Radio Tomography: Environmental Inference from Wireless Network Signal Strength

Neal Patwari

THE UNIVERSITY OF UTAH

SPAN
Sensing and Processing Across Networks

Utah IEEE SP/COM Chapter Seminar

Outline

Outline

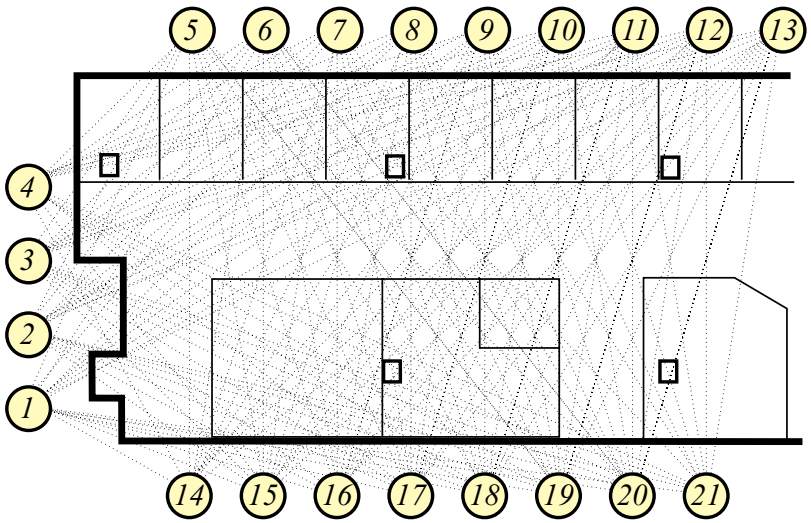
Device-free localization (DFL) Applications

- RFID identifies, locates people's tags
- How about people, objects not tagged?
- Apps: emergency response, smart homes, context-aware computing

DFL: Technologies

- Video cameras. Don't work in dark, through smoke or walls. Privacy concerns.
- Thermal imagers. Limited by walls. High cost.
- IR Motion detectors. Limited by walls. High false alarms.
- Ultra wideband (UWB) radar. High cost.
- Received signal strength (RSS) in a wireless network

RSS-DFL: Measure many spatially distinct links



- Mesh network of N transceivers $\rightarrow \mathcal{O}\left(N^2\right)$ RSS measurements
- Link RSS changes due to people in environment near link
- One person / object affects multiple links

DFL Ideas From Many Sources

- IPSN 2007 Extreme Sensing Competition: won by RSS
- Hero lab at U.M.: Motion detection w/ RSS vectors
- U. Utah link shadowing correlation study

Channel Modeling

Generic model for received power:

$$P_a = \bar{P}(d_a) - X_a$$

- P_a: measured received power on link a: at node r_a transmitted by node t_a (dBm),
- $\bar{P}(d_a)$: model for large-scale fading: Ensemble mean dBm received power at distance d_a.
- X_a: shadowing, small-scale fading loss, measurement error

Question: Are $\{X_a\}_a$ independent?

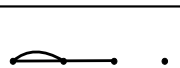
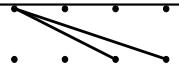
Deployments for Channel Modeling

- Fifteen indoor and six outdoor measurement campaigns
- Results: close links have correlated X_a [1]

[1] P. Agrawal and N. Patwari, "Correlated Link Shadow Fading in Multi-hop Wireless Networks," *IEEE Trans. Wireless Commun.*, August 2009.

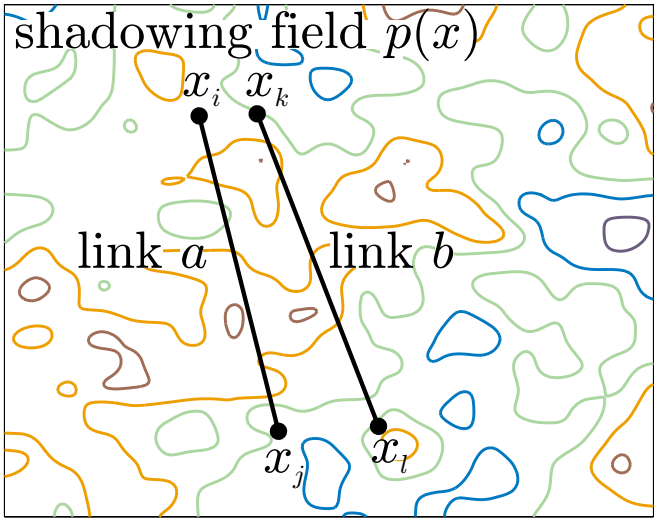
Experimental Correlation Results

Link Geometry vs. Correlation Coefficient (Observed)

	Geom-etry	Meas-ured ρ		Geom-etry	Meas-ured ρ
1		0.33***	**4**		0.14***
2		0.21***	**5**		0.21***
3		0.05	**6**		0.23***

*** $p < 0.005$

What mechanism explains shadowing correlation?



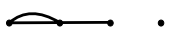
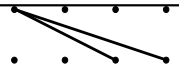
- Spatially correlated shadowing field $p(\mathbf{x})$
- Assume X_i, for $i \in \{a, b\}$ are integrals of $p(\mathbf{x})$

$$X_i = \frac{1}{\|\mathbf{x}_{t_i} - \mathbf{x}_{r_i}\|^{1/2}} \int_{\mathbf{x}_{t_i}}^{\mathbf{x}_{r_i}} p(\mathbf{y}) d\mathbf{y}. \quad (1)$$

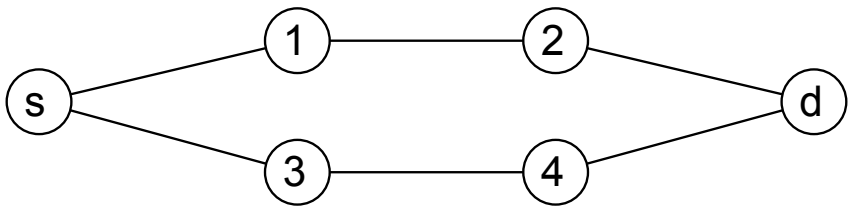
- Mutual dependence on $p(\mathbf{x}) \rightarrow$ correlation of X_a, X_b

Experimental Correlation Results

Link Geometry vs. Correlation Coefficient (Observed, Model)

		Correlation ρ				Correlation ρ	
	Geom-etry	Meas-ured	Prop. Model		Geom-etry	Meas-ured	Prop. Model
1		0.33***	0.31	**4**		0.14***	0.15
2		0.21***	0.25	**5**		0.21***	0.22
3		0.05	0.06	**6**		0.23***	0.26

Impact of correlation on sensor networks



- Multiple routes are not independent!
- Route diversity: links fade simultaneously more often
- Localization: RSS errors don't "average out" after many links. But correlation = spatial information.
- Correlation implies spatial field $p(\mathbf{y})$ can be estimated[2]

[2] N. Patwari, P. Agrawal, "Effects of Correlated Shadowing: Connectivity, Localization, and RF Tomography," *IPSN 2008*, April, 2008.

Outline

Loss is Linear with Dynamic Object Shadowing Field

- Two shadowing fields: 1) Static, 2) Dynamic
- Let $p(\mathbf{y})$ be the dynamic dB shadowing loss field
- Let X_a be the "dynamic" shadowing loss (change from "empty" condition)

Discrete-space Loss Field Model

- Consider simultaneously all M pair-wise links:

$$\mathbf{x} = W\mathbf{p} + \mathbf{n}$$

- $\mathbf{x} = [X_1, \ldots X_M]^T$ = measured losses (dB) vs. "empty"
- $\mathbf{p} = [p_1, \ldots p_N]^T$ = discretized loss field (dB/voxel)
- $W = [[w_{i,j}]]_{i,j}$ = weights; $\mathbf{n}$ = noise

Shadowing Field Estimation Problems

- Measure $\mathbf{x}$, assume known W. Estimate $\mathbf{p}$.
- Ill-posed! Pixels $\gg$ links, other issues
- Low SNR: RSS varies without human motion in area.
- Linear model isn't true physics; best W is unknown.

