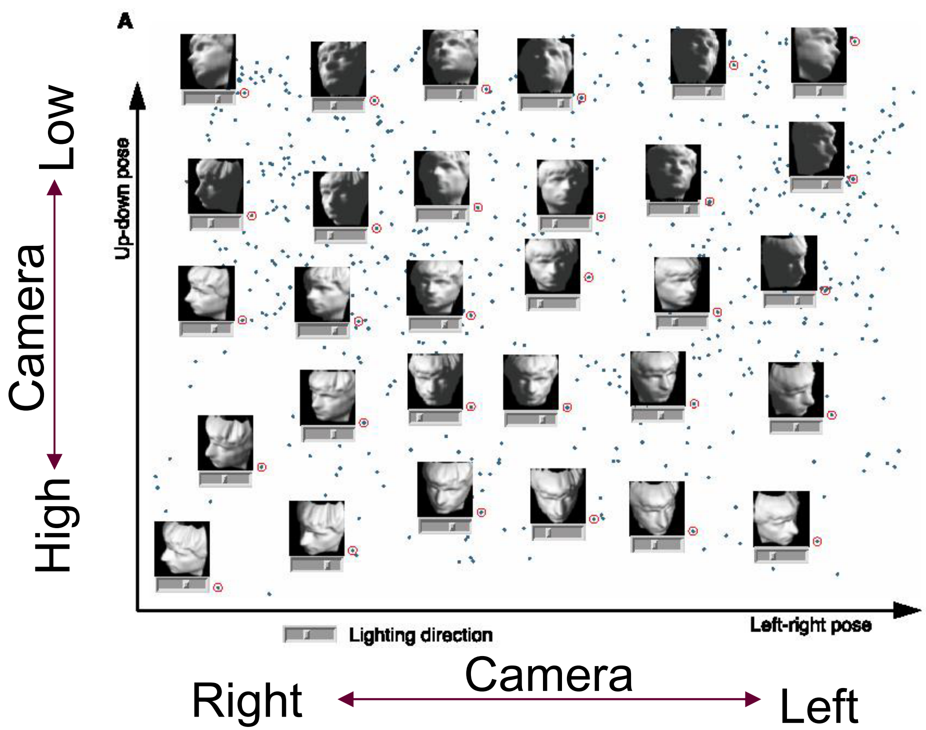


Figure 4.6: **The intrinsic geometric structure (represented using Isomap K=6) of a sequence of 64x64 pixel images of a face rendered with different poses and lighting directions.**

[8] J.B. Tenenbaum, V. de Silva, J.C. Langford "A Global Geometric Framework for Nonlinear Dimensionality Reduction" *Science*, 22 Dec 2000.

Compare Manifold Learning Algorithms

	MDS-MAP [11] or Isomap	*dwMDS [12]*	*Laplacian Eigenmap [13]*
Distance or Similarity?	Distance	Distance	Similarity
Cost to Minimize	$\sum_{i,j} \left(\|\mathbf{z}_i - \mathbf{z}_j\|^2 - \tilde{\delta}_{i,j}^2 \right)^2$	$\sum_{i,j} w_{i,j} \left(\|\mathbf{z}_i - \mathbf{z}_j\| - \delta_{i,j} \right)^2$	$\sum_{i,j} w_{i,j} \|\mathbf{z}_i - \mathbf{z}_j\|^2$
Algorithm Basis	Eigen-decomposition	Iterative, distributed majorization	Eigen-de-composition
Notes	Sensitive to large range errors	Can incorporate prior info	Natural for connectivity

[11] Y. Shang, W. Ruml, Y. Zhang, M.P.J. Fromherz, "Localization from mere connectivity," in Mobihoc '03, June 2003, pp. 201–212.

[12] J. Costa, N. Patwari, A.O. Hero III "Distributed Weighted Multidimensional Scaling for Node Localization in Sensor Networks", *IEEE/ACM Trans. Sensor Networks*, to appear Dec. 2005.

[13] N. Patwari, A.O. Hero III "Adaptive neighborhoods for manifold learning-based sensor localization", *IEEE SPAWC 2005*, June 2005.

