Lecture 5.2: WiFi Sensing

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Contents

WiFi Sensing

- "The next big wireless movement" – By Ray Liu, IEEE President, Founder & CEO of Origin AI

Multipath Everywhere!

- Motion Detection
- Sleep Monitoring
- Fall Detection
- Gait Recognition
- Gesture Control
- Wellbeing Monitoring
- Activity Monitoring
- Location Tracking
- Many More…

WiFi Sensing interprets the multipath disruptions for sensing.

No Cameras, No Wearables, No Sensors

Wireless
Contactless
Sensorless

Contents

Review: What is CSI?

A data perspective w/ zero SP background & zero memory about previous lectures

- $\mathbf{H}(\mathbf{t}) = [H(t, f_1), H(t, f_2), \cdots, H(t, f_N)]$
  - Complex number: $H(t, f_i) = a_i + jb_i$
  - Amplitude: $|H(t, f_i)| = \sqrt{a_i^2 + b_i^2}$ ← `abs()`
  - Phase: $\phi_i = \tan^{-1}\frac{b_i}{a_i}$ ← `phase()`

- Time series of $\mathbf{H}(\mathbf{t})$

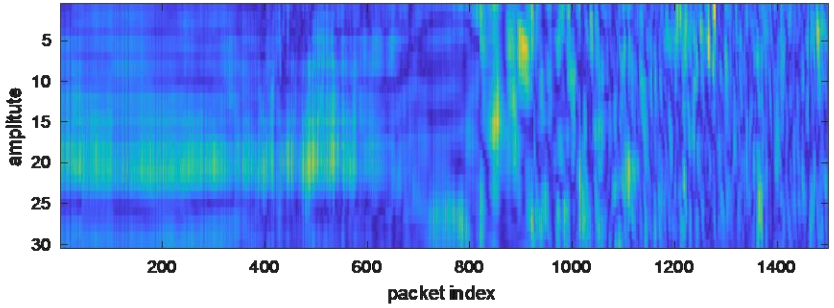
Time Series of CSI

$$\begin{bmatrix} H(1, f_1) & \cdots & H(M, f_1) \\ \vdots & \ddots & \vdots \\ H(1, f_N) & \cdots & H(M, f_N) \end{bmatrix}$$

Time Series of CSI Amplitude

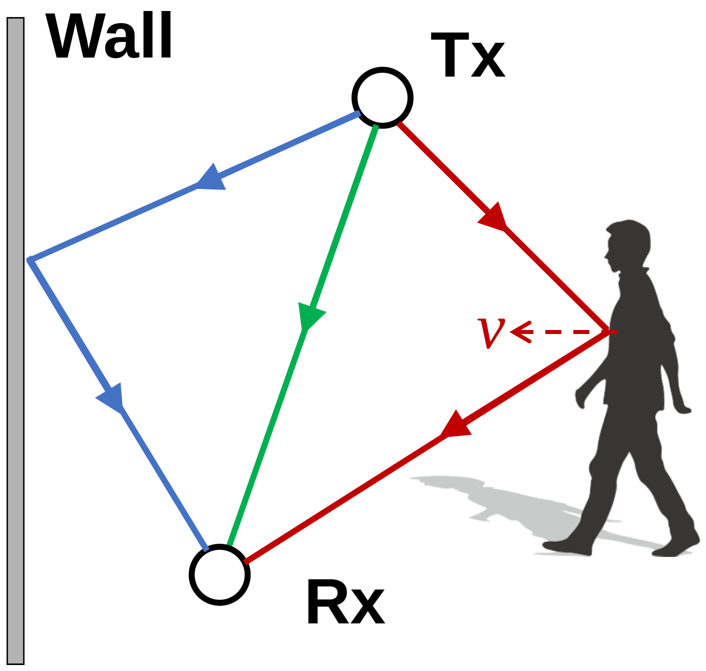
$$\begin{bmatrix} |H(1, f_1)| & \cdots & |H(M, f_1)| \\ \vdots & \ddots & \vdots \\ |H(1, f_N)| & \cdots & |H(M, f_N)| \end{bmatrix}$$