Initial Spatial Model

- What is loss in link l vs. person's position?
- No validated spatial model exists for W
- Our initial model: Pixels k in ellipse (w/ foci at TX and RX) have $W_{l,k} = 1$, zero o.w.

Real-time Approaches to Image Estimation

- Real-time requirement: look for linear algorithm

$$\hat{\mathbf{p}} = \Pi \mathbf{x}$$

- Projection Π needs only be calculated once
- Complexity: Order of # Links $\times$ # pixels

Regularized Image Estimation Algorithms

1. Tikanov Regularized inverse: minimize penalized squared error [3]

$$f(\mathbf{p}) = \|W\mathbf{p} - \mathbf{x}\|^2 + \alpha\|Q\mathbf{p}\|^2$$

when Q is the derivative:

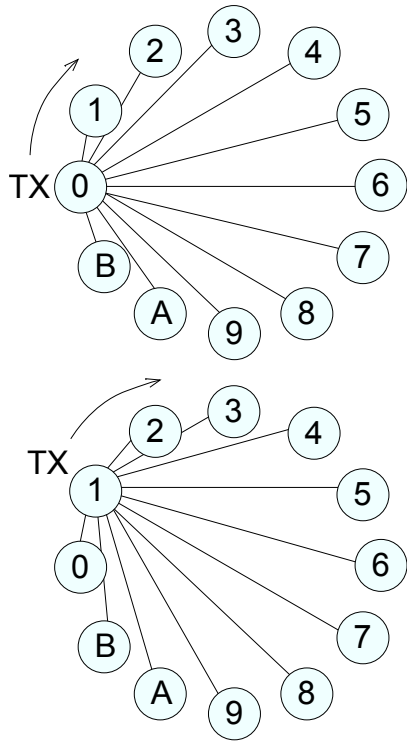
$$\Pi_{Tik} = \left[W^T W + \alpha(D_X^T D_X + D_Y^T D_Y)\right]^{-1} W^T$$

2. Assume correlated $\mathbf{p}$ and use regularized least squares.

$$\Pi_{RLS} = \left(W^T W + \alpha C_{\mathbf{p}}^{-1}\right)^{-1} W^T$$

[3] J. Wilson and N. Patwari, "Radio Tomographic Imaging with Wireless Networks", *IEEE Transactions on Mobile Computing*, May 2010.

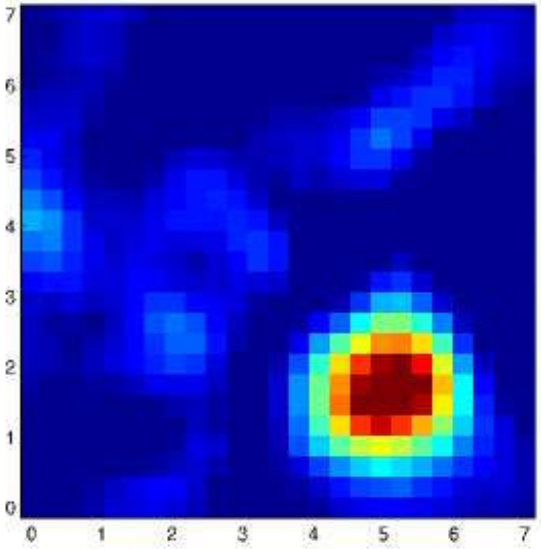
Real-Time Implementation: Testbed



- Crossbow Telosb, 2.4 GHz, IEEE 802.15.4
- SPIN: Token passing MAC; when one transmits, others measure RSS
- Open source: `http://span.ece.utah.edu/spin`
- Packet data: latest measured RSS values
- Laptop-connected mote overhears all traffic
- Complete meas't of **p** 3-4 times/sec (28 nodes)

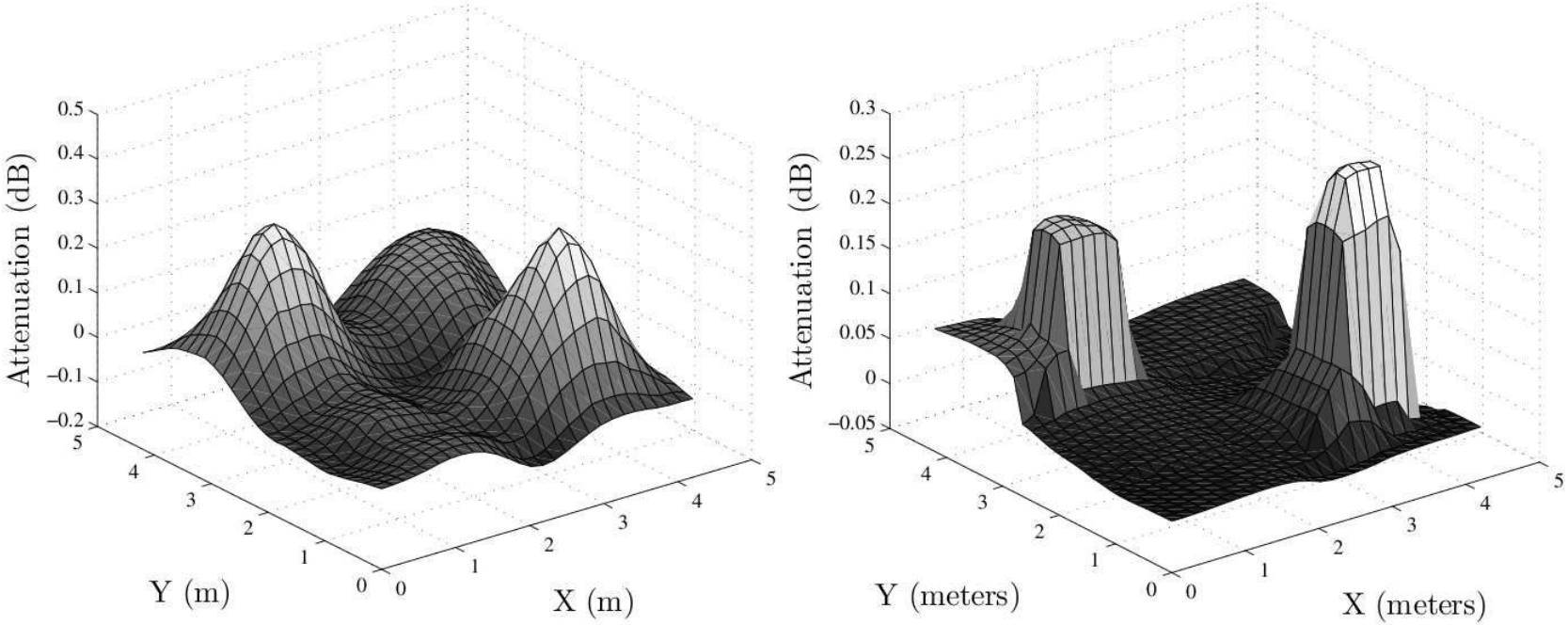
Video

- Video clip: Atrium of Warnock Engineering Building



Alternate Algorithms: TV

- Use total variation (TV) norm to pull out sparsity of image [4]