Example: 7 by 7 Grid of Devices

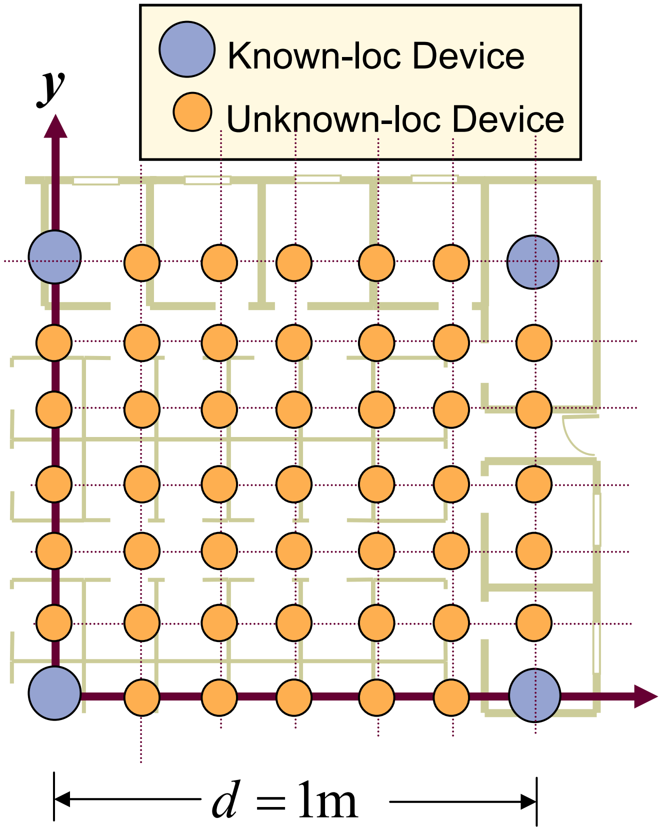
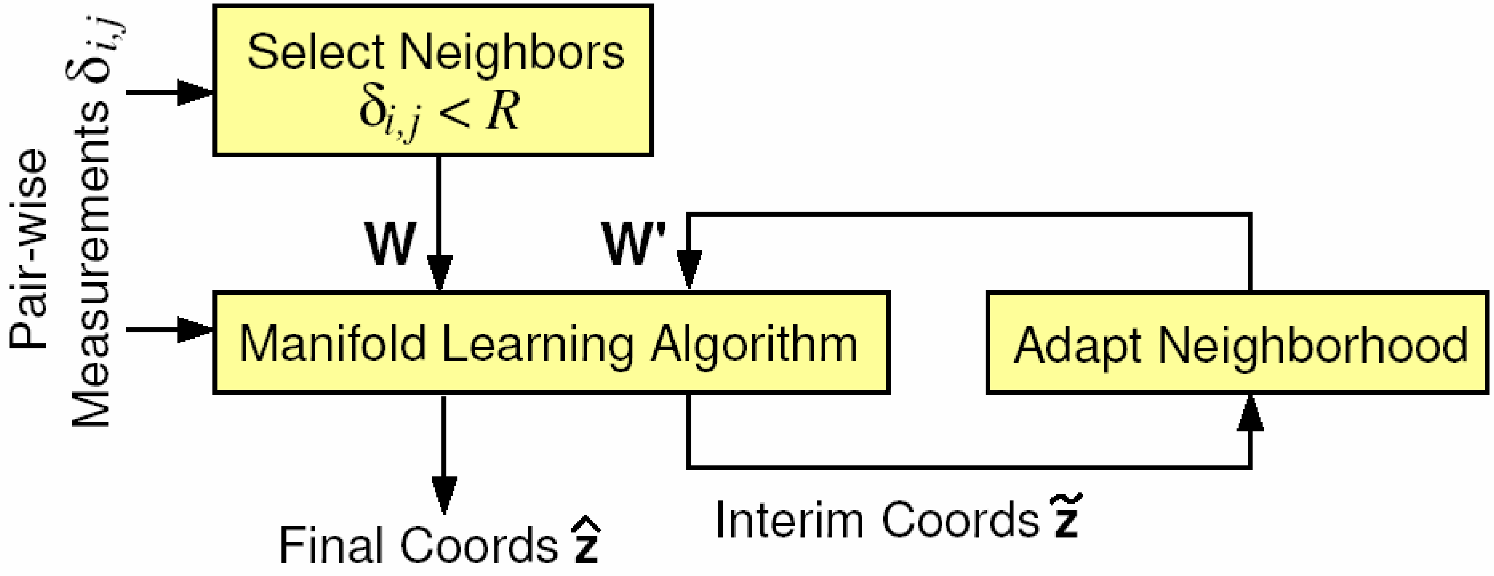


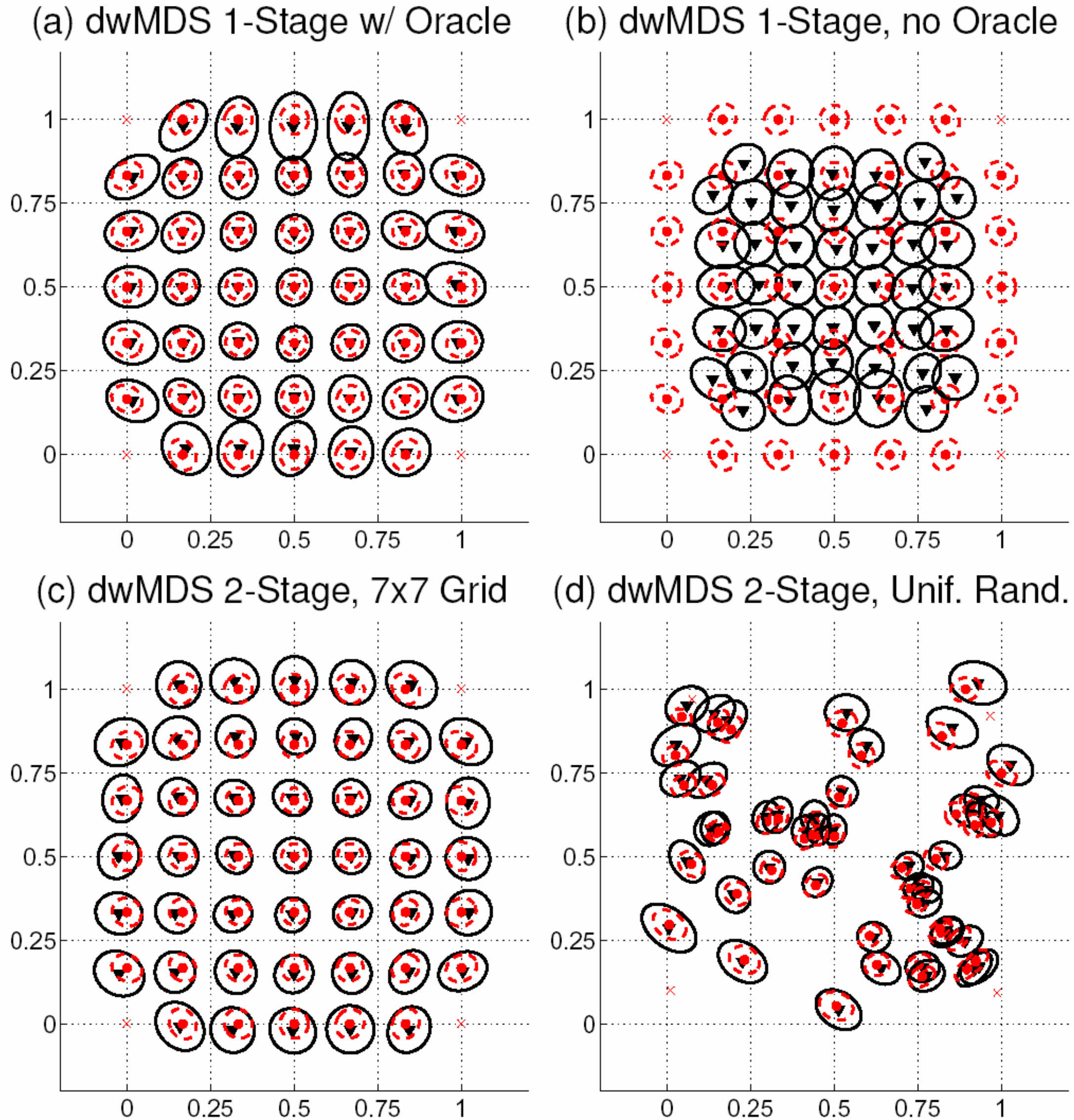
Figure: *Actual device locations in the 7 by 7 grid example*

