

# Intelligent Systems with Wireless Network

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# Outline

## 1 5G and Intelligent System Applications

- 5G Applications at GE
- Industrial Intelligent Systems

## 2 Case 1: Localization of People in Wireless Network

- Device Free Localization
- Robust Estimators

## 3 Case 2: Patient Wireless Sensing

- Pressure Ulcer Application
- Room Occupancy Application



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# 5G Applications at GE

## ■ GE Aviation

- Sensor data collection from aircraft engines
- Wireless communication for different ranges

## ■ GE Healthcare

- Patient monitoring
- Medical image data collection (CT/MR images)

## ■ GE Power and Renewable

- Wireless sensors (remove cables to reduce cost)
- Real-time control (reduce latency)



# GE Applications and DoD 5G Initiative

- Time-sensitive network for industrial asset real-time control
- Reduce latency for wireless sensor data collection
- Remove cables to reduce cost
- GE Research in DoD 5G initiative





# Aerial Inspection for Oil and Gas

- Autonomous Asset Inspection with Drones
- Project leads to a new business of GE Ventures <sup>1</sup>



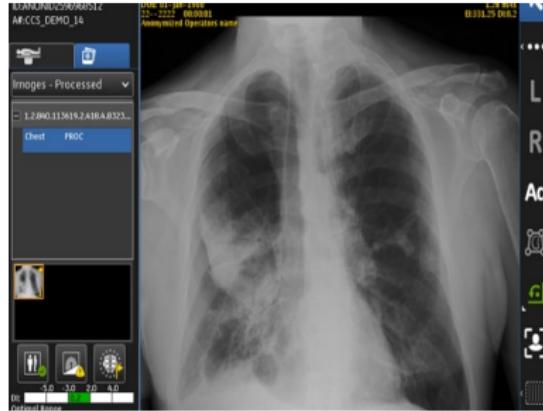
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<sup>1</sup> <https://www.reuters.com/article/us-ge-drones/exclusive-ge-begins-testing-drones-to-inspect-refineries-factories-executive-idUSKBN1940I3>



# Medical Imaging: X-ray and Ultrasound

- Mobile X Ray System <sup>2</sup>
- Ultrasound Probe Tracking



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<sup>2</sup><https://www.cnbc.com/2019/09/12/ges-health-unit-wins-first-fda-clearance-for-ai-powered-x-ray-system.html>



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Device Free Localization



# Radio Tomographic Imaging (RTI): Model-based DFL



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



Device Free Localization



## Why Use RF Sensor Network for DFL?

- Video cameras: Don't work in dark, through smoke or walls. Privacy concerns.
- IR Motion detectors: Limited by walls. High false alarms.
- Military radars: High cost.
- Received signal strength (RSS) from RF sensor network: Noisy but low cost, not limited to line-of-sight scenario

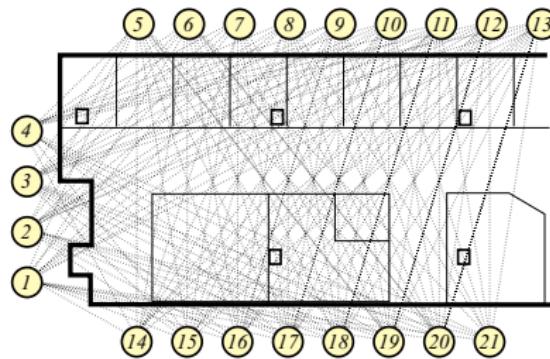


Device Free Localization



## RSS-DFL: Measure 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



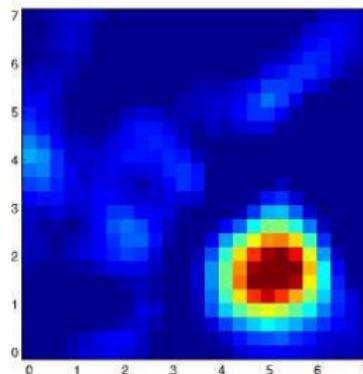
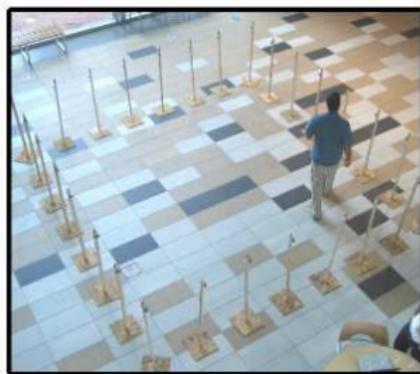