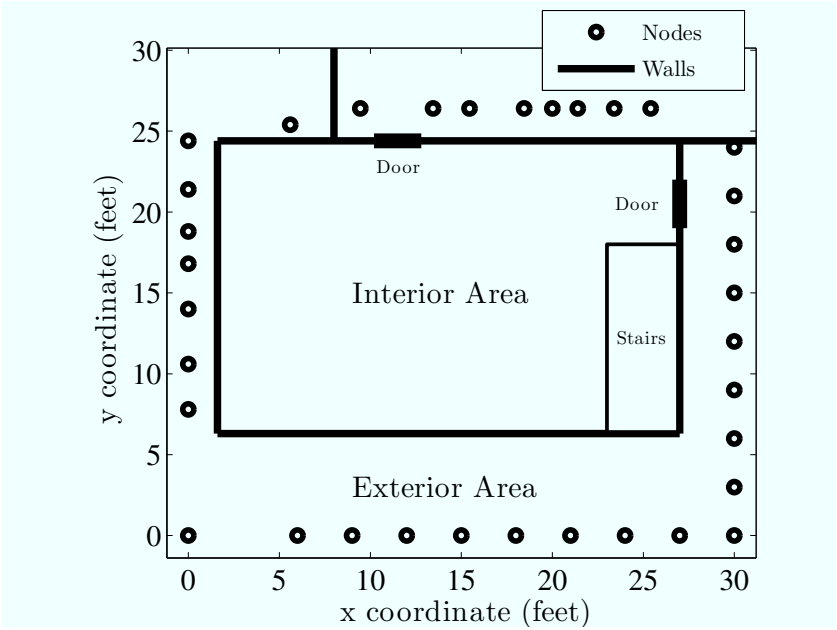


[4] J. Wilson and N. Patwari, "Regularization Methods for Radio Tomographic Imaging," in Proc. *2009 Virginia Tech Wireless Symposium*.

Outline

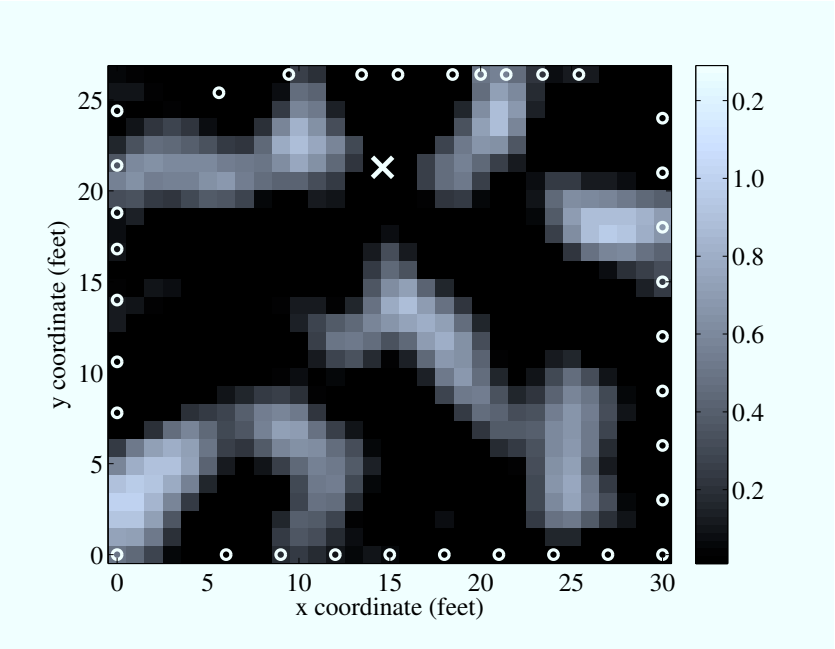
Through-wall Deployment Tests

- Tested system with 34 nodes, outside of external walls of area of house [5]



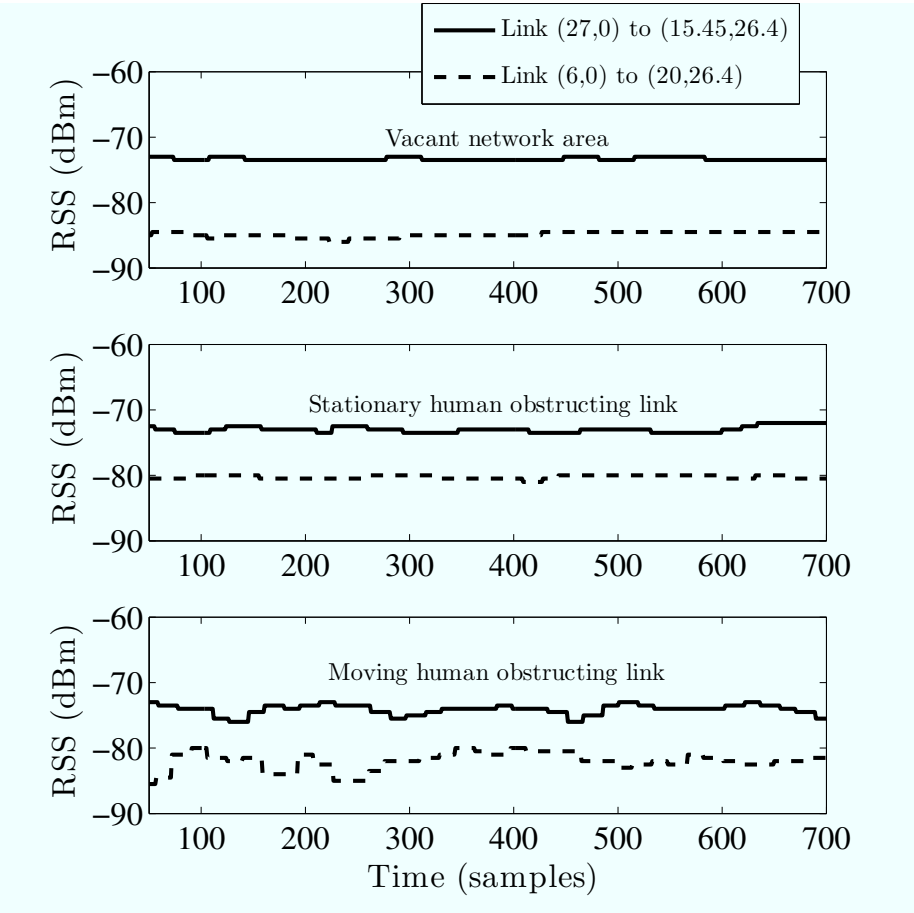
[5] J. Wilson and N. Patwari, "See Through Walls: Motion Tracking Using Variance-Based Radio Tomography Networks", IEEE Transactions on Mobile Computing, (accepted).

Problem: Low SNR



- RTI does not indicate actual image human location (X)

Problem: What Happened?



- Moving people affect RSS, but change is up *and* down
- E.g.: Blocking person increases RSS (- - - -)
- E.g.: Moving person increases RSS variance (both links)

Demo: Person-induced Temporal Fading

Run live demo of RSS measurements with two nodes.