- 4 *known-location* devices
- 45 *unknown-location* devices
- Run 100 trials per estimator to find mean and covariance
- Compare estimator covariance to CRB

Iterative self-localization algorithm

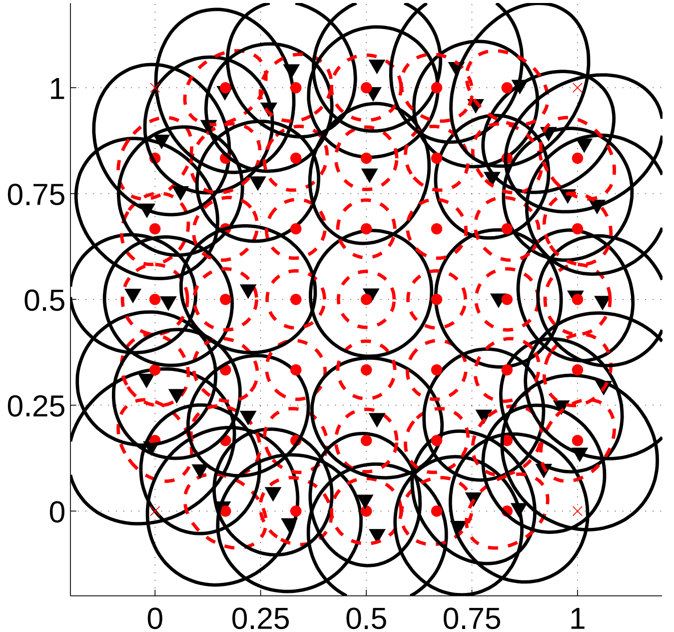


Simulation of dwMDS: RSS



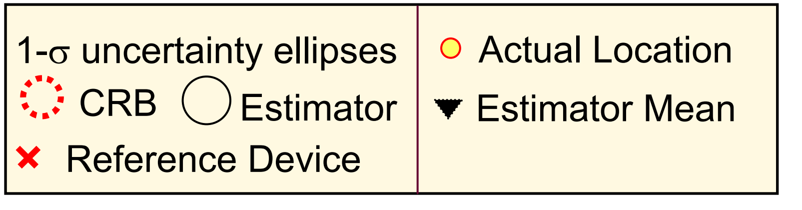
Simulation of Isomap: Connectivity

- Measure Connectivity
- Use Isomap / MDS-MAP [11]