Device Free Localization



# Radio Tomographic Imaging (RTI)

- Model-based, no training needed
- Submeter accuracy, real-time implementation

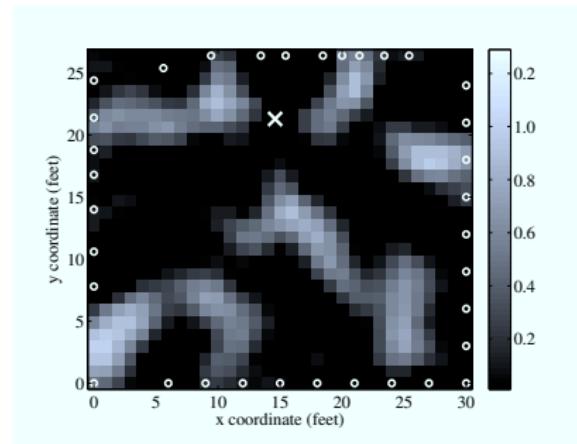




Device Free Localization

## Problem of Through-wall Test

- Tested system with 34 nodes, outside of external walls of area of house
- Shadowing-based RTI does not indicate actual human location (X)

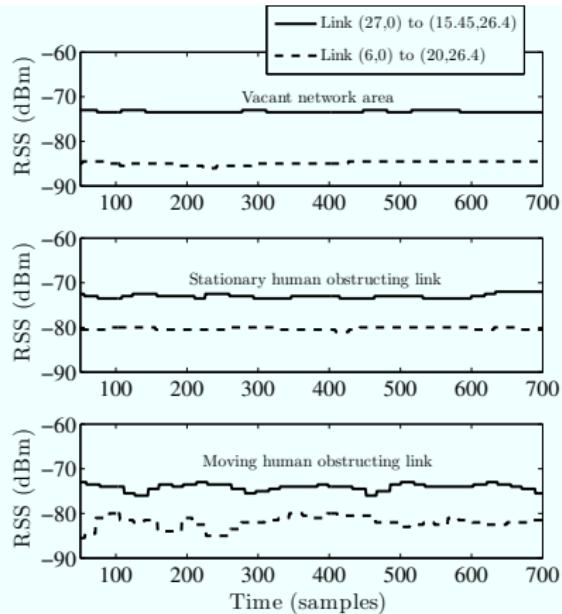




Device Free Localization



# What Happened?



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



Device Free Localization



## Idea: Use Variance to Image Motion

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

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

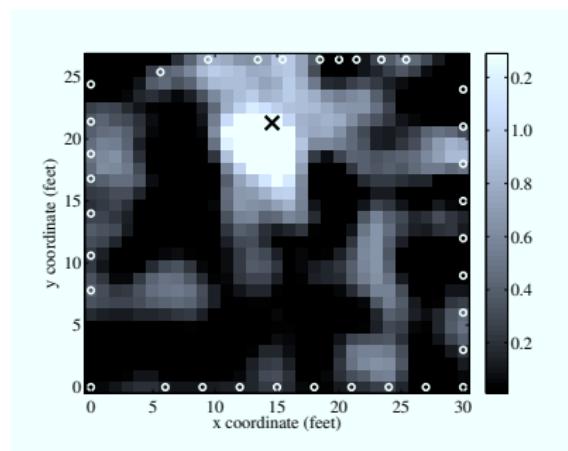
- $\mathbf{s} = [s_1, \dots, s_M]^T$  = windowed sample variance
- $\mathbf{m} = [m_1, \dots, m_N]^T$  = motion  $\in [0, 1]$
- $W = [[w_{i,j}]]_{i,j}$  = variance added to link  $i$  caused by motion in pixel  $j$