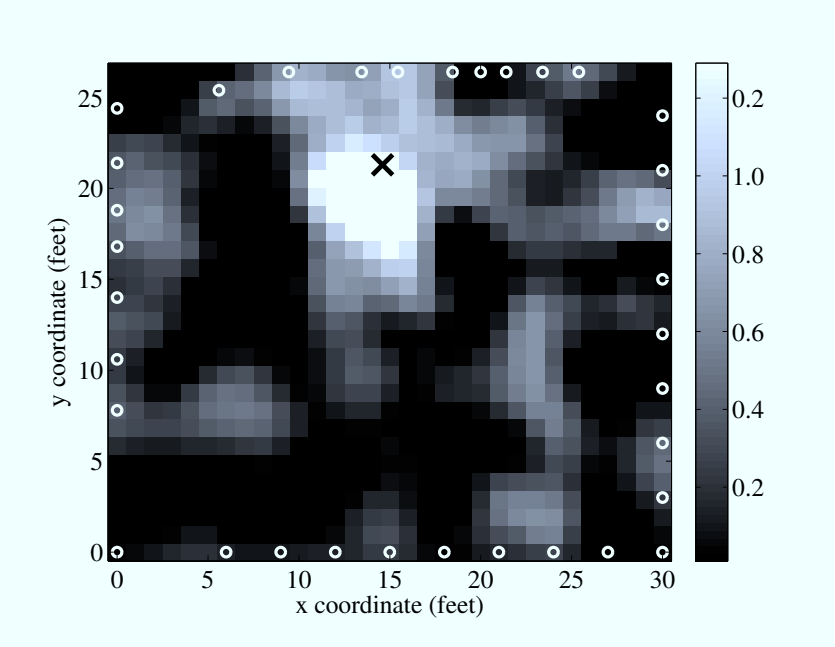
Idea: Use Variance to Image Motion

- Model: Assume variance is linear combination of motion occurring in each pixel:

$$\mathbf{s} = W\mathbf{m} + \mathbf{n}$$

- $\mathbf{s} = [s_1, \ldots s_M]^T$ = windowed sample variance
- $\mathbf{m} = [m_1, \ldots m_N]^T$ = motion $\in [0, 1]$
- $W = [[w_{i,j}]]_{i,j}$ = variance added to link i caused by motion in voxel j

Variance-based Radio Tomographic Imaging



- Apply regularized inversion to estimate **m**.
- VRTI image indicates actual image human location (X)

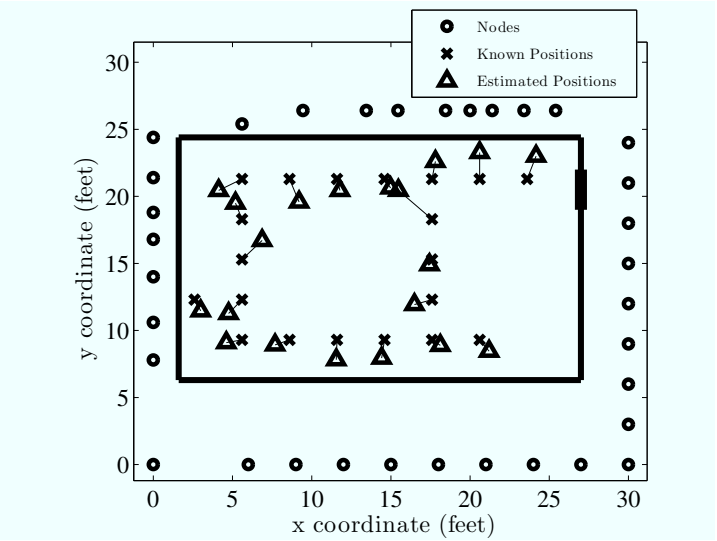
VRTI Video

- Advice: Use YouTube (>150k hits for two videos)

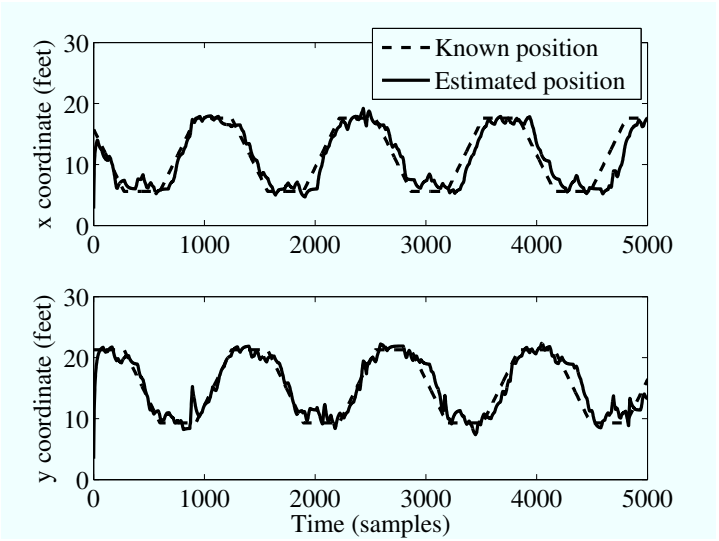
VRTI-based Tracking

1. Spot motion test: avg. error = 0.45 m
2. Track image max w/ Kalman filter: avg. error = 0.63 m

(1)



(2)



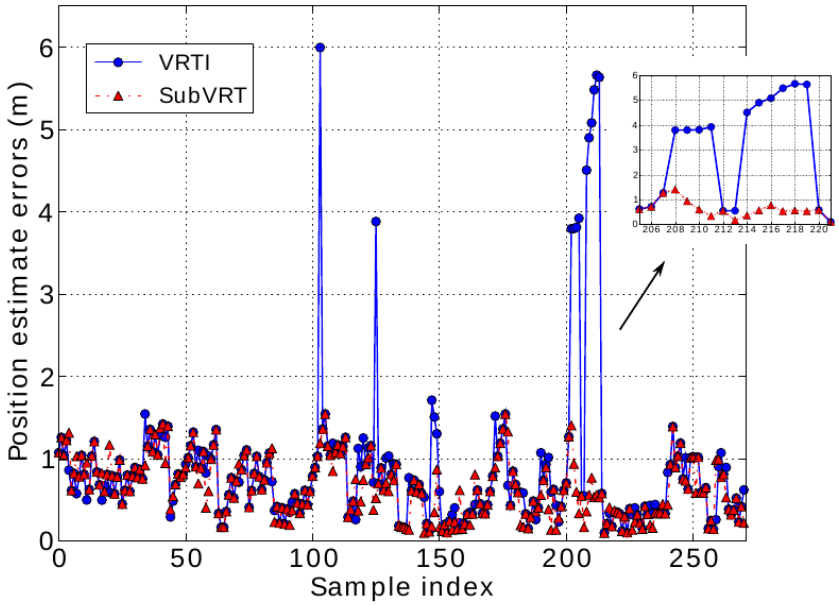
Problem: Noise from Intrinsic Motion

Intrinsic motion: *e.g.*fans, moving machines, wind.

Figure: Identical experiments show very different VRTI performance on a (Left) still vs. (Right) windy day.

Intrinsic Noise Solution: SubVRT

- SubVRT, subspace decomposition for VRTI[6]
- In windy experiment, location error reduced by $> 40\%$.



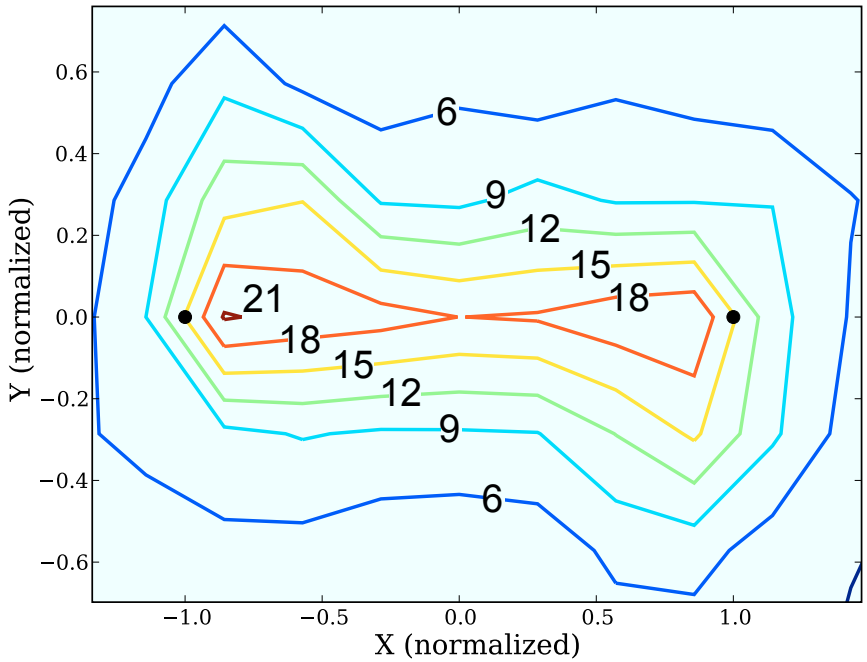
[6] Y. Zhao, N. Patwari, "Noise reduction for variance-based device-free localization and tracking", *SECON 2011*.

