Radio Tomographic Localization in Wireless Sensor Networks

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Outline

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Device Free Localization (DFL) Applications

- RFID technique, locates people's tags [a]
- How about people, objects not tagged?
- Applications: emergency response, smart homes, context-aware computing, etc.

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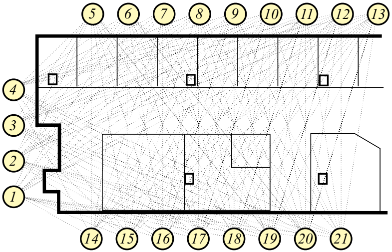
[a] Y. Zhao, N. Patwari, P. Agrawal, and M. Rabbat, "Directed by Directionality: Benefiting from the Gain Pattern of Active RFID Badges," *IEEE Transactions on Mobile Computing*, May 2011.

DFL: Technologies

- Video cameras. Don't work in dark, through smoke or walls. Privacy concerns.
- 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

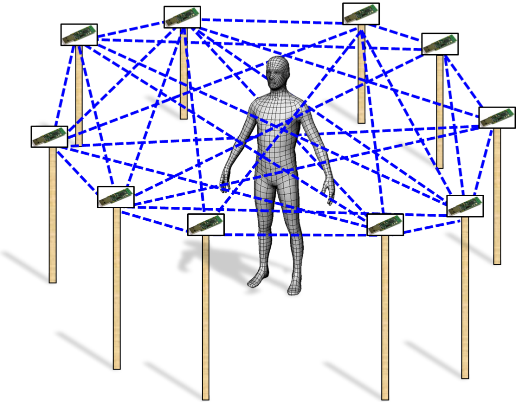


- Mesh network of N transceivers $\rightarrow \mathcal{O}\left(N^2\right)$ RSS measurements
- Link RSS changes due to people in environment near link
- One person / object affects multiple links

Radio Tomographic Imaging (RTI)

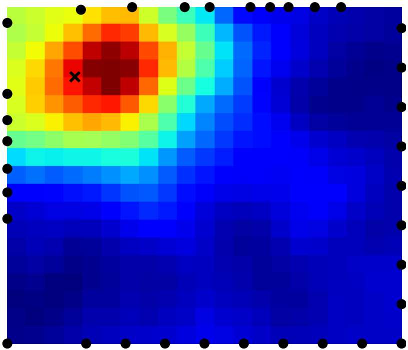
Model-based DFL,
no training needed

- Attenuation
- Reflection
- Scattering



RTI Image Example

- Divide the network area into many pixels
- Pixel value represents the probability of human presence/motion



Outline

Shadowing-Based RTI

- First model-based RSS-DFL method
- Use shadowing caused by human body to locate people
- From experiments of wireless channel modeling in a network

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?

Experiments for Channel Modeling

- Fifteen indoor and six outdoor measurement campaigns
- Results: close links have correlated X_a [1]
- Observations: Two shadowing fields: 1) Static, 2) Dynamic

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

Discrete-space Shadowing Field Model

- Model: Relates shadowing measurements with discretized dynamic shadowing field
- Consider simultaneously all M pair-wise links:

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

  - $\mathbf{y} = [y_1, \ldots y_M]^T$ = measured shadowing losses;
  - $\mathbf{p} = [p_1, \ldots p_N]^T$ = discretized dynamic shadowing field;
  - $W = [[w_{i,j}]]_{i,j}$ = weights;
  - $\mathbf{n}$ = noise.

Dynamic Shadowing Field Estimation

Estimate dynamic shadowing field from measurements

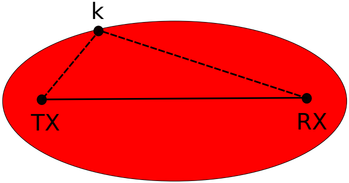
- Assume known W, measure $\mathbf{y}$, estimate $\mathbf{p}$

Problems

1. Linear model isn't true physics; best W is unknown;
2. Ill-posed! Pixels $\gg$ links;
3. Low SNR: RSS varies without human motion in area.