Device Free Localization

# Variance-based Radio Tomographic Imaging

- Ill-posed: apply regularized inversion to estimate  $\mathbf{m}$ .
- VRTI image indicates actual human location (X)





Device Free Localization



# VRTI Video



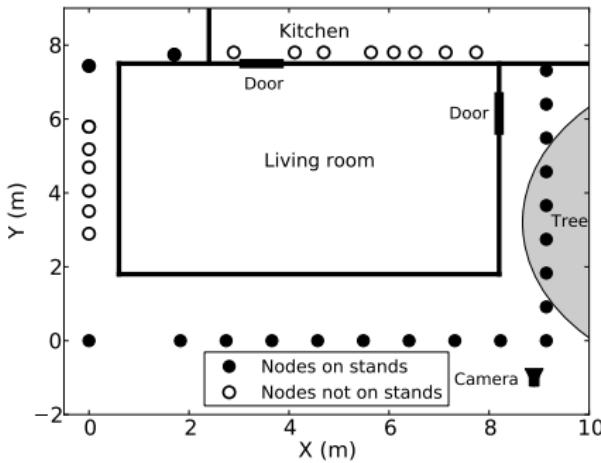
- <http://span.ece.utah.edu/radio-tomographic-imaging>  
(avg. error = 0.63 m)



# Start From Two 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.



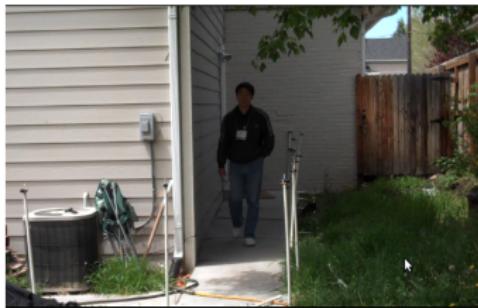


Robust Estimators



## Problem of VRTI: Noise from Intrinsic Motion

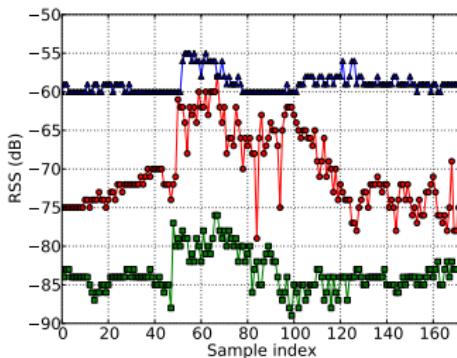
- Identical experiments show very different VRTI performance on a still (Left) vs. windy day (Right)





# RSS Variations Due to Intrinsic Motion

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



- 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 <sup>3</sup>

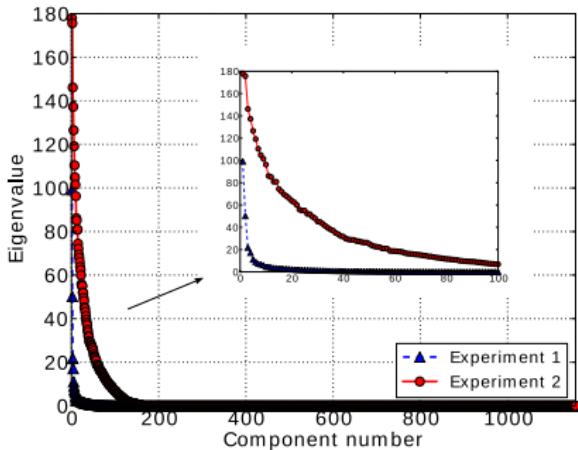
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<sup>3</sup>Y. Zhao and N. Patwari, "Noise reduction for variance-based device-free localization and tracking", *IEEE SECON 2011*.