Time Series of CSI Amplitude



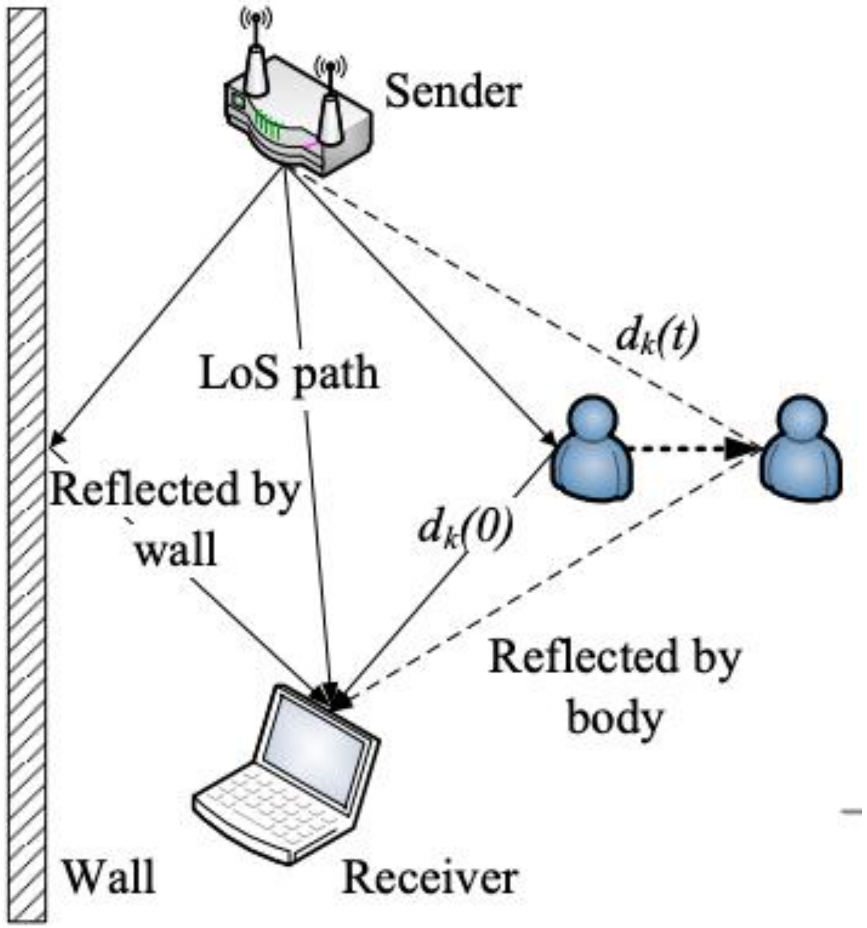
Geometric Parameters

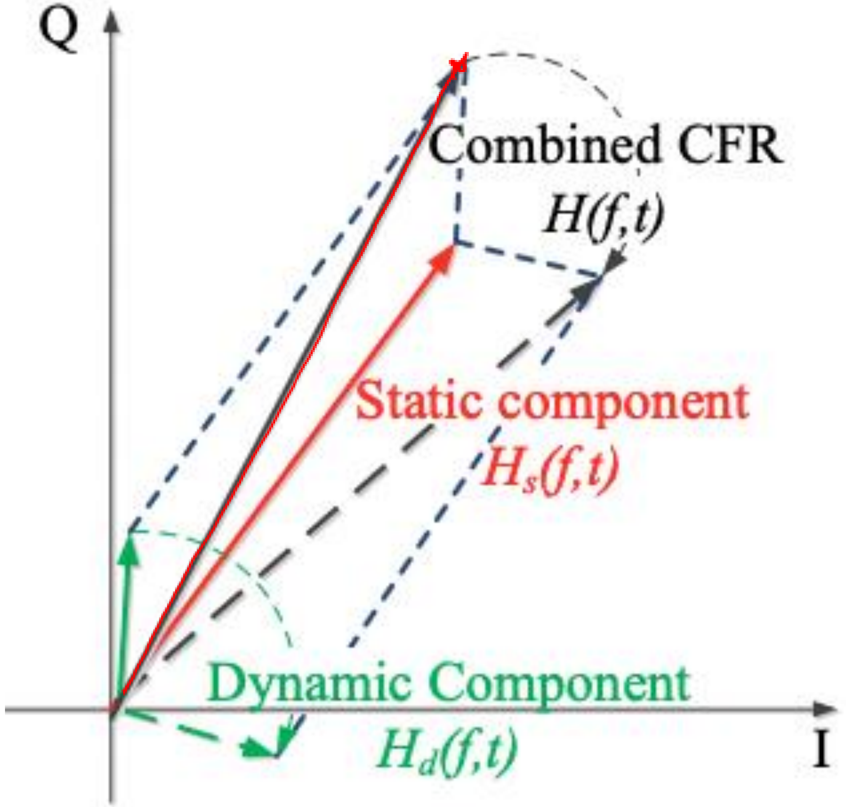
- Time of Flight (ToF)
  - Range
- Time Difference of Arrival (TDoA)
- Angle of Arrival (AoA)
- Doppler Frequency Shift (DFS)
  - Velocity



- Resolve the above parameters of (major) multipath signals

CSI Dynamics





Understanding and modeling of wifi signal based human activity recognition, MobiCom 2015

CSI Dynamics

$$H(t,f) = \sum_{l \in \Omega} a_l(t) \exp(-j2\pi f \tau_l(t))$$

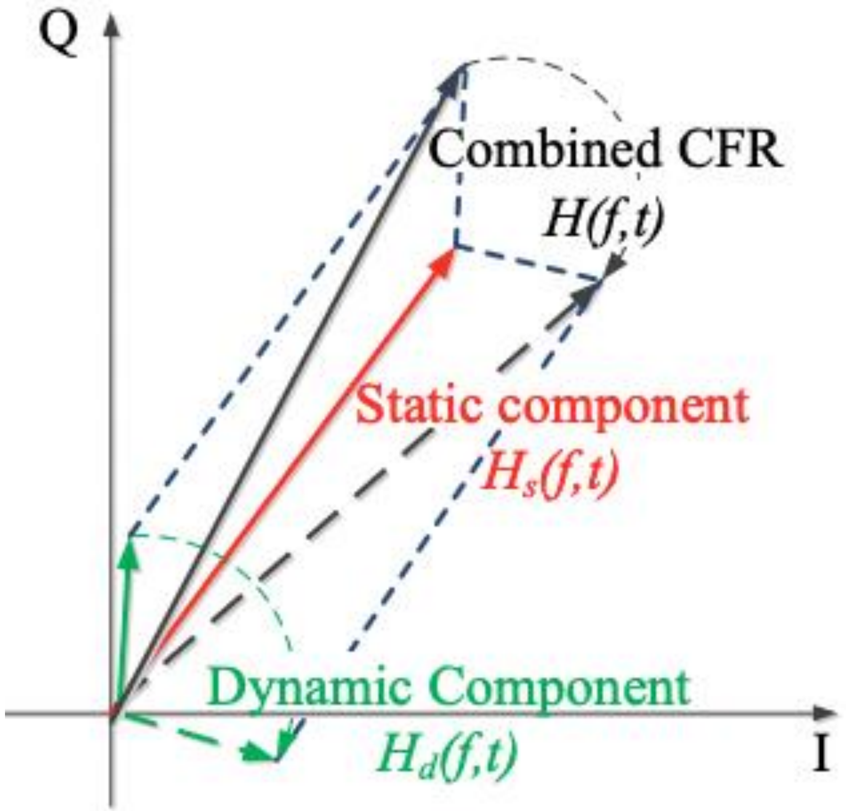
$$H(f,t) = \underline{H_S(f,t)} + \underline{H_D(f,t)}$$

Static components

Dynamic components

$H_D(f,t)$ has approximately zero mean

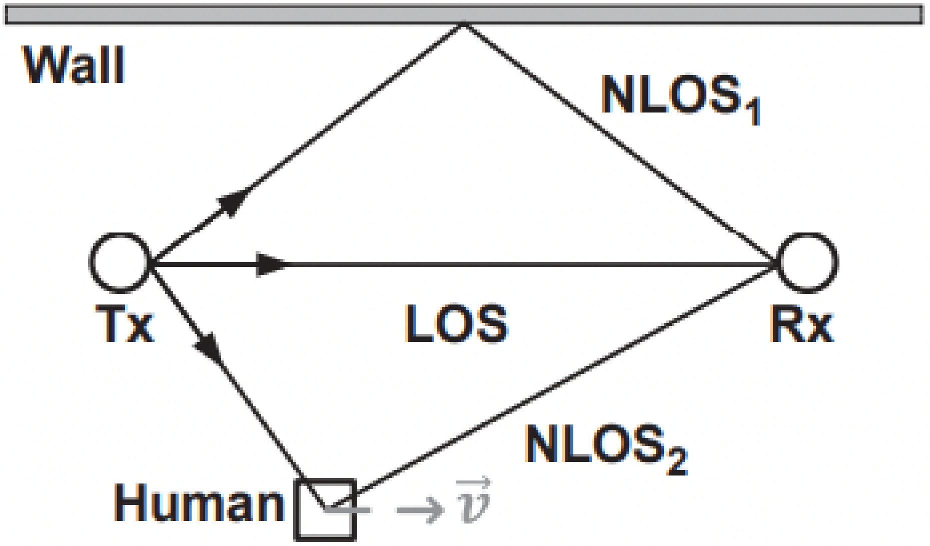
→ Therefore, $H(f,t)$ has approximately zero mean by removing the static part $\mathrm{H}_S(f,t)$.



CSI Dynamics to DFS

- Doppler Frequency Shifts
  - Caused by (reflection) path length changes
  - $f_D(t) = -\frac{1}{\lambda}\underline{\frac{d}{dt}d(t)} = -f\frac{d}{dt}\tau(t)$

Path Length Change
Rate (PLCR)



Ideal CSI: $$H(f,t) = H_S(f,t) + \sum_{l \in \Omega_D} \alpha_l(t) e^{j2\pi \int_{-\infty}^{t} f_{D_l}(u)du}$$