Need: Spatial Model for Variance

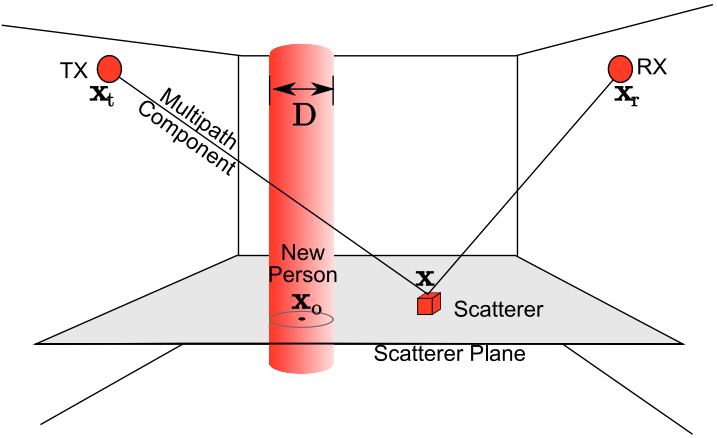
- Where does motion have highest impact on RSS variance?
  1. Near TX, RX [Yao et. al. 2008]
  2. At midpoint between TX, RX [Zhang et. al. 2007]
  3. Our work: In (narrow) ellipse w/ TX & RX as foci
  4. Pixels which intersect link line [Kanso and Rabbat 2009]
- Need for measurements, analytical models

Variance Measurement

- Measurement at THE UNIVERSITY OF UTAH Bookstore, nodes on shelves
- Normalize link, person position s.t. $\mathbf{x}_r = (-1, 0)$, $\mathbf{x}_t = (1,0)$
- Find average variance by human position w.r.t. RX, TX



Analytic Model: Intro



- Do simple standard multipath assumptions explain data? [a]
- Human = tall cylinder diameter D [Ghaddar et. al. 2004, Huang et. al. 2006]
- Scatterers/Reflectors in a plane. TX, RX, in plane Δz above.
- Propagation via single bounce

[a] N. Patwari and J. Wilson, "Spatial Models for Human Motion-Induced Signal Streng IEEE Trans. Info. Forensics & Security, Sept. 2011.

Analytic Model: Details

- Locations: TX $\mathbf{x}_t$, RX $\mathbf{x}_r$, bounce at $\mathbf{x}$
- Propagation mechanism (a) scattering or (b) reflection

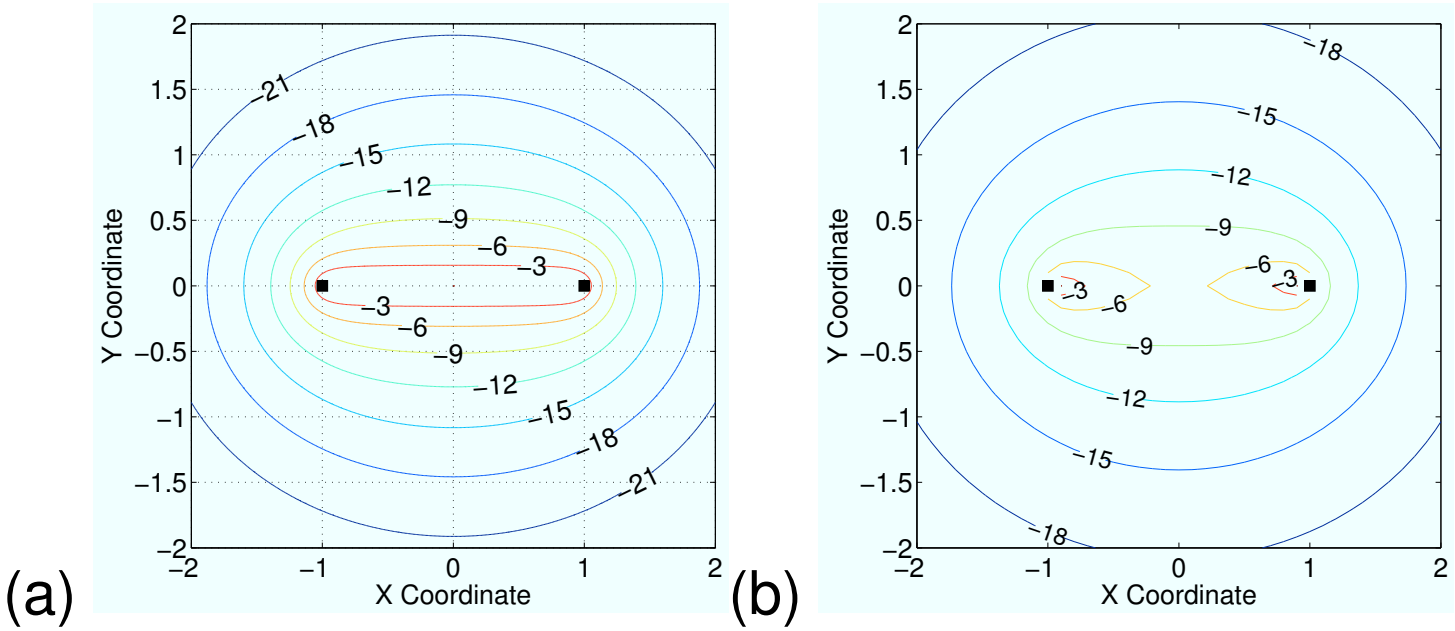
$$\text{(a):} \qquad P_s(\mathbf{x}) = \frac{c_s}{\|\mathbf{x}_t - \mathbf{x}\|^2 \|\mathbf{x}_r - \mathbf{x}\|^2}$$

$$\text{(b):} \qquad P_r(\mathbf{x}) = \frac{c_r}{(\|\mathbf{x}_t - \mathbf{x}\| + \|\mathbf{x}_r - \mathbf{x}\|)^{n_p}}$$

- $c_r, c_s, n_p \in \mathbb{R}^+$ are propagation parameters [Nørklit & Andersen 1998, Liberti and Rappaport 1996]
- Variance prop. to expected total affected power (ETAP)

Analytic Model: Results

- Variance $\propto$ spatial functions:



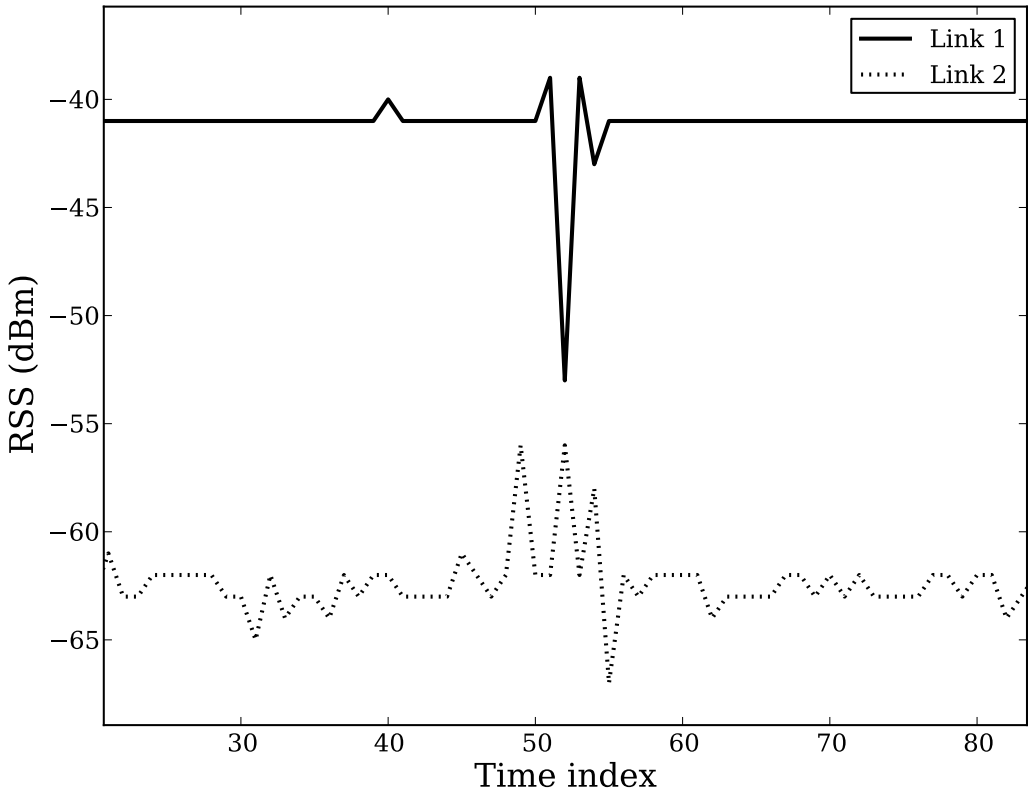
- Ours & [Yao 2008]: similar to reflection ETAP, low Δz
- Those of [Zhang 2007]: high Δz, either modality

Outline

Problems: Tracking from RSS

- Tracking motion from image estimate is ad hoc
- Image estimate may be very poor when DFL is possible
- VRTI only tracks people in motion, not stationary people
- Change in mean and variance only two aspects of a r.v.
- What would Bayes do? NEED: distribution parameterized by peoples' locations

A Tale of Two Links



Outcome: Fade-Level based Model

Link distributions are different, based on *fade level*: [7]

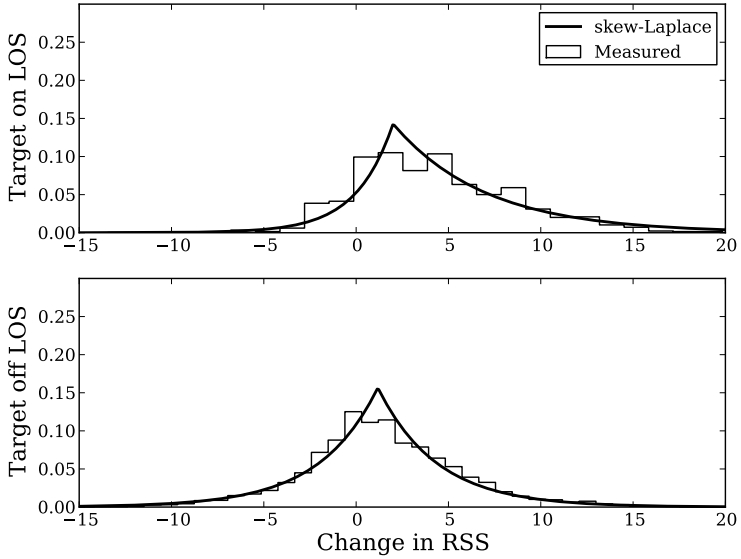
- If a link is in deep fade: RSS and variance increase when obstructed
- If a link is in anti-fade: RSS decreases when obstructed

[7] J. Wilson and N. Patwari, "A Fade Level Skew-Laplace Signal Strength Model for Device-Free Localization With Wireless Networks", IEEE Trans. Mobile Computing, appeared online 12 May 2011.

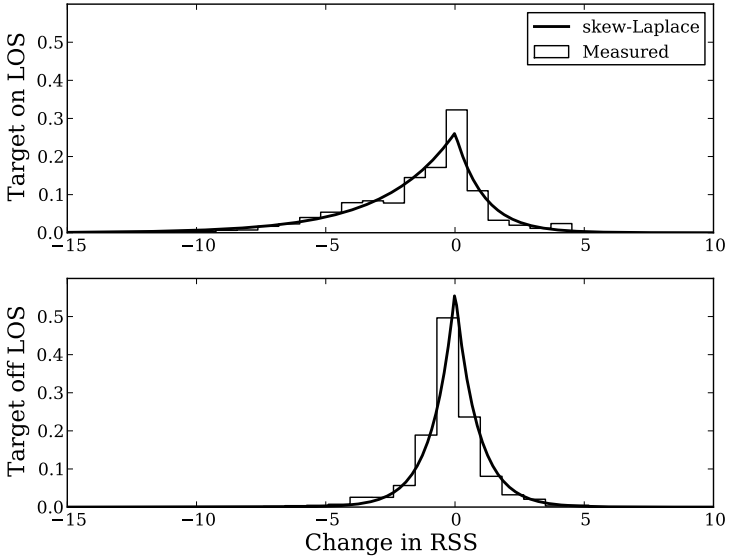
Fade-Level Model Justification

$P_{i,j}$ is power in phasor sum of multipath.

- (a) When sum is in a null, change tends to "pull it out"
- (b) When in constructive sum, change will "pull it down"



(a)



(b)

Fade-Level based Model

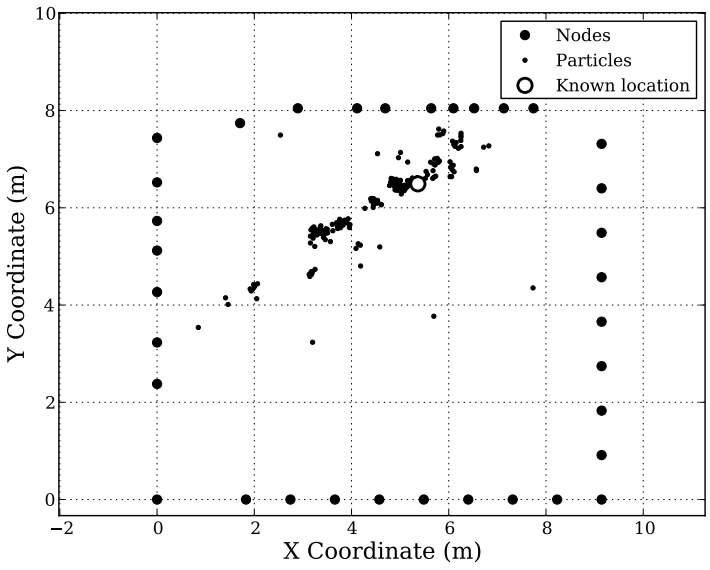
- Fade level = RSS model - meas't:

$$F = \bar{P}(d_{i,j}) - P_{i,j}$$

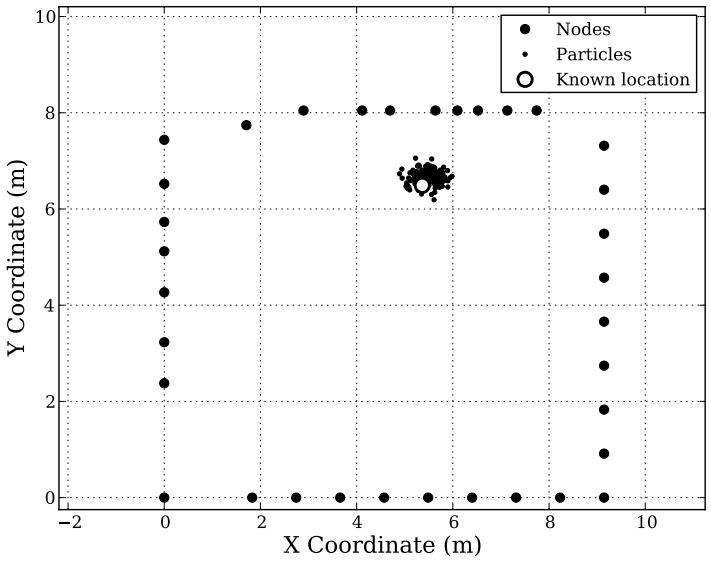
- Determined in calibration (known sensor locations)
- Skew-Laplace pdf parameters: linear function of F

Particle Filter

- Need: track when meas'ts are non-Gaussian, non-linear
- Particle filtering: Bayesian coordinate est. given meas'ts
- Convergence as links more / less likely using (a) 15% of meas'ts, (b) 30% of meas'ts.

