Robust Estimators for Variance-based Radio Tomographic Imaging and Tracking

Yang Zhao

GE Global Research Center

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Outline

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Device Free Localization (DFL)

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

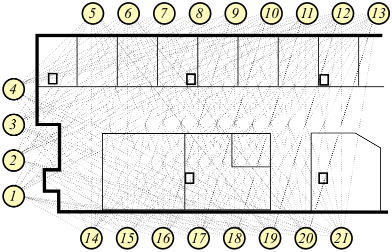
[a] Y. Zhao, N. Patwari, P. Agrawal, and M. Rabbat, "Directed by Directionality: Benefiting from the Gain Pattern of Active RFID Badges," *IEEE Transactions on Mobile Computing*, May 2011.

Why Use Wireless Sensor Networks for DFL?

- 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) from a wireless network: Noisy but low cost.

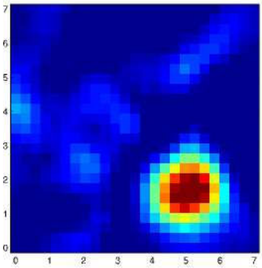
RSS-DFL: Measure Spatially Distinct Links

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



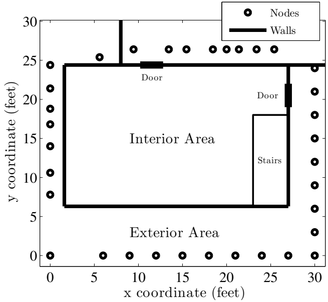
Radio Tomographic Imaging (RTI)

- Model-based, no training needed
- Real-time implementation



Through-wall Test

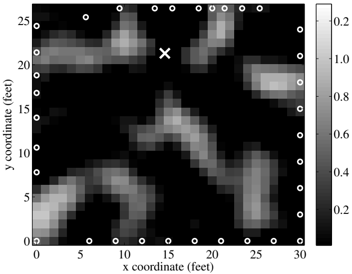
- Tested system with 34 nodes, outside of external walls of area of house [1]



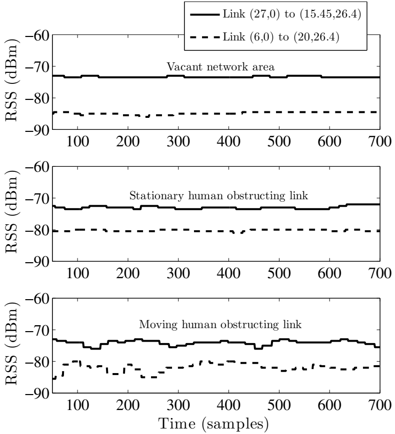
[1] J. Wilson and N. Patwari, “See Through Walls: Motion Tracking Using Variance-Based Radio Tomography Networks”, IEEE Transactions on Mobile Computing, 2011.

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

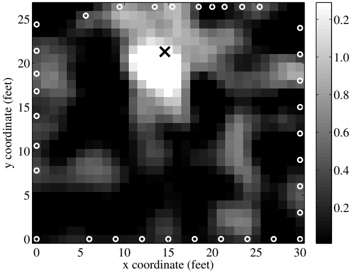
- Model: Assume variance is linear combination of motion occurring in each pixel:

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

- $\mathbf{s} = [s_1, \ldots s_M]^T$ = 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 human location (X)



VRTI Video

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

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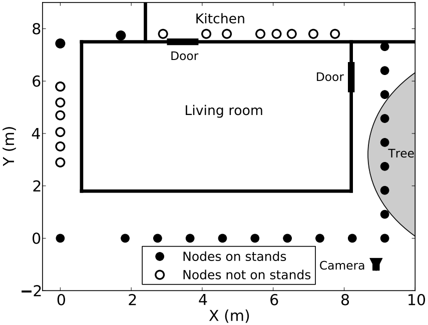
Experiments

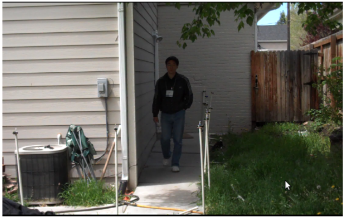
Experiments 1 and 2 are performed

- in the same residential house
- using 34 TelosB nodes, and TinyOS Spin program
- following the same procedure: calibration and real-time measurements.