Measured CSI: $$\hat{H}(f,t) = H(f,t)e^{-j2\pi(\Delta_t f + \Delta_f t)}$$

CSI to DFS

- CSI at frequency (subcarrier) f, at time t with K propagation paths

amplitude of path k at time t

$$H(f,t) = \sum_{k=1}^{K} \alpha_k(t) e^{j \boxed{2\pi f \tau_k(t)}}$$

propagation delay of path k at time t

phase of path k

- In case of motions

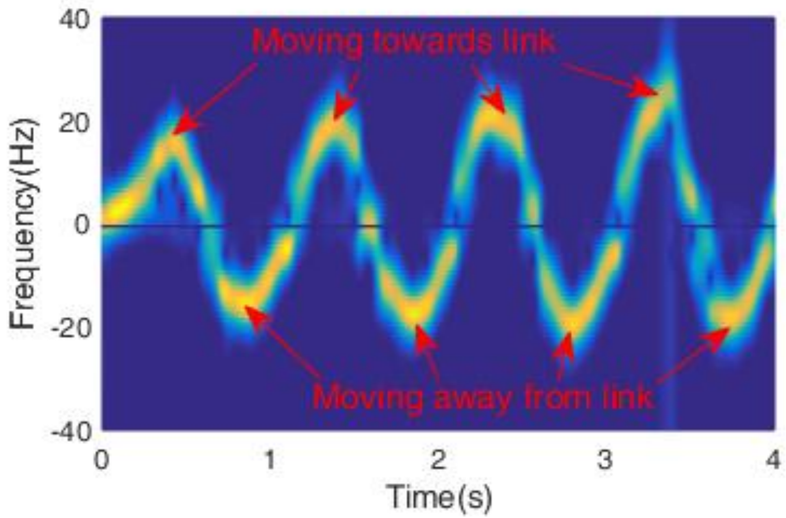
doppler frequency shift of (dynamic) path k

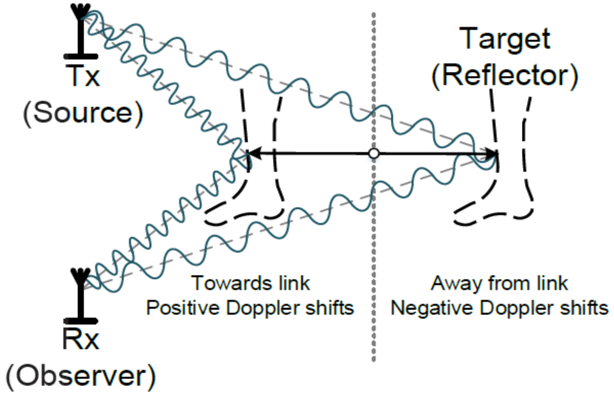
$$H(f,t) = \underbrace{\boxed{H_{static}(f)}}_{\text{CSI of static paths}} + \underbrace{\boxed{\sum_{k \in K_{dynamic}} \alpha_k(t) e^{j2\pi \boxed{\int_{-\infty}^{t} f_{D_k}(u)du}}}}_{\text{CSI of dynamic paths}}$$

Integral of frequency over time ∝ phase

CSI to DFS: Example

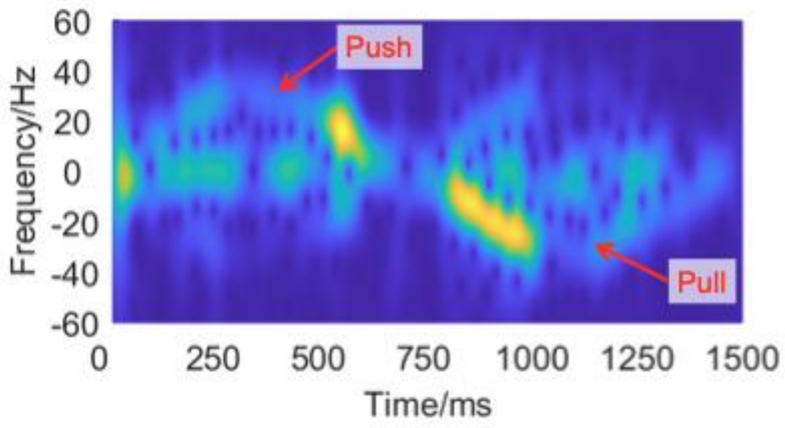
CSI of dynamic paths (spectrogram)

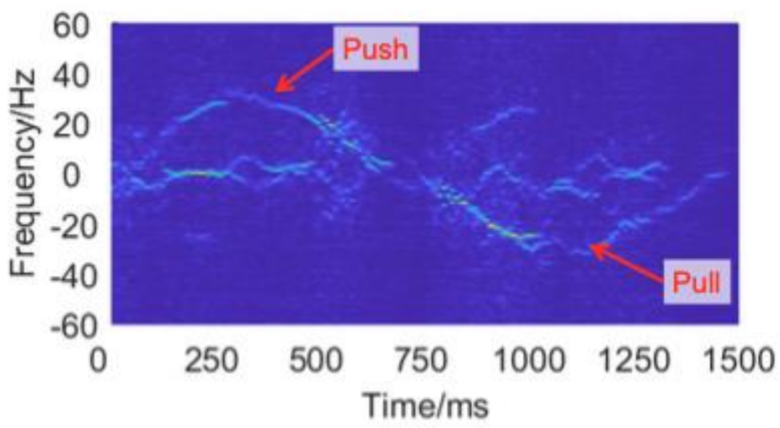




Spectrogram generation by STFT

- Short-time Fourier transform



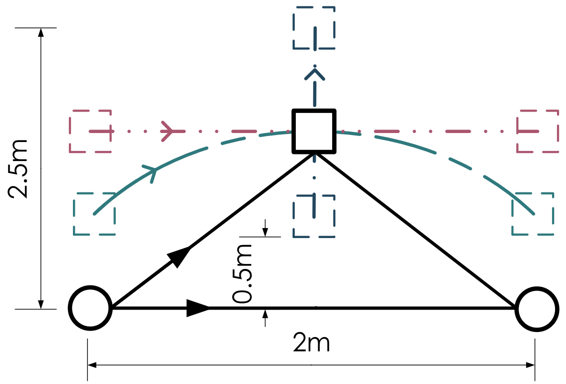


Two practical issues of DFS

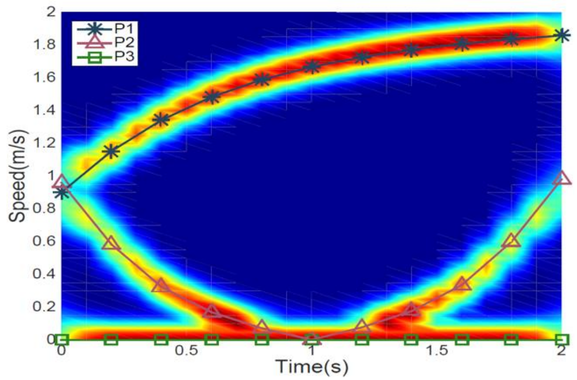
- Issue I: Phase Errors

Ideal CSI: $$H(f,t) = H_S(f,t) + \sum_{l\in\Omega_{\mathrm{D}}} \alpha_l(t) e^{j2\pi\int_{-\infty}^{t} f_{D_l}(u)du}$$

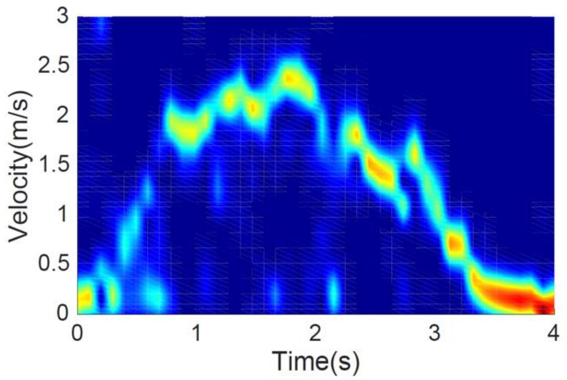
Measured CSI: $$\hat{H}(f,t) = H(f,t)e^{-j2\pi(\Delta_t f + \Delta_f t)}$$



Walking Scenarios



Ideal Spectrograms



Real Spectrograms

[Inferring Motion Direction using Commodity Wi-Fi for Interactive Exergames, ACM CHI 2017]

