Radio Tomography: Environmental Inference from Wireless Network Signal Strength

Neal Patwari

Utah IEEE SP/COM Chapter Seminar
Outline

1. Introduction
2. Shadowing-based RTI
3. Variance-based RTI
4. Bayesian DFL
5. Breathing Inference
6. Conclusion
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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.
- 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 $\rightarrow \mathcal{O}(N^2)$ 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 $X_a$ \(^1\)

Experimental Correlation Results

Link Geometry vs. Correlation Coefficient (Observed)

<table>
<thead>
<tr>
<th>Geometry</th>
<th>Measured $\rho$</th>
<th>Geometry</th>
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</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.33***</td>
<td>4</td>
<td>0.14***</td>
</tr>
<tr>
<td>2</td>
<td>0.21***</td>
<td>5</td>
<td>0.21***</td>
</tr>
<tr>
<td>3</td>
<td>0.05</td>
<td>6</td>
<td>0.23***</td>
</tr>
</tbody>
</table>

*** $p < 0.005$
What mechanism explains shadowing correlation?

- Spatially correlated shadowing field $p(x)$
- Assume $X_i$, for $i \in \{a, b\}$ are integrals of $p(x)$
  \[ X_i = \frac{1}{\|x_{t_i} - x_{r_i}\|^{1/2}} \int_{x_{t_i}}^{x_{r_i}} p(y)\,dy. \]  
    \hspace{1cm} (1)
- Mutual dependence on $p(x) \rightarrow$ correlation of $X_a, X_b$
## Experimental Correlation Results

### Link Geometry vs. Correlation Coefficient (Observed, Model)

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<tr>
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<th>Prop. Model Correlation $\rho$</th>
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<td>0.26</td>
</tr>
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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 $p(y)$ can be estimated$^2$

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$^2$N. Patwari, P. Agrawal, “Effects of Correlated Shadowing: Connectivity, Localization, and RF Tomography,”

*IPSN 2008*, April, 2008.
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Loss is Linear with Dynamic Object Shadowing Field

- Two shadowing fields: 1) Static, 2) Dynamic
- Let $\rho(y)$ 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:

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

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

- Projection \( \Pi \) needs only be calculated once

- Complexity: Order of \# Links \( \times \) \# pixels
Regularized Image Estimation Algorithms

1. Tikanov Regularized inverse: minimize penalized squared error

\[ f(p) = \| Wp - x \|^2 + \alpha \| Qp \|^2 \]

when \( Q \) is the derivative:

\[ \Pi_{Tik} = \left( W^T W + \alpha \left( D_x^T D_x + D_y^T D_y \right) \right)^{-1} W^T \]

2. Assume correlated \( p \) and use regularized least squares.

\[ \Pi_{RLS} = \left( W^T W + \alpha C_p^{-1} \right)^{-1} W^T \]

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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 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

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Through-wall Deployment Tests

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

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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:
  \[ s = Wm + n \]
  
  \( s = [s_1, \ldots, s_M]^T \) = windowed sample variance
  
  \( m = [m_1, \ldots, m_N]^T \) = 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 ($X$)
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
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 \(> 40\%\).

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\(^6\) 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 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 \(\Delta z\) above.
- Propagation via single bounce

Analytic Model: Details

- Locations: TX $x_t$, RX $x_r$, bounce at $x$
- Propagation mechanism (a) scattering or (b) reflection

(a): $P_s(x) = \frac{c_s}{\|x_t - x\|^2 \|x_r - x\|^2}$

(b): $P_r(x) = \frac{c_r}{(\|x_t - x\| + \|x_r - x\|)^{n_p}}$

- $c_r, c_s, n_p \in \mathbb{R}^+$ 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:

(a) 

(b) 

- Ours & [Yao 2008]: similar to reflection ETAP, low \( \Delta z \)
- Those of [Zhang 2007]: high \( \Delta z \), either modality
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

Radio Tomography: Environmental Inference from Wireless Network Signal Strength
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

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\( P_{i,j} \) 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”
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.
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
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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 CO₂ 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

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

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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.
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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
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Questions and Comments

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