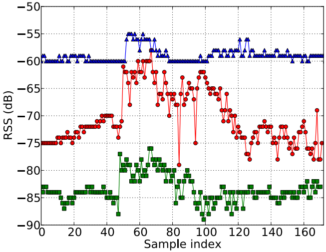
Problem of VRTI: Noise from Intrinsic Motion

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



RSS variations due to intrinsic motion

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



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

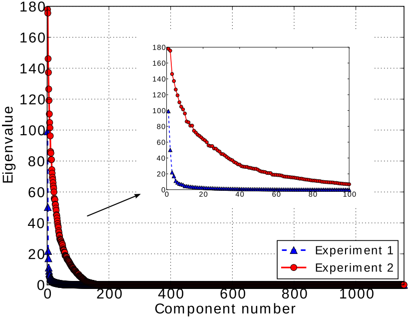
Subspace Variance-based Radio Tomography (SubVRT)

- Principal component analysis (PCA): capture the major feature of intrinsic motion
- Subspace decomposition: remove/reduce the effect of intrinsic motion [2]

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

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



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 $\tilde{\mathbf{s}}_r = \Pi_E \mathbf{s}_r$:

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

Estimates from VRTI and SubVRT

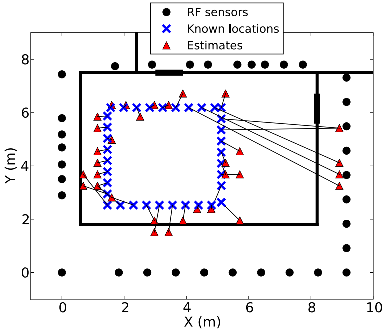


Figure : VRTI estimates.

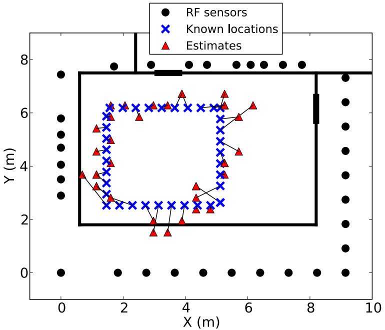
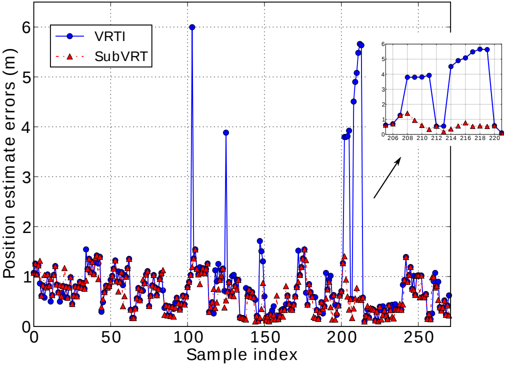


Figure : SubVRT estimates.

Performance Improvement

- In windy experiment, location error reduced by $> 40\%$



Real-time SubVRT Demo

- Use an electronic fan to create intrinsic motion (noise)
- Robust localization performance

Least Squares Solution

- Idea: Instead of performing PCA on the covariance matrix, use the covariance matrix directly
- Formulation: [3]

$$
\begin{aligned}
\hat{\mathbf{m}} &= \Pi_3 \mathbf{s}_r \\
\Pi_3 &= (W^T C_{\mathbf{n}}^{-1} W + C_{\mathbf{m}}^{-1})^{-1} W^T C_{\mathbf{n}}^{-1}.
\end{aligned}
$$

[3] Y. Zhao and N. Patwari, “Robust Estimators for Variance-Based Device Free Localization and Tracking”, IEEE Transactions on Mobile Computing, Oct. 2015.