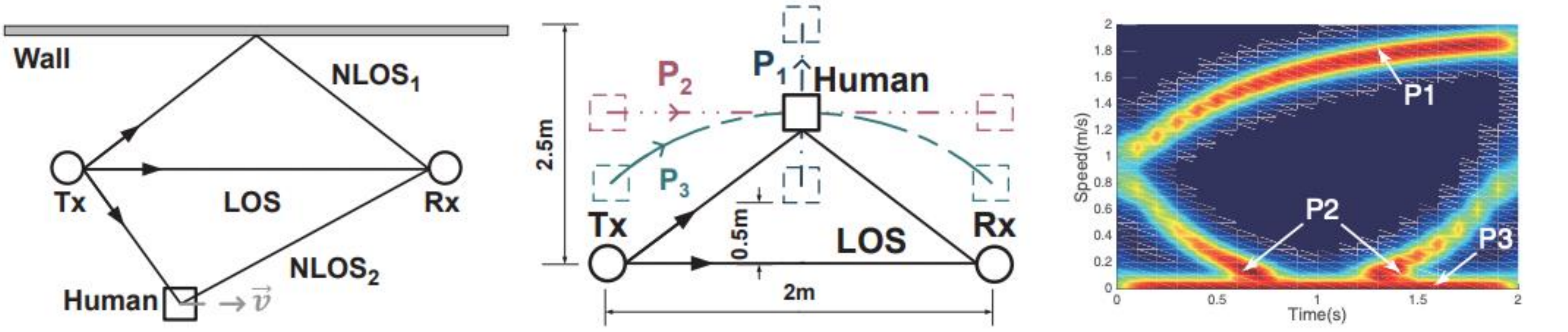
Two practical issues of DFS

- Issue I: Phase Errors
- Solution I (Discard phase): Use CSI power only
  - $\left|\hat{H}(f,t)\right|^2 = |H(f,t)|^2$
  - Eliminates the impact of phase errors
  - But also loses the sign of DFS
- Solution II (Phase cleaning): Linear phase fitting
  - Ideally, the phase offsets are linear across subcarriers
- Solution III (Phase cleaning): Antenna difference
  - Different antennas share the same CFO, CTO (but not initial offset)
  - Conjugate multiplication of CSI on multiple antennas
  - Needs at least two antennas; initial offset needs manual calibration

You are facing the Mona Lisa: Spot localization using PHY layer information, ACM MobiSys'12
Inferring motion direction using commodity wi-fi for interactive exergames, ACM CHI'17

Two practical issues of DFS

- Issue II: Partial Speed
  - DFS from CSI does not reveal complete speed
  - Even with accurate phase and thus accurate DFS, the speed depends on the location and moving direction



(a) Multipath propagation. (b) Human walking paths P_1, P_2, P_3 (c) PLCRs calculated from the three scenario in (b)

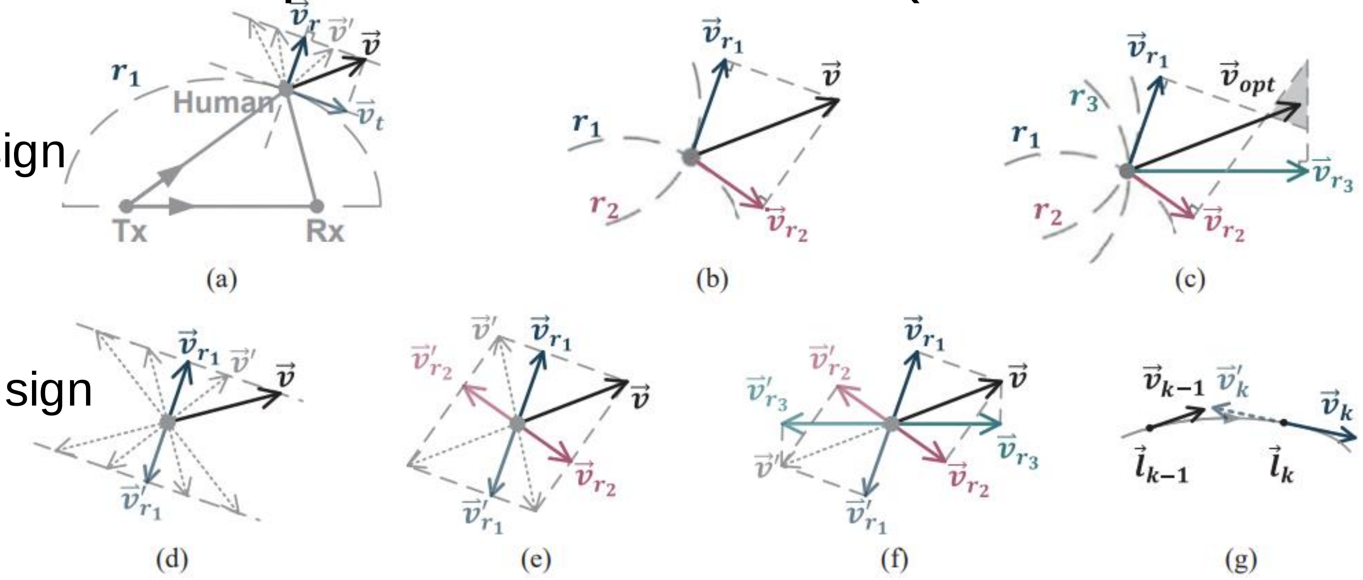
Widar: Decimeter-Level Passive Tracking via Velocity Monitoring with Commodity Wi-Fi, ACM MobiHoc 2017

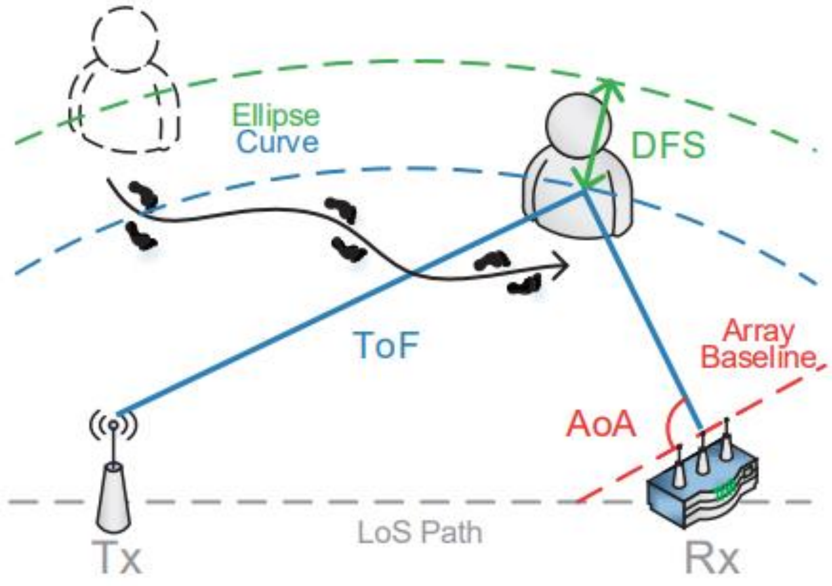
Two practical issues of DFS

- Issue II: Partial Speed
- Solution
  - Fuse information from multiple links
  - Joint parameter estimation (AoA, ToF, DFS, etc)