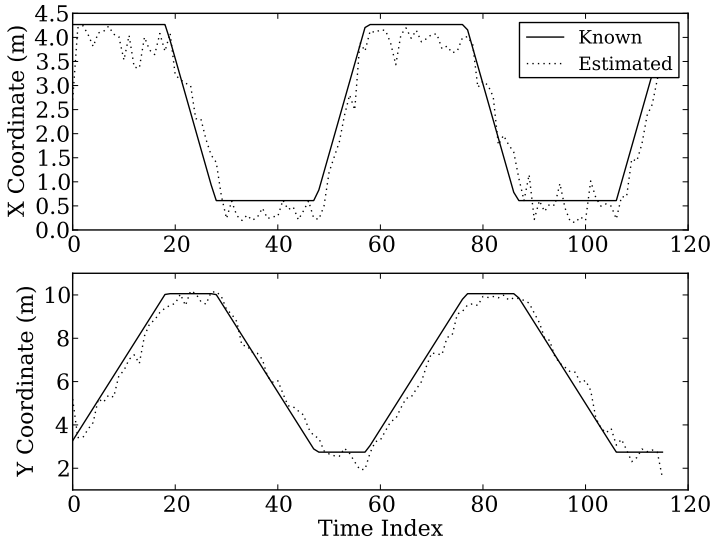


(a)



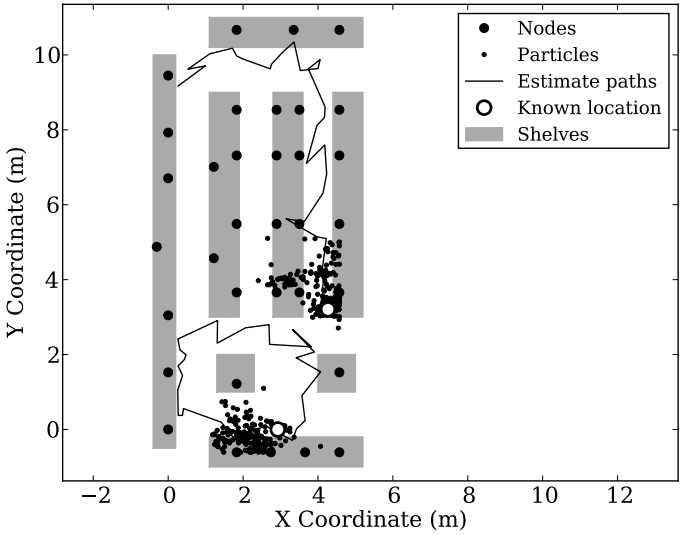
(b)

Tracking Results



- Person walks in rectangular path
- Estimate avg. error: 0.58 m
- Through-home: 0.90 m
- Needs: proposal methods, human dynamics models

Two-Person Tracking Results



- Two people walk in rectangles
- Estimate avg. error: 0.84 m
- Through-home: 1.10 m

Outline

Observation-Led Motivation

- Some links, sometimes, change RSS due to inhalation, exhalation
- Only a small percentage
- Can we enable *reliable* breathing monitoring
- Value: Contact free, through walls

Applications

- Baby / patient breathing monitor
- Elder care
- Detect breathing in rubble
- Limitation: Measure change in chest, not respiration

Experiments: Medical Appl

- Clinical room, Anesthesiology, SOM
- Subject: breathing w/ metronome
- Connected to end-tidal CO_2 monitor
- Our system: 20 transceivers bedside
- Each link 4 measurements / sec

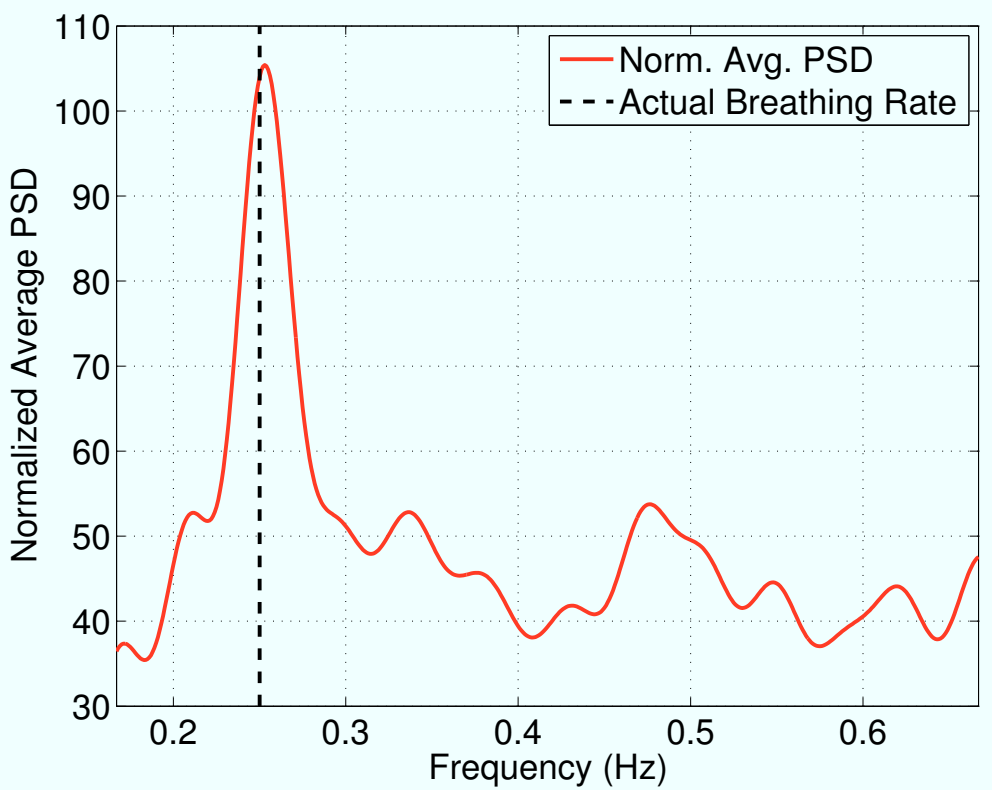
Algorithms

- Filter out DC using IIR filter
- Approx. MLE:
  1. Sum links' squared DTFT
  2. If too low, no breathing (!)
  3. If not, max is at breathing rate
- Linear: Low complexity, can be real time

Results

Average spectrum plot [8]

- 30 seconds of data
- Estimated rate: 15.18 bpm
- Actual rate: 15.00 bpm



[8] N. Patwari, J. Wilson, S. Ananthanarayanan P.R., S. K. Kasera, D. Westenskow, "Monitoring Breathing via Signal Strength in Wireless Networks", arXiv:1109.3898v1.