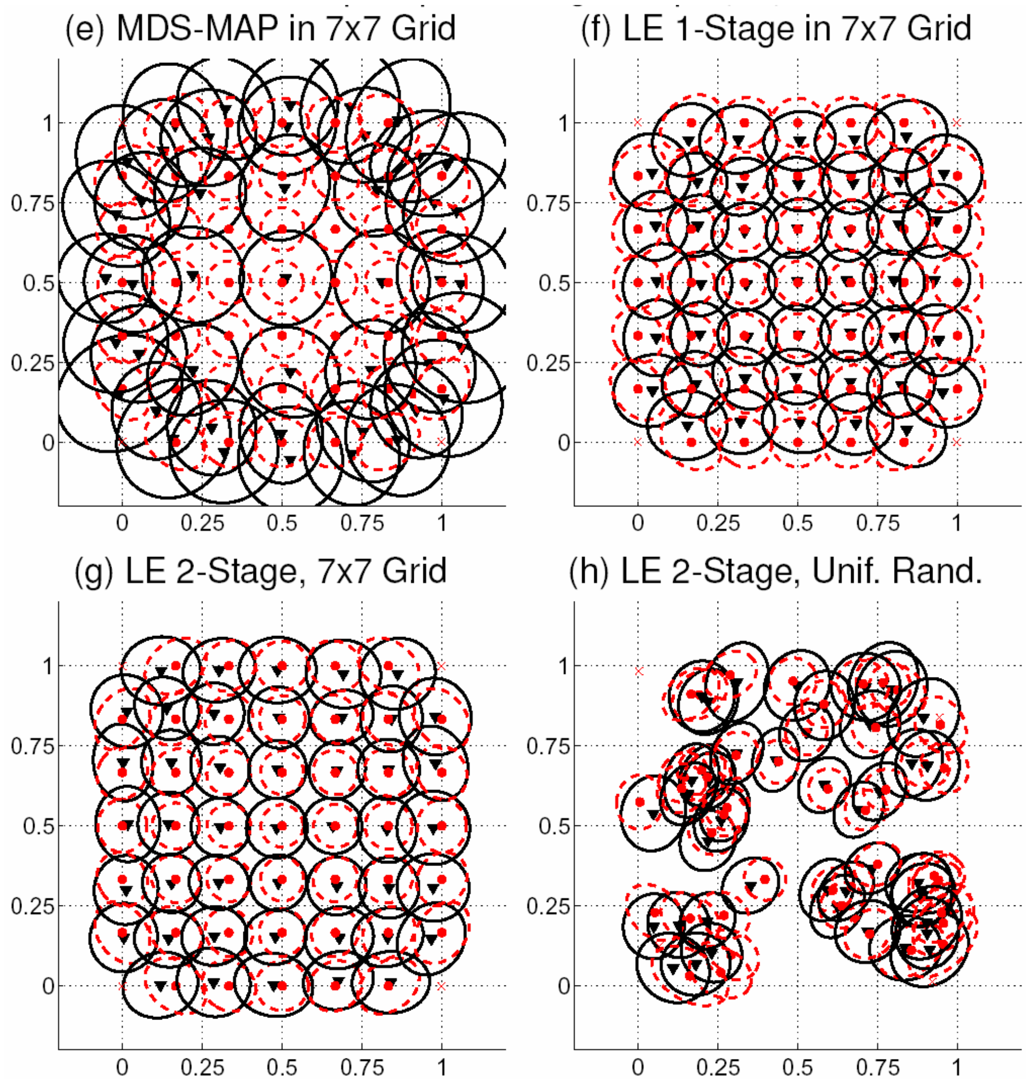
MDS-Map with $R = 0.5$

Key:



[11]Y. Shang, W. Ruml, Y. Zhang, M.P.J. Fromherz, "Localization from mere connectivity," in Mobihoc '03, June 2003, pp. 201–212.

Comparison to LE: Connectivity

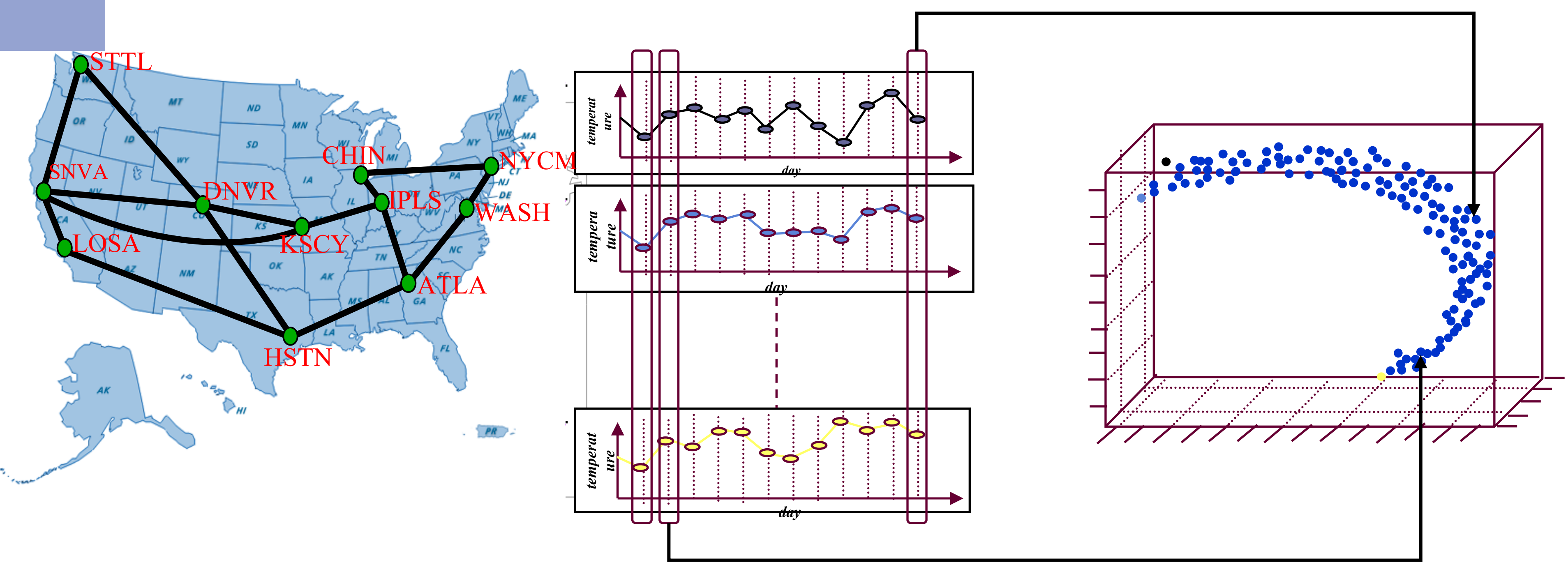


[13] N. Patwari, A.O. Hero, "Adaptive Neighborhoods for Manifold Learning-based Sensor Localization," *IEEE Signal Processing & Wireless Commun. Conf. (SPAWC)*, June 2005.