w/ DFS sign

w/o DFS sign

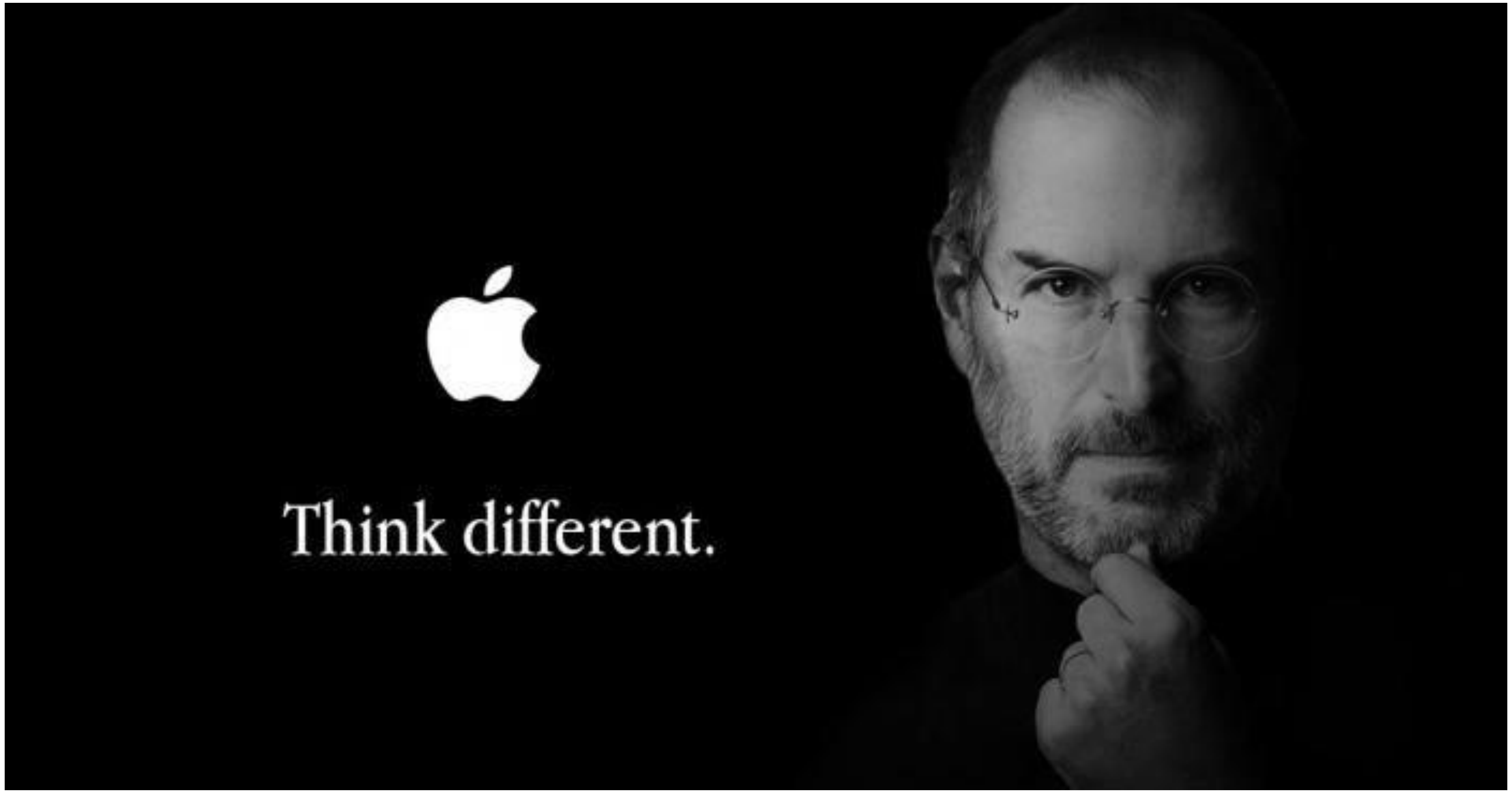




Widar2.0: Passive Human Tracking with a Single Wi-Fi Link, ACM MobiSys 2018

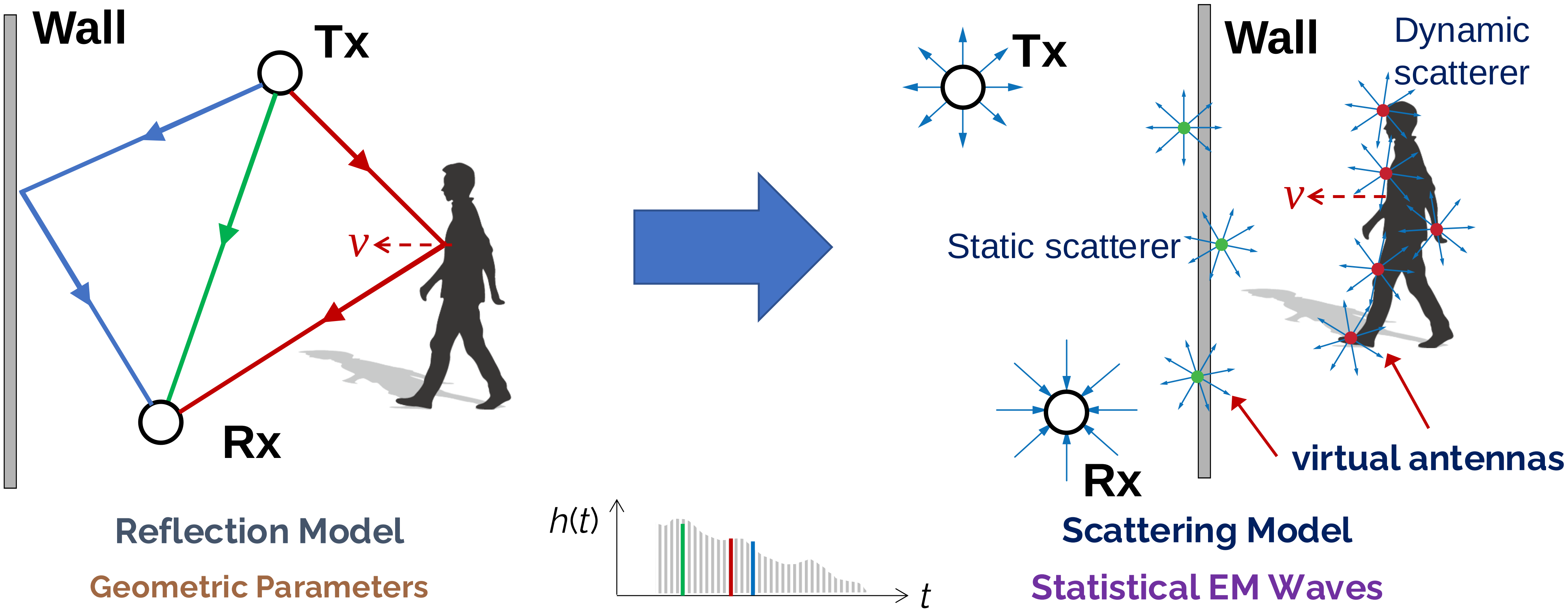
We need a better model

- To overcome these fundamental and practical problems.



Contents

Scattering Model



Multipaths → Scatterers → Virtual Antennas!

Wu, C., Zhang, F., Hu, Y., & Liu, K. R.. GaitWay: Monitoring and Recognizing Gait Speed Through the Walls. IEEE TMC 2020.
Zhang, F., Chen, C., Wang, B., & Liu, K. R.. WiSpeed: A statistical electromagnetic approach for device-free indoor speed estimation. IEEE IOTJ, 2018.