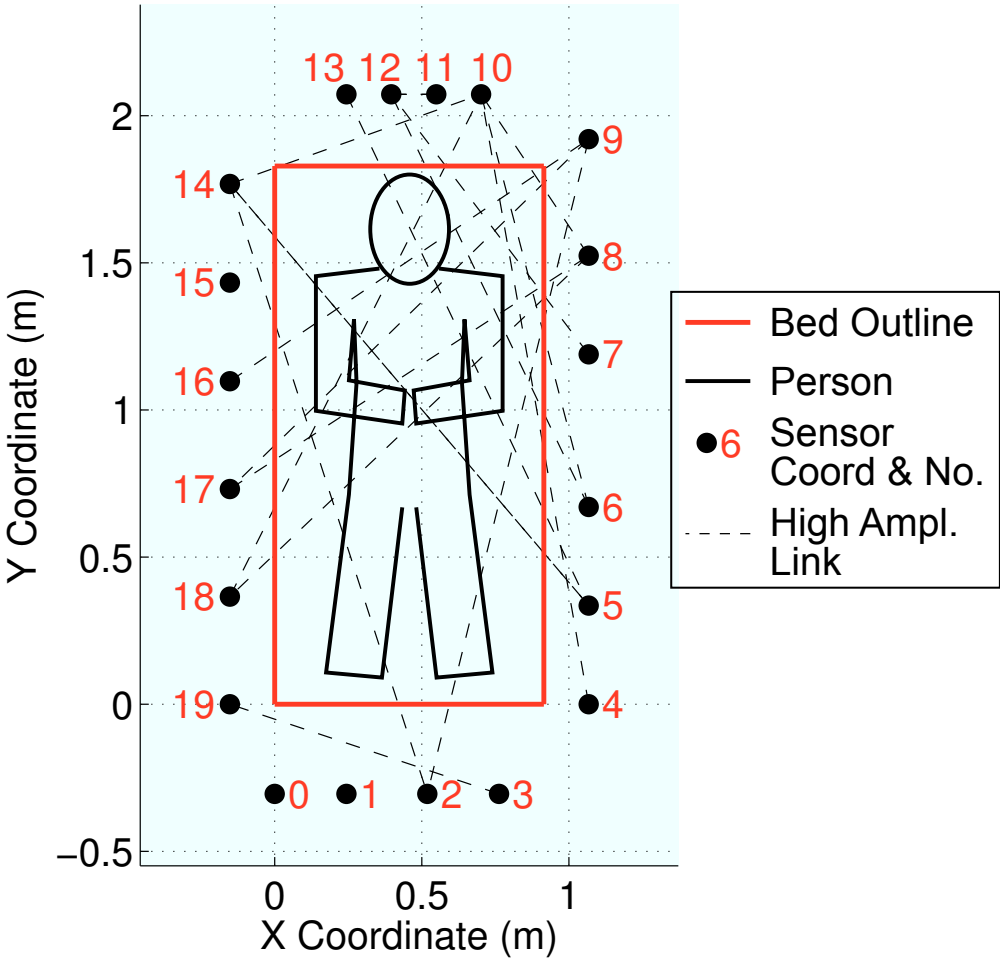
Results

- Need to use link data simultaneously
- BPM within 0.2-0.4 of actual
- With 25-30s data, perfect detection
- Better than capnometer
- Transceiver height didn't matter
- Directional antennas keep focus on bed

Results

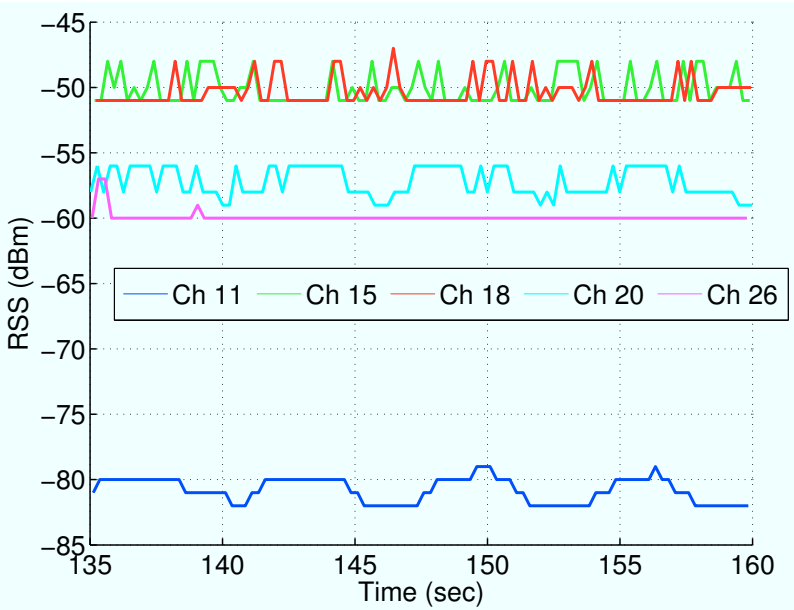
Links that detect breathing tend to be:

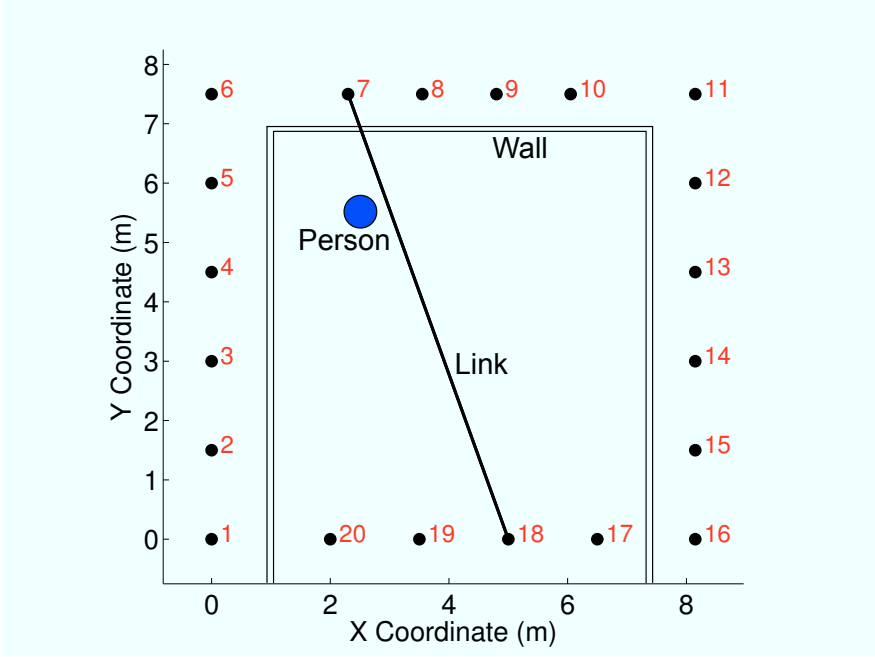
- those that cross through the chest
- those in a deep fade



Multi-channel Results

RSS on five different channels: Low RSS links exhibit breathing[9]





[9] O. Kaltiokallio, manuscript in preparation, 2012.

Outline

Recap: Fading is a Environmental Signal

- The wireless network is the sensor
- Objects in environment change the RSS
- Models of RSS changes $\rightarrow$ algorithms
- RSS device free location (DFL), "Radio Tomography"
- Real-time imaging, localization, breathing monitoring

Commercialization

- Security sensor: Tomographic Motion Detection (TMD)
- Big need: warehouse security systems
- Hidden, low false alarm rate, can't "get around" it

Current Work: Large-scale Reliable Systems

- Deploy across 15,000 sq. feet in building
- DFL in low-link density
- Multi-channel DFL
- Better Bayesian solutions

Acknowledgements

- Dr. Joey Wilson
- Dr. Piyush Agrawal
- Yang Zhao
- Dr. Maurizio Bocca
- Ossi Kaltiokallio
- University of Utah SPAN Lab

Career award ECCS-0748206, CPS award 1035565

Questions and Comments

More info on `http://span.ece.utah.edu/`