Estimation of Covariance matrix $C_{\mathbf{n}}$

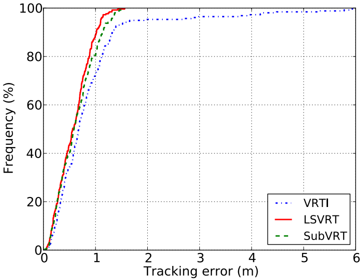
- The sample covariance estimator: ill-posed for high dimensional problem
- Ledoit-Wolf estimator: a linear combination of the sample covariance matrix and a scaled identity matrix:

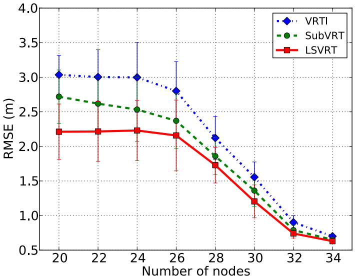
$$C_{\mathbf{n}} = \nu\mu I + (1-\nu)C^*_{\mathbf{n}}$$

  - $C^*_{\mathbf{n}}$ is the sample covariance matrix of noise **n**
  - μ is the scaling parameter for the identity matrix I
  - ν is the shrinkage parameter that shrinks the sample covariance towards the scaled identity matrix

Further Improvement

- No need to choose the *k* parameter as in SubVRT





Tracking

- Apply Kalman filter to location estimates for tracking

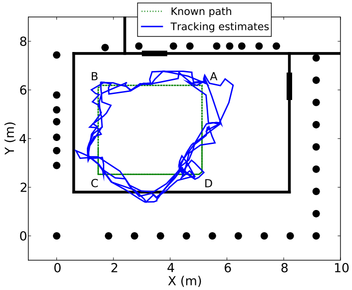


Figure : SubVRT estimate as input

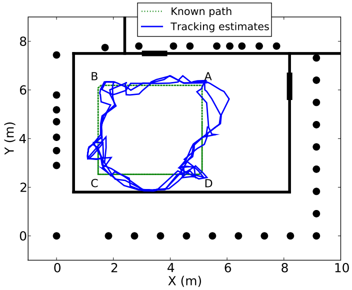


Figure : LSVRT estimate as input

Outline

Conclusion

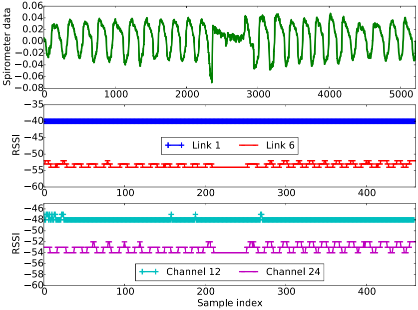
- VRTI can detect and locate people even through-walls, but it is sensitive to intrinsic motion
- SubVRT uses subspace decomposition method and is more robust with calibration measurements
- LSVRT further uses covariance matrices of noise and prior to improve the robustness of VRTI

Commercialization of RTI

- Security sensor: Tomographic Motion Detection (TMD)
- Big need: warehouse security systems
- Hidden, low false alarm rate, cannot “get around” it

Respiration Monitoring Using Wireless Network

- RSS changes periodically even when a person stays still [4]

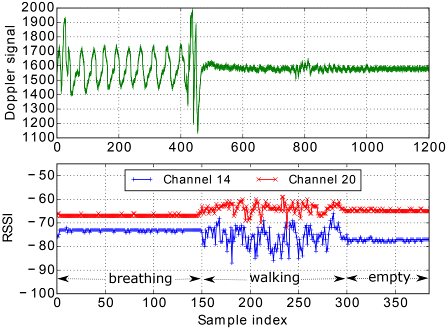


[4] Y. Zhao, et al., "Respiration Monitoring using a Wireless Network with Space and Frequency Diversities", IEEE ICCE 2016.

Experiments at GE Global Research

Human Activity Monitoring Using Doppler and RSS

- Fusion with Doppler sensor [5]



[5] Y. Zhao, et al., "Non-invasive Human Activity Monitoring using a Low-cost Doppler Sensor and an RF Link", ACM SenSys, Nov. 2015.

Acknowledgements

- Prof. Neal Patwari at University of Utah
- Department of Veterans Affairs