Statistical EM Approach

- Decomposition of Received Electric Field

$$\vec{E}_{RX}(t,f) = \underbrace{\sum_{i\in\Omega_s(t)} \vec{E}_i(t,f)}_{\text{Static scatterers}} + \underbrace{\sum_{j\in\Omega_d(t)} \vec{E}_j(t,f)}_{\text{dynamic scatterers}}$$

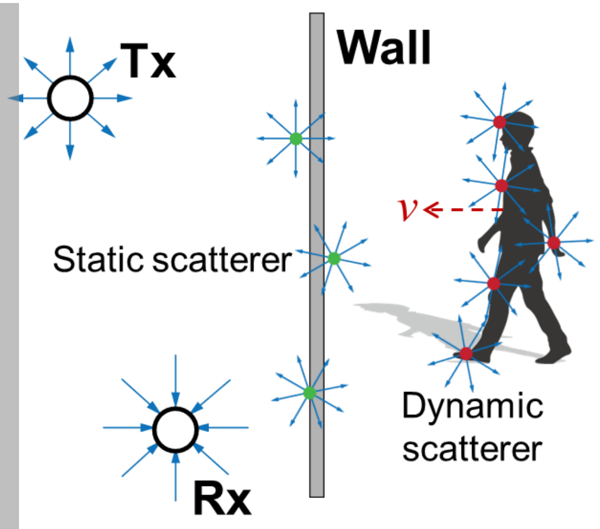
- Autocorrelation Function (ACF) of $\vec{E}_i(t,f)$:

$$\boxed{\begin{aligned} \rho_{E_{ix}}(\tau,f) &= \rho_{E_{iy}}(\tau,f) \\ &= \frac{3}{2}\left[\frac{\sin(kv_i\tau)}{kv_i\tau} - \frac{1}{(kv_i\tau)^2}\left(\frac{\sin(kv_i\tau)}{kv_i\tau} - \cos(kv_i\tau)\right)\right], \\ \rho_{E_{iz}}(\tau,f) &= \frac{3}{(kv_i\tau)^2}\left[\frac{\sin(kv_i\tau)}{kv_i\tau} - \cos(kv_i\tau)\right]. \end{aligned}}$$

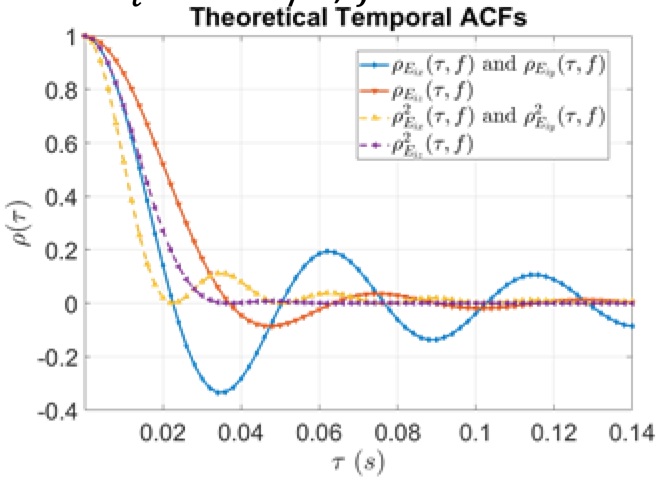
$$\boxed{\rho_{E_{iu}}(\tau,f) = F_u(kv_i\tau), \forall u \in \{x,y,z\}}$$

$k = 1/\lambda$: wavenumber; v_i: speed of scatterer i

The ACF is a function of speed!



Set $v_i = 1\ m/s, f = 5.805$ GHz

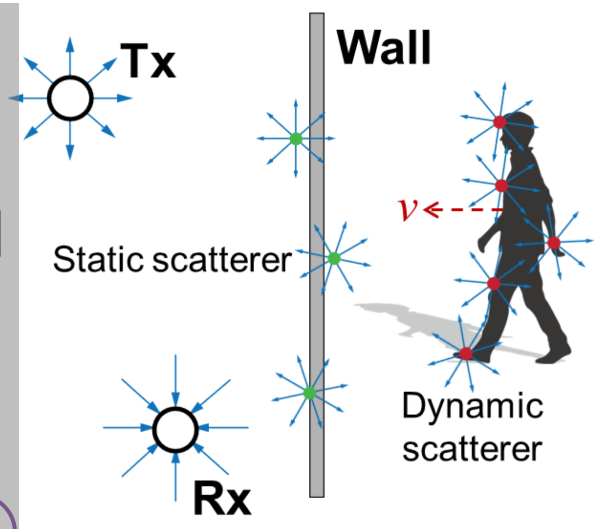


Statistical EM Approach

- From $\vec{E}_i(t,f)$ to CSI:
- In practice, $\vec{E}_{Rx}(t,f)$ is a vector and cannot be measured by WiFi directly.
- Instead, the power of $\vec{E}_{Rx}(t,f)$ is measured:

Power of CSI: $G(t,f) \triangleq |H(t,f)|^2 = \|\vec{E}_{Rx}(t,f)\|^2 + \varepsilon(t,f)$

ACF of $\mathrm{G(t,f)}$: $\rho_G(\tau,f) \approx C(f)\left(E_d^2(f)\rho_{E_{ix}}^2(\tau,f) + E_s^2(f)\rho_{E_{ix}}(\tau,f) + \delta(\tau)\sigma^2(f)\right)$



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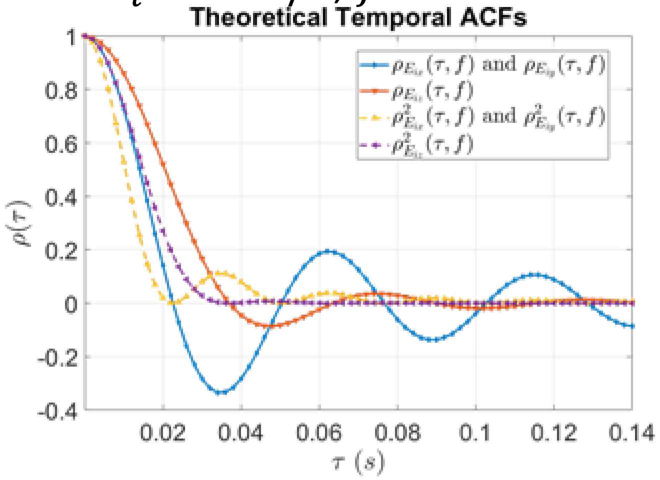


<u>The model allows:</u>

- Speed Estimation
- Motion Detection
- Breathing Rate Estimation

Review: What is ACF?

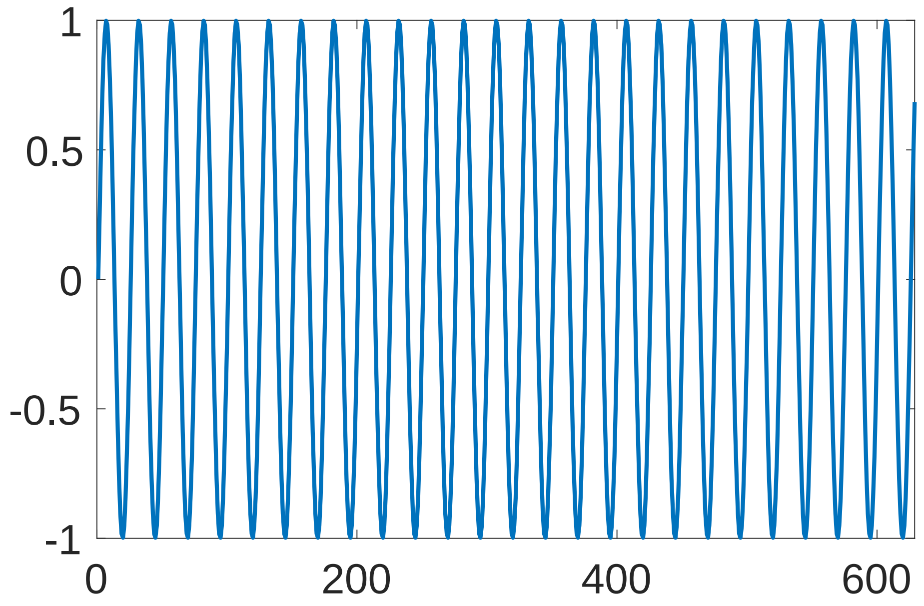
- Correlation of a signal (the same variables) with a delayed/lagged copy of itself