# 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:  $\hat{U} = [\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_k]$  and  $\tilde{U} = [\mathbf{u}_{k+1}, \mathbf{u}_{k+2}, \dots, \mathbf{u}_L]$ .
- 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  $\tilde{\mathbf{s}}$ :

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

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



Robust Estimators



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

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

O  
OO  
OOO

Robust Estimators

# Estimates from VRTI and SubVRT

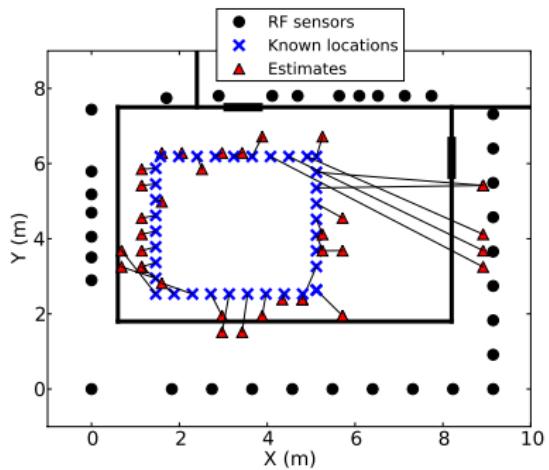


Figure: VRTI estimates.

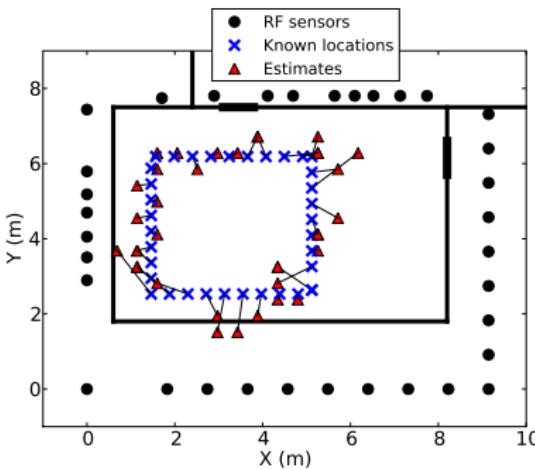
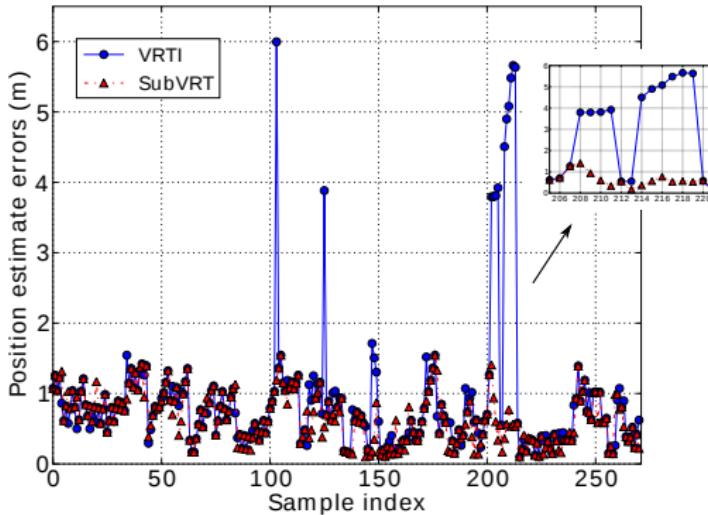


Figure: SubVRT estimates.



# Performance Improvement

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





Robust Estimators



# Real-time SubVRT Demo in SECON

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





Robust Estimators



# Least Squares Solution

- Idea: Instead of performing PCA on the covariance matrix, use the covariance matrix directly
- Formulation: <sup>4</sup>

$$\hat{\mathbf{m}} = \Pi_3 \mathbf{s}_r$$

$$\Pi_3 = (W^T C_{\mathbf{n}}^{-1} W + C_{\mathbf{m}}^{-1})^{-1} W^T C_{\mathbf{n}}^{-1}.$$