Initial Spatial Model

- 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 otherwise. [2]



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

Linear Model Leads to Real-time Image Estimation

- Real-time requirement: look for linear algorithm

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

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

Ill-Posed Problem: Regularized Algorithms

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

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

when Q is the derivative:

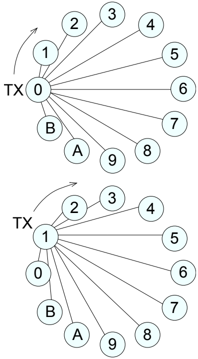
$$\Pi_{Tik} = \left[W^T W + \alpha(D_X^T D_X + D_Y^T D_Y)\right]^{-1} W^T$$

2. Assume correlated **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.

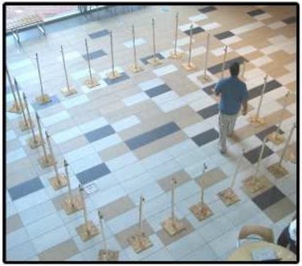
Real-Time Implementation: Testbed

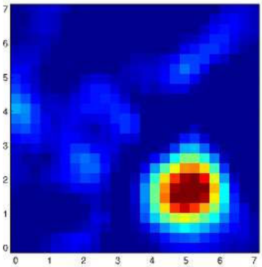


- Crossbow Telosb, 2.4 GHz, IEEE 802.15.4
- Spin: Token passing MAC; when one transmits, others measure RSS
- Open source: `http://span.ece.utah.edu/spin`
- Packet data: latest measured RSS values
- Laptop-connected mote overhears all traffic

Video

- Video clip: span.ece.utah.edu/radio-tomographic-imaging

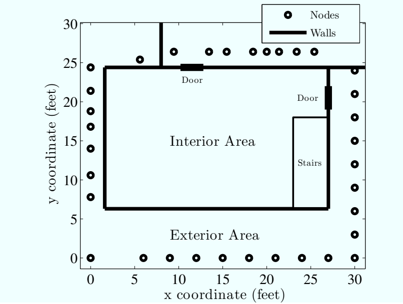




Outline

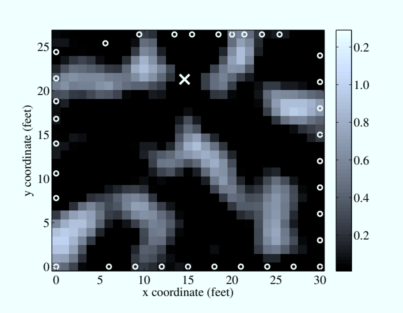
Through-wall Deployment Tests

- Tested system with 34 nodes, outside of external walls of area of house [4]



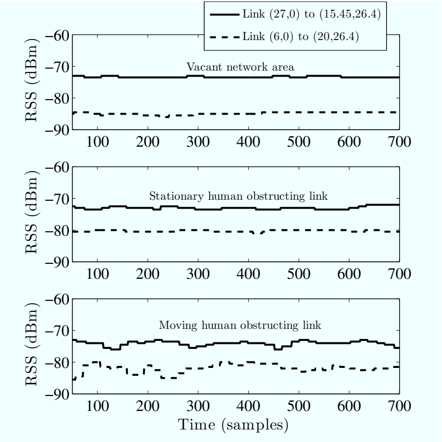
[4] J. Wilson and N. Patwari, "See Through Walls: Motion Tracking Using Variance-Based Radio Tomography Networks", IEEE Transactions on Mobile Computing, 2011.

Problem



- Shadowing-based RTI does not indicate actual human location (X)

Problem: What Happened?



- SNR is too low due to multipath effect
- Blocking person increases RSS (- - - -)
- But, moving person increases RSS variance (both links)

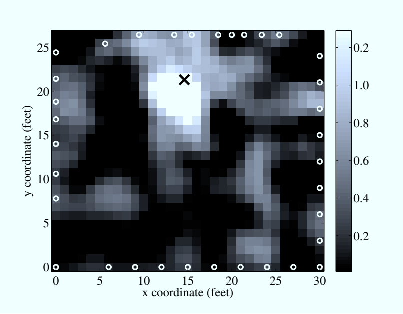
Idea: Use Variance to Image Motion

- 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

- http://span.ece.utah.edu/radio-tomographic-imaging (avg. error = 0.63 m)

Problem of VRTI: Noise from Intrinsic Motion

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

RSS variations due to intrinsic motion

- Intrinsic motion: motion of objects that are intrinsic parts of an environment, *e.g.*, fans, moving machines, wind.