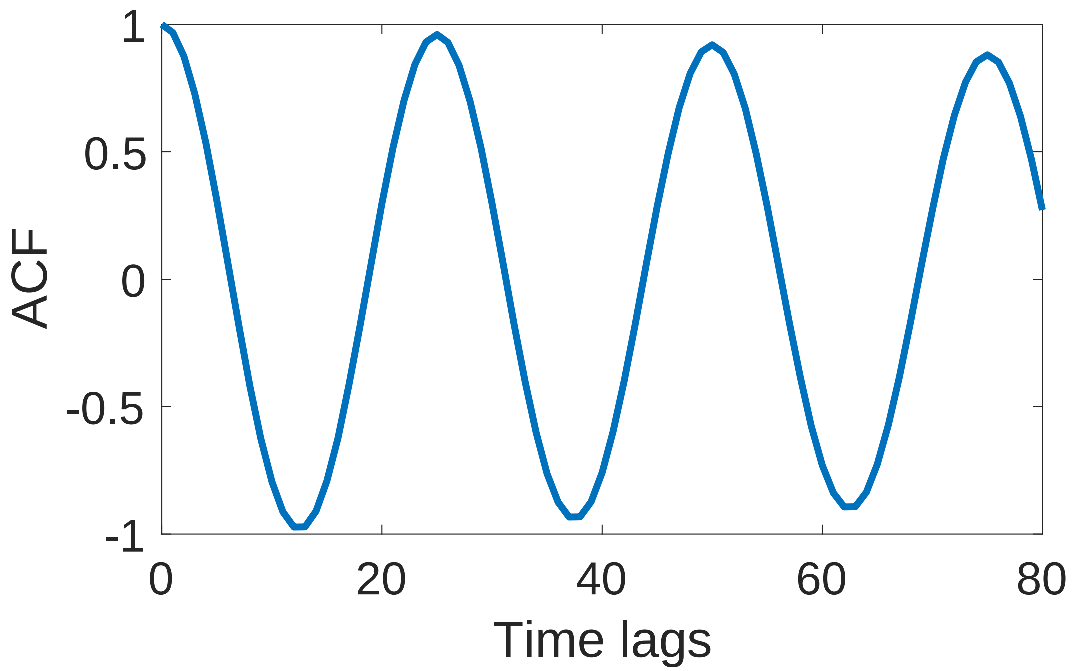
- We only consider a discrete time series $\mathrm{x}[\mathrm{t}], \mathrm{t} = 1, \cdots T$, the ACF is

$$r[k] = \frac{\sum_{t=k+1}^{T}(x[t] - \bar{x})(x[t-k] - \bar{x})}{\sum_{t=1}^{T}(x[t] - \bar{x})^2}$$

Review: What is ACF?

- Value range [-1, 1]
- A tool for finding period in the time domain ← `autocorr()`





Passive Speed Estimation

Applications

Fall Detection

Gait Recognition

Activity Monitoring

Passive Tracking

Existing Solutions

Camera

Very expensive
complicated calibration

Doppler Effect

Incomplete speed, LOS,
vulnerable to interferences

Time-of-Flight

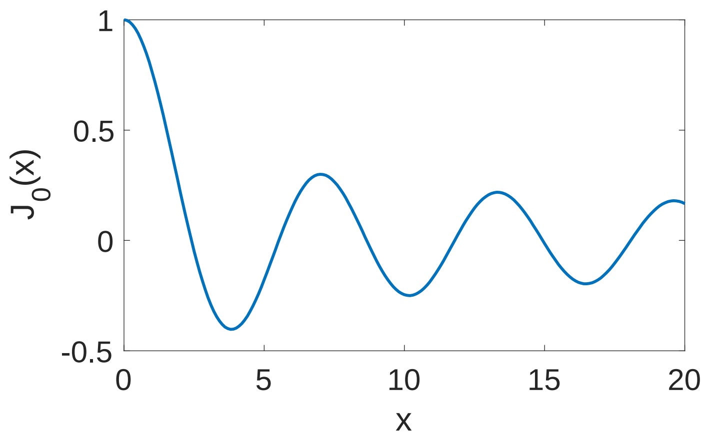
Inaccurate, LOS, barely
feasible on WiFi

Speed Estimation with WiFi

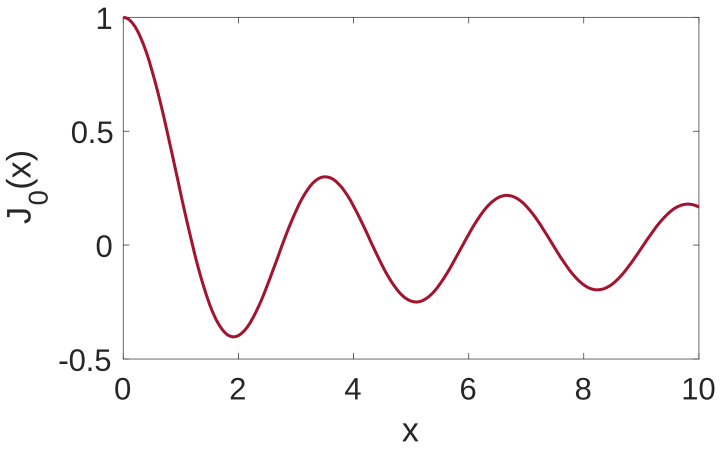
- Estimate speed from patterns of $\rho_H(\tau, f)$

$$\rho_H(\tau, f) = \frac{\sum_{i\in\Omega_d} \sigma^2_{F_i}(f) + \sigma^2(f)\delta(\tau)}{\sum_{i\in\Omega_d} \sigma^2_{F_i}(f) + \sigma^2(f)} \underline{J_0(kv\tau)} \triangleq \alpha(f) J_0(kv\tau)$$

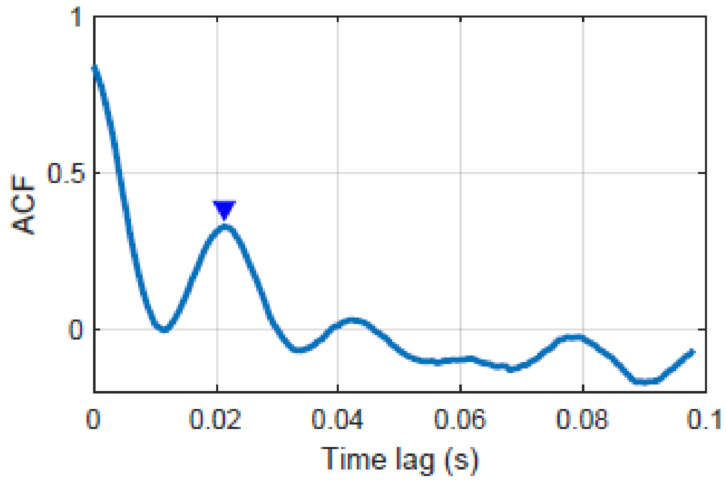
0th-order Bessel function of the first kind