Application: Adaptive Internet Anomaly Detection

- Spatio-temporal measurement vector:

$$\mathbf{x}(t) = [\mathbf{x}_1(t), \ldots, \mathbf{x}_N(t)] \quad \forall t = 1 \ldots \tau$$



Internet anomaly detection

- Anomalies: Worm outbreaks, DoS attacks, Intrusion activity (scans)
- Monitor: Collect set from sensors (routers) in space and time
- Hypothesis: Anomalies will change distribution of traffic across sensors
  - ‘Distribution’: traffic by src/dst port, IP addresses; packet sizes, etc.
- Problem: How do you find ‘anomalous’ relationships across space?

[14] N. Patwari, A. O. Hero, A. Pacholski, “Manifold Learning Visualization of Network Traffic Data”, ACM Wksp on Mining Net. Data (MineNet’05), Aug 2005.

Router Map: High-Dim. Traffic Vectors

- Sensors at routers measure # flows per source IP address
  - 07-Jan-2005 during 15:45-15:50 UTD
  - Packets are sampled 1/100
  - Last 11 bits zeroed for privacy -> data are 2^{21}–length (sparse) vectors

- NYCM measures:

SRC IP	Flows
140.123.64.0	19925
204.179.120.0	4587
130.14.24.0	3713
128.112.128.0	2649
207.68.176.0	2031
207.68.168.0	1817
128.187.200.0	1683
140.247.56.0	1560
158.42.128.0	1513
⋮	⋮

- WASH measures:

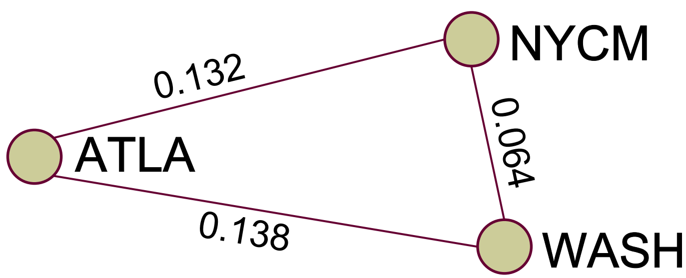
SRC IP	Flows
140.123.64.0	20090
130.14.24.0	9965
130.91.40.0	6772
128.112.128.0	2766
152.2.208.0	2700
158.42.128.0	1578
158.130.0.0	1523
207.68.176.0	1509
128.112.136.0	1428
⋮	⋮

- ATLA measures:

SRC IP	Flows
171.66.120.0	1597
130.14.24.0	1210
207.68.176.0	1076
158.130.0.0	897
207.68.168.0	888
206.240.24.0	728
130.91.40.0	716
207.46.248.0	714
169.229.48.0	705
⋮	⋮

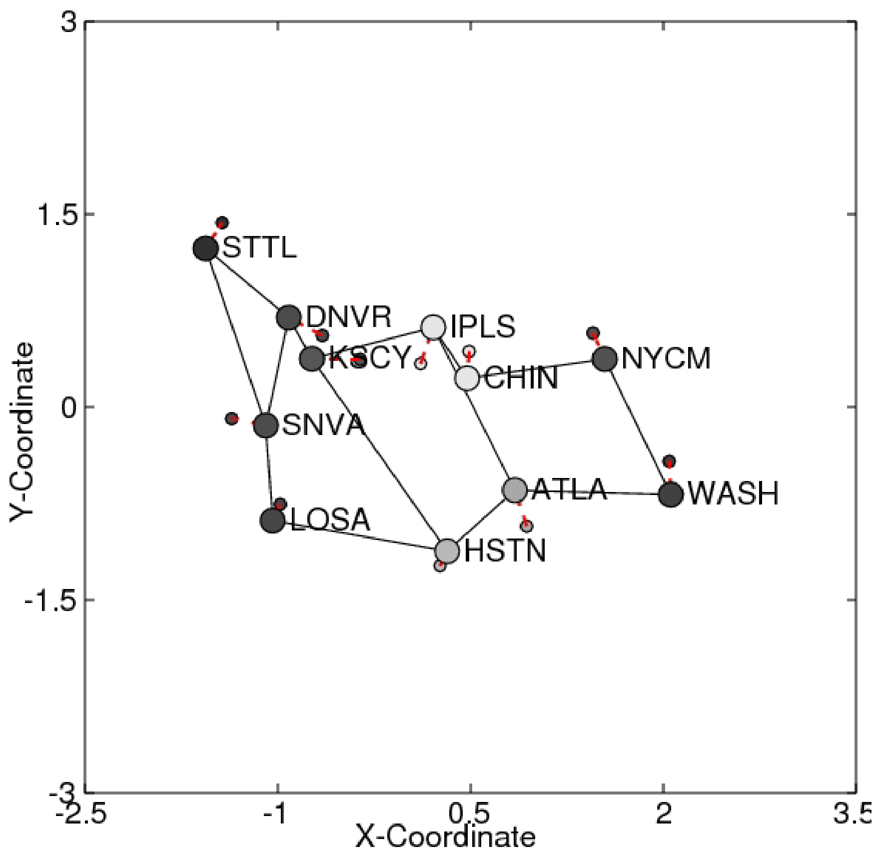
Data Vector Localization Algorithm

- Place Routers on a map so that Euclidean distances $\{\delta_{i,j}\}$ between vectors is preserved
  - Traffic histograms (normalized so sum == 1)
  - Example from previous slide