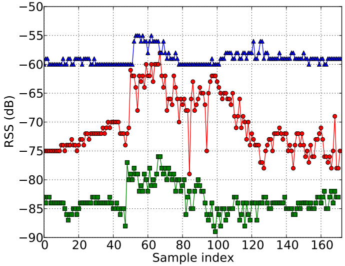


Figure: RSS during calibration in windy day experiment.

- Extrinsic motion: motion of people and other objects that enter and leave an environment

Subspace Variance-based Radio Tomography (SubVRT)

Major steps in SubVRT

- Principal component analysis (PCA): capture the major feature of intrinsic motion
- Subspace decomposition: remove/reduce the effect of intrinsic motion

PCA on calibration measurements

- Calibration measurements $\mathbf{s}_c$ only contain the effect from intrinsic motion
- Estimate the covariance matrix $C_{\mathbf{s}_c}$ of $\mathbf{s}_c$
- Perform SVD on $C_{\mathbf{s}_c}$: $C_{\mathbf{s}_c} = U \Lambda U^T$
- Capture intrinsic motion by the first k eigenvectors

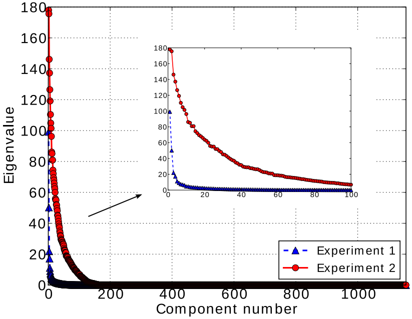


Figure: Scree plot.

Subspace decomposition

- Divide all eigenvectors into two sets: $\hat{U} = [\mathbf{u}_1, \mathbf{u}_2, \cdots, \mathbf{u}_k]$ and $\tilde{U} = [\mathbf{u}_{k+1}, \mathbf{u}_{k+2}, \cdots, \mathbf{u}_L]$.
- One subspace is spanned by $\hat{U}$ – the intrinsic subspace, the other is spanned by $\tilde{U}$ – the extrinsic subspace
- Project $\mathbf{s}$ on intrinsic and extrinsic subspaces to obtain intrinsic signal component $\hat{\mathbf{s}}$ and extrinsic signal component $\tilde{\mathbf{s}}$:

$$\hat{\mathbf{s}} = \Pi_I \mathbf{s} = \hat{U}\hat{U}^T \mathbf{s}$$

$$\tilde{\mathbf{s}} = \Pi_E \mathbf{s} = (I - \hat{U}\hat{U}^T)\mathbf{s}$$

SubVRT formulation

VRTI

Using real-time measurement vector $\mathbf{s}_r$, the Tikhonov regularized solution is:

$$\hat{\mathbf{m}} = \Pi_1 \mathbf{s}_r \quad \text{where } \Pi_1 = (W^T W + \alpha Q^T Q)^{-1} W^T$$

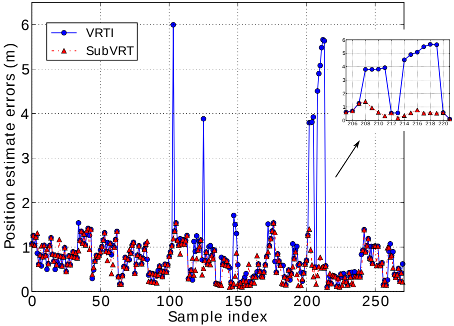
SubVRT

Using decomposed extrinsic signal component $\tilde{\mathbf{s}}_r = \Pi_E \mathbf{s}_r$:

$$\hat{\mathbf{m}} = \Pi_2 \mathbf{s}_r \quad \text{where } \Pi_2 = (W^T W + \alpha Q^T Q)^{-1} W^T \Pi_E$$