$J_0(x)$



$J_0(2x)$



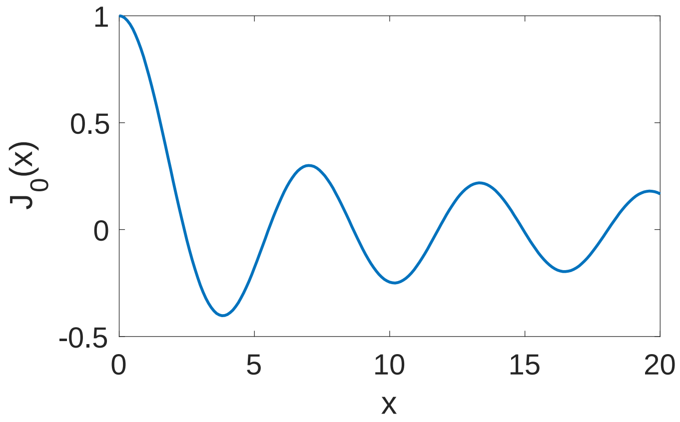
$\alpha\, J_0(\mathrm{a}x)$

Speed Estimation with WiFi

- Estimate speed from patterns of $\rho_H(\tau, f)$

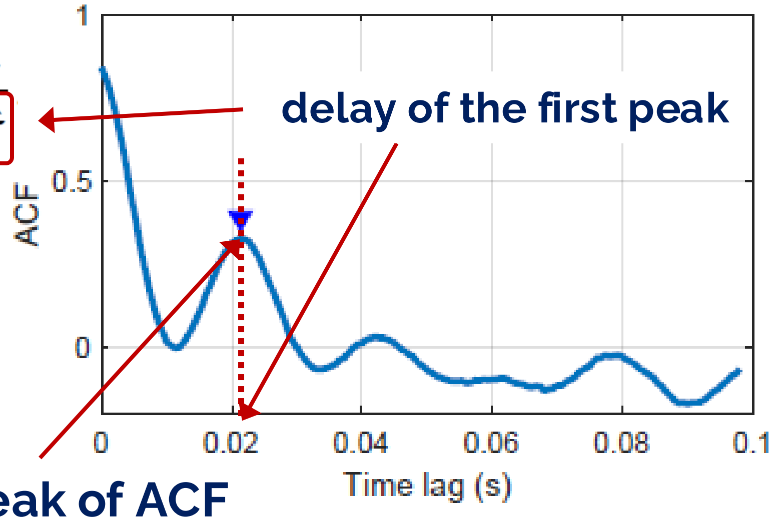
$$\rho_H(\tau, f) = \frac{\sum_{i\in\Omega_d} \sigma_{F_i}^2(f) + \sigma^2(f)\delta(\tau)}{\sum_{i\in\Omega_d} \sigma_{F_i}^2(f) + \sigma^2(f)} \underline{J_0(kv\tau)} \triangleq \alpha(f) J_0(kv\tau)$$

0th-order Bessel function of the first kind

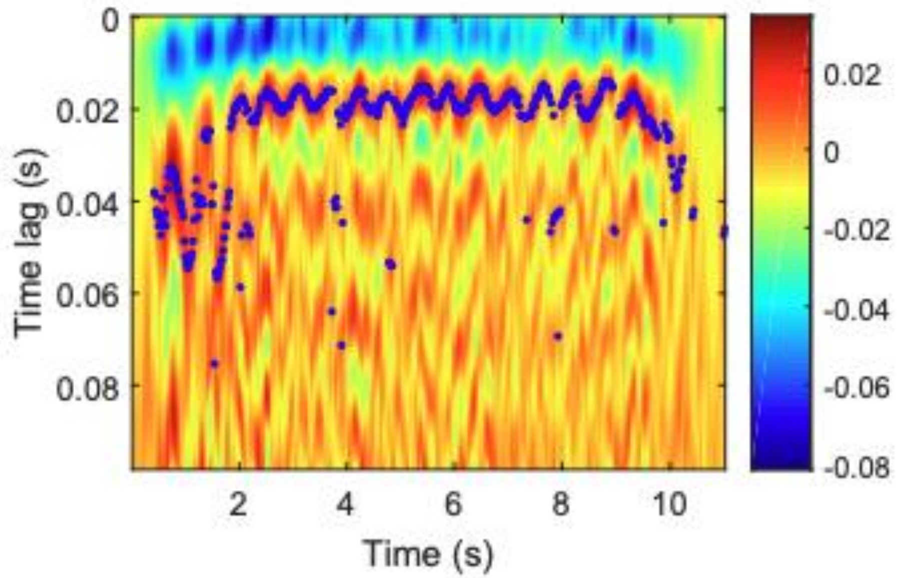


$$\hat{v} = \frac{x_0}{k\hat{\tau}} = \frac{x_0\lambda}{2\pi\boxed{\hat{\tau}}}$$

delay of the first peak

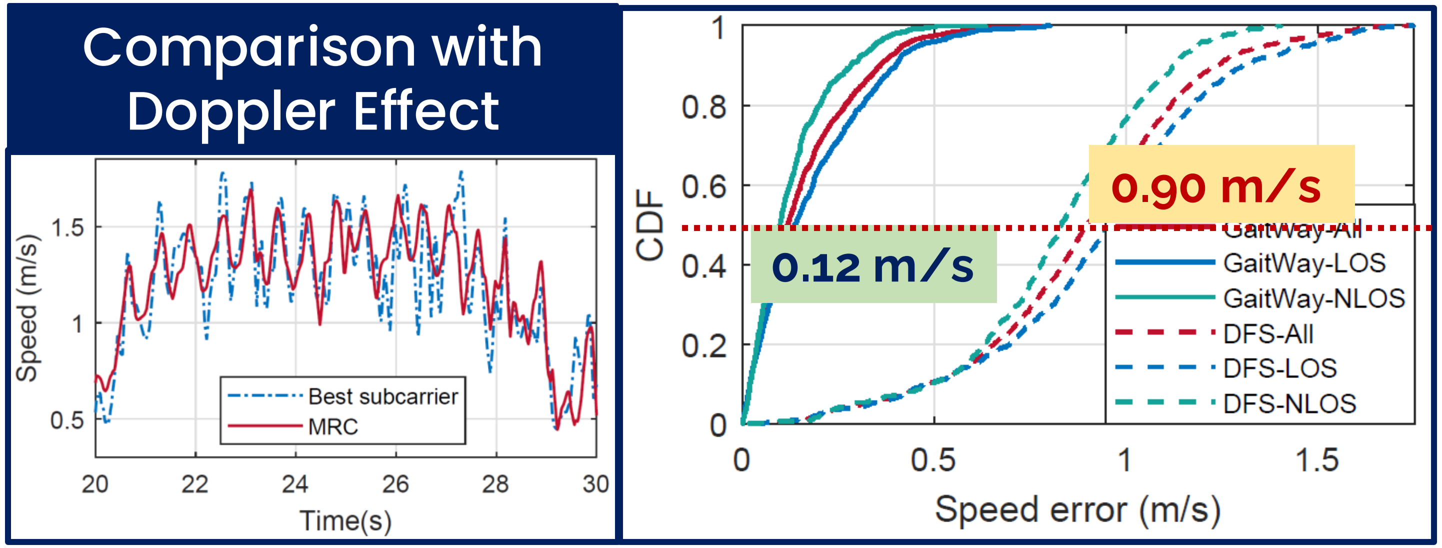


first peak of ACF



Speed Estimation