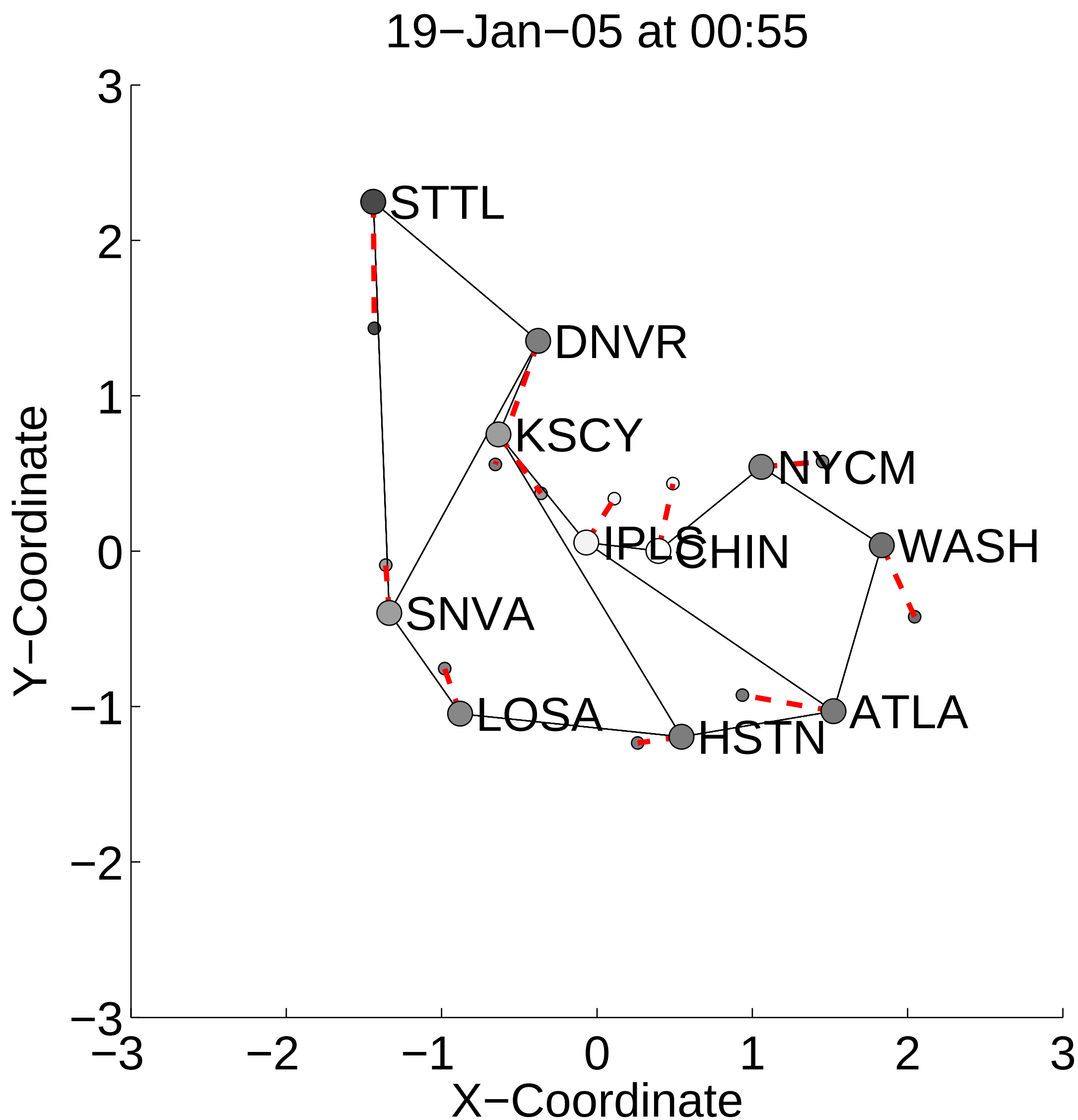
Results: Sensor Map Example

- Typical router map, 18-Jan 17:00 UTD
- Sensors (routers) as positioned by dwMDS
- Coordinates are normalized (flows) so are unitless
- Lines show physical Abilene links
- Small dots (- - -) show distance from 4-week mean coord