Improvement

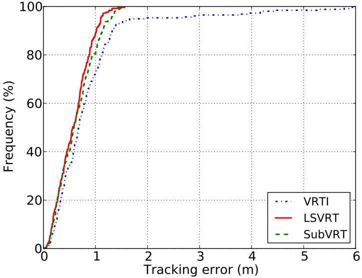
- In windy experiment, location error reduced by $> 40\%$ [5]
- Video comparison

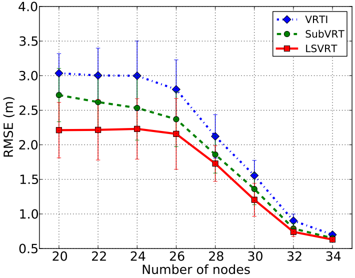


[5] Y. Zhao and N. Patwari, "Noise reduction for variance-based device-free localization and tracking", *IEEE SECON 2011*.

Alternative solution: Least squares method

- Instead of performing PCA on the covariance matrix of the calibration measurements, use the covariance matrix directly in the RTI formulation [6]





[6] Y. Zhao and N. Patwari, "Robust Estimators for Variance-Based Device Free Localization and Tracking", IEEE Transactions on Signal Processing, (submitted).

Outline

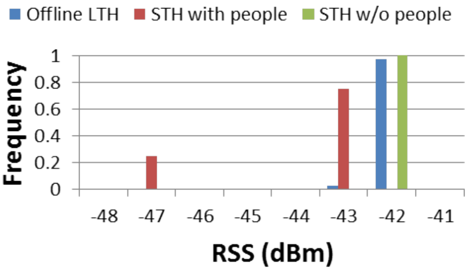
From Observations of RSS Histograms

Two types of RSS histogram:

- Short-term histogram (STH): RSS histogram of a link in a short-time window (a few RSS samples)
- Long-term histogram (LTH): RSS histogram during a long term period (hundreds of RSS samples)

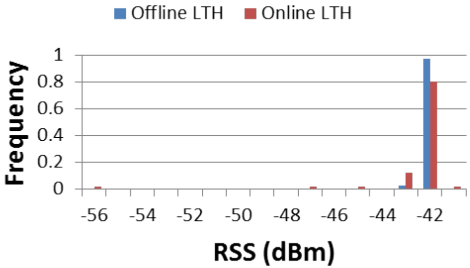
Observation 1

- Short-term histogram (STH) with people present near the link is significantly different from long-term histogram (LTH).

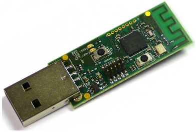


Observation 2

- High similarity between offline LTH and online LTH



New Testbed



- TI CC2531, 2.4 GHz, IEEE 802.15.4
- Spin protocol (C version)
- RSS sampling rate of 3 ms per sample

Histogram Distance-Based RTI

- Able to locate stationary and moving people, no training or empty-room calibration needed (paper in preparation)

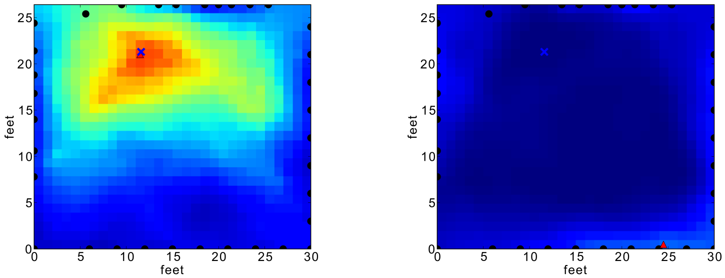


Figure: Histogram distance-based RTI (Left) can locate a stationary person while variance-based RTI (Right) cannot.

Outline

Summary

Features	SRTI	VRTI	SubVRT	HD-RTI
Training?	No	No	No	No
Through-wall?	No	Yes	Yes	Yes
Online calibration?	No	NA	No	Yes
Stationary people?	Yes	No	No	Yes

Table: Comparison of Different RTI methods.

Current and Future Work: Large-scale Reliable Systems

- Deploy across 1400 sq. meter in building
- DFL in low-link density
- Multi-channel DFL
- Better Bayesian solutions

Questions and Comments

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