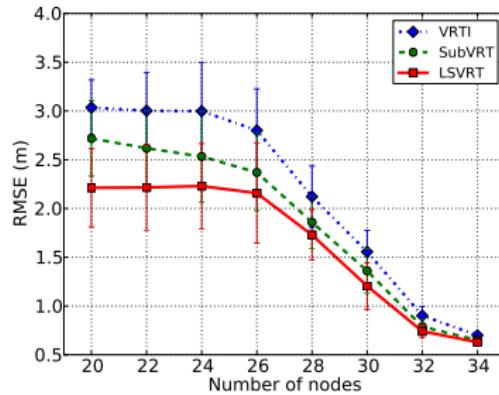
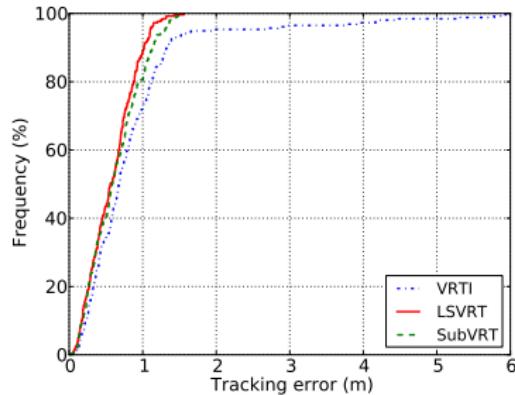
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<sup>4</sup> Y. Zhao and N. Patwari, "Robust Estimators for Variance-Based Device Free Localization and Tracking", IEEE Transactions on Mobile Computing, Oct. 2015.



# Further Improvement

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



# Tracking

- Apply Kalman filter to location estimates for tracking

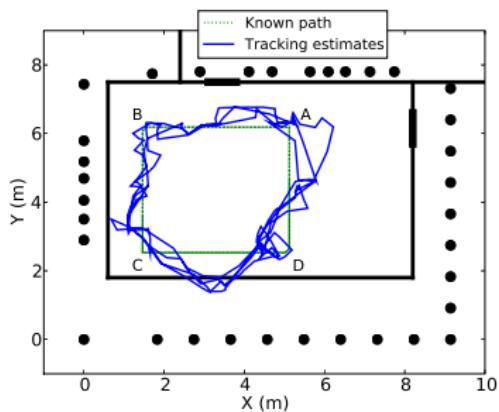


Figure: SubVRT estimate as input

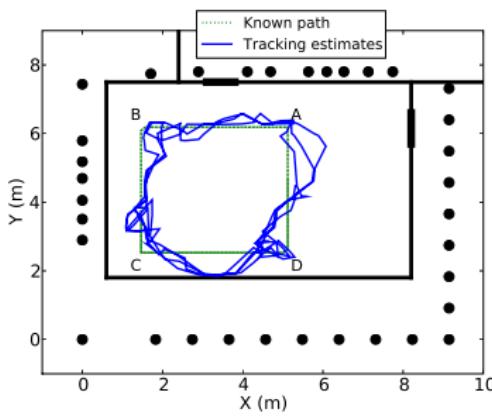


Figure: LSVRT estimate as input



# RTI Localization Algorithms

- 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 uses covariance matrices of noise and prior to further improve the robustness of VRTI
- Kernel distance-based RTI (KRTI) is further developed to locate stationary and moving people through walls<sup>5</sup>

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<sup>5</sup>Y. Zhao, et al., "Radio tomographic imaging and tracking of stationary and moving people via kernel distance",



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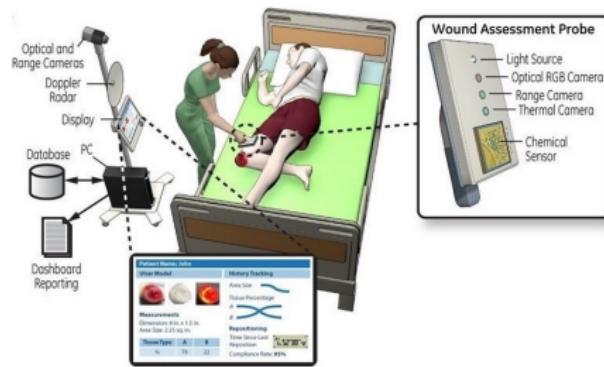
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# Pressure Ulcer Prevention and Care