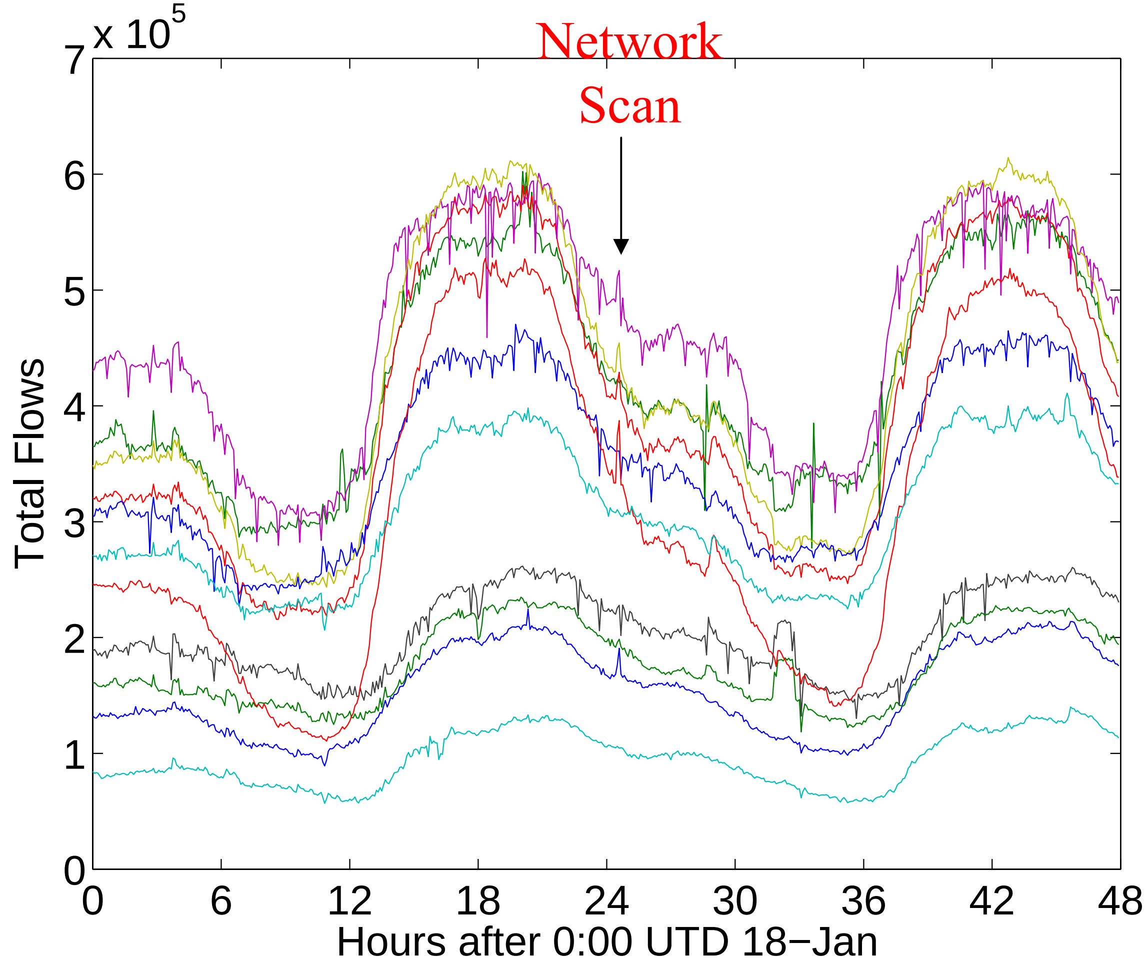
Maps Respond to Anomalous Traffic

- Wed. 19-Jan 2005, 0:00-1:00 UTD
- At 0:30, 0:35: large network scan
  - 22,000 anomalous flows observed at STTL, DNVR, KSCY, IPLS, ATLA
  - 60-byte, TCP
  - From a few Miss. State U. IPs, Src Port < 1024
  - To range of Microsoft IPs, Dest Port 113



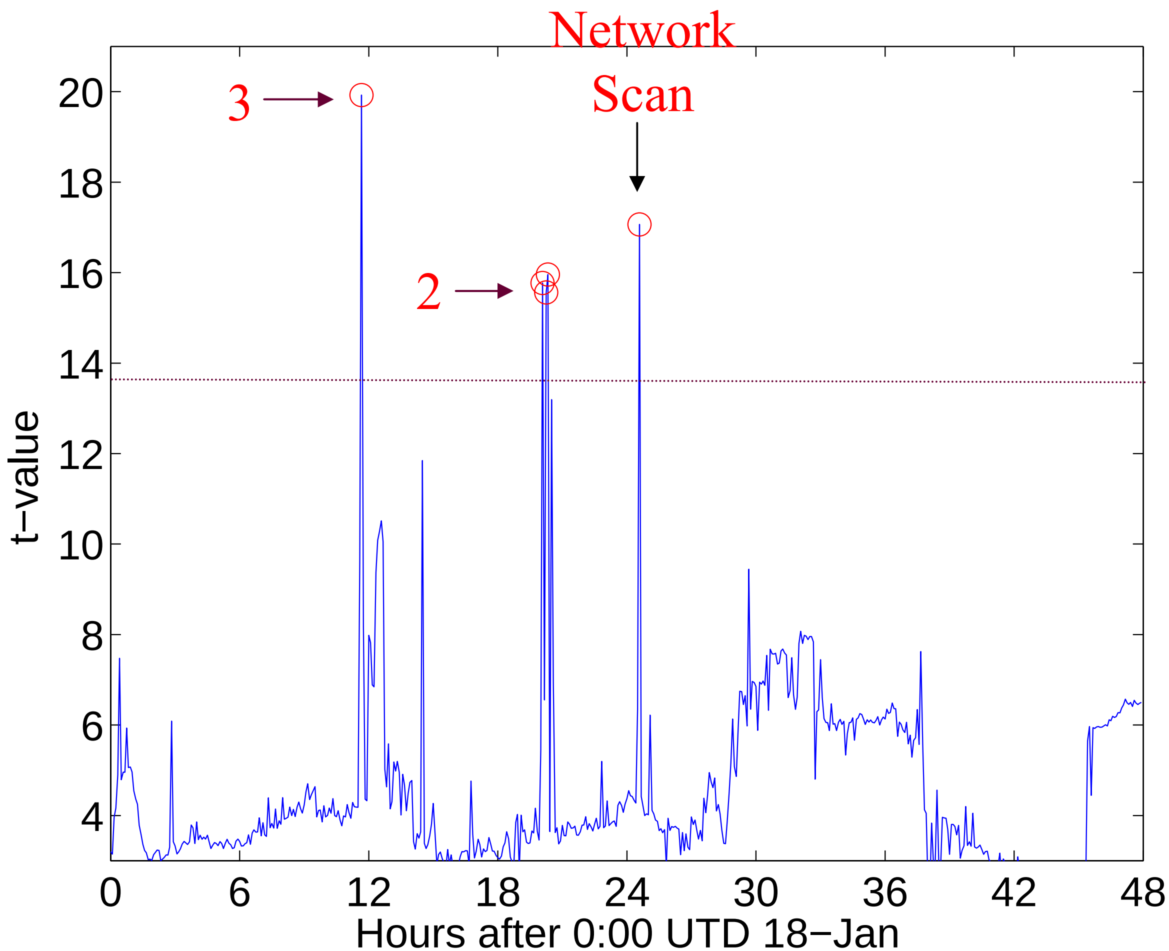
Pure Time Series: Small Change

- Abilene Backbone Total Flows, by router
- 18-19 Jan



Automatic Detection Algorithm

- *Multivariate t-test* comparing the current coords to a history of coordinates
- Declare alarm when t-value exceeds threshold
- Eg: 18-19 Jan-05



2: 45kflow port scan from .tw to .dk

3: 46kflow port scan from .tw to .pl

Conclusions

- Approach grounded in optimization and information theory
- Parametric model gives useful performance bounds
- Algorithms too strongly coupled to models are brittle.
- Need for model-free algorithms that are capable of learning the important statistics
- Future work:
  - Decentralized decisionmaking
  - Communication bandwidth constraints
  - Joint target tracking and self-localization

Publications (available on http://www.eecs.umich.edu/~hero)

- Journal articles
  - D. Blatt and A. O. Hero, "Energy based sensor network source localization via projection onto convex sets (POCS)", (submitted) *IEEE Trans. on Signal processing*, Feb. 2005.
  - D. Blatt, A. O. Hero and H. Gauchman, "A convergent incremental gradient algorithm with a constant stepsize", (submitted) *SIAM Journal on Optimization*, Sept. 2004.
  - J. A. Costa, N. Patwari, A. O. Hero, “Distributed Weighted Multidimensional Scaling for Node Localization in Sensor Networks”, (to appear) ACM/IEEE Journal on Sensor Networks.
  - N. Patwari, J. Ash, S. Kyperountas, A. O. Hero, R. M. Moses, N. S. Correal, “Locating the Nodes” *IEEE Signal Processing,* July 2005.
  - N. Patwari, A. O. Hero, M. Perkins, N. S. Correal, R. J. O'Dea, “Relative Location Estimation in Wireless Sensor Networks”, *IEEE Trans. Signal Processing*, Aug. 2003.
- ACM conference papers
  - N. Patwari, A. O. Hero, A. Pacholski, “Manifold Learning Visualization of Network Traffic Data”, ACM Wksp on Mining Net. Data (MineNet’05), Aug 2005.
  - N. Patwari, A. O. Hero, “Using Proximity and Quantized RSS for Sensor Localization in Wireless Networks”, ACM Wksp. on Wireless Sensor Nets. and Appl. (WSNA’03), Sept. 2003.

Publications

- IEEE conference papers
  - D. Blatt and A.O. Hero, "APOCS: a convergent source localization algorithm for sensor networks," *IEEE Workshop on Statistical Signal Processing (SSP),* Bordeaux, July 2005.
  - C. Kreucher, K. Kastella, and A. Hero. Multiplatform Information-based Sensor Management. *The Proceedings of the SPIE Defense Transformation and Network-Centric Systems Symposium*, volume 5820, pages 141-151, March 28 - April 1 2005
  - N. Patwari, A. O. Hero, “Adaptive Neighborhoods for Manifold Learning-based Sensor Localization,” *IEEE Signal Processing & Wireless Commun. Conf. (SPAWC)*, June 2005.
  - J. A. Costa, N. Patwari, A. O. Hero, “Achieving High-Accuracy Distributed Localization in Sensor Networks”, IEEE Int. Conf. on Acoustics, Speech, & Signal Processing (ICASSP), March, 2005. (Student Paper Contest Finalist)
  - N. Patwari, A. O. Hero, “Manifold Learning Algorithms for Localization in Wireless Sensor Networks”, *IEEE Int. Conf. on Acoustics, Speech, & Signal Processing (ICASSP)*, May 2004.
  - N. Patwari, A. O. Hero, B. Sadler, “Hierarchical Censoring Sensors for Change Detection”, *IEEE Wksp on Statistical Signal Processing (SSP)*, Sept. 2003.
  - N. Patwari, A. O. Hero, “Hierarchical Censoring for Distributed Detection in Wireless Sensor Networks”, *IEEE Int. Conf. on Acoustics, Speech, & Signal Processing (ICASSP)*, April 2003.
  - N. Patwari, A. O. Hero, “Location Estimation Accuracy in Wireless Sensor Networks”, *2002 IEEE Asilomar Conf. on Signals & Systems*, Nov. 2002.
  - N. Patwari, Y. Wang, R. J. O'Dea, “The Importance of the Multipoint-to-Multipoint Indoor Radio Channel in Ad Hoc Networks”, *IEEE Wireless Commun. & Netw. Conf. (WCNC)*, March 2002.