## Mobile system for patient motion sensing<sup>6</sup>



<sup>6</sup> M. Chang et al., "Multimodal Sensor System for Pressure Ulcer Wound Assessment and Care," in IEEE

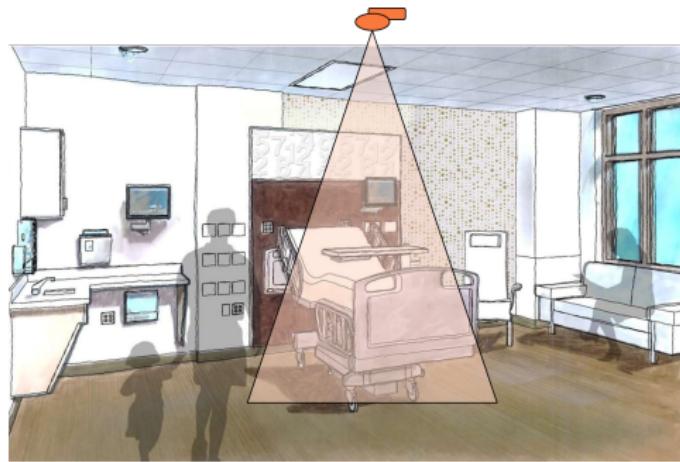


Room Occupancy Application

# Hospital Operation Management

## Dual Doppler occupancy sensor<sup>7</sup>

- Detection of sleeping patients
- Room-level coverage
- No privacy concern
- Low-cost



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<sup>7</sup> Y. Zhao, et al., "Occupancy and Activity Monitoring with Doppler Sensing and Edge Analytics", ACM SenSys,

Nov. 2016.

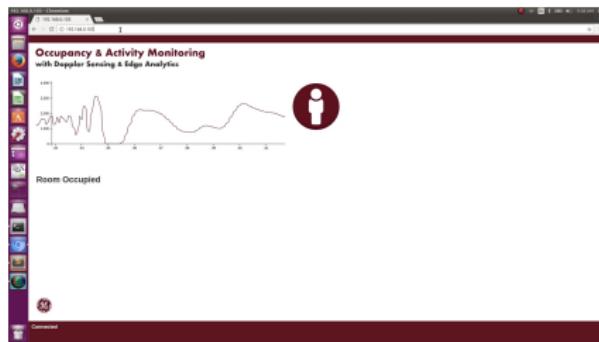
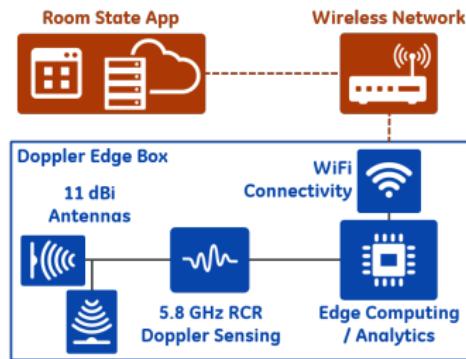


Room Occupancy Application



# SenSys Demo

Real-time demo to monitor respiration of multiple people<sup>8</sup>



<sup>8</sup> Y. Zhao, et al., "Occupancy and Activity Monitoring with Doppler Sensing and Edge Analytics", ACM SenSys,

Nov. 2016.



Room Occupancy Application



# Multi-modality Sensing System

Four types of data: RGB image, Depth image, Doppler and RSS from three devices<sup>9</sup>



(a) Kinect RGB-D  
camera



(b) Doppler sensor



(c) CC2531 wireless  
node

<sup>9</sup>

Y. Zhao, et al., "Occupancy Sensing and Activity Recognition with Cameras and Wireless Sensors", ACM

SenSys DATA workshop, 2019



# Human Subject Study and Dataset

- Human subject study with over a dozen participants (Vital signs monitoring)
- Dataset (wireless sensors) published for human activity recognition

<https://doi.org/10.5281/zenodo.3454785>





# Thank you!

## Acknowledgment

- Dr. Ting Yu at Google Cloud AI
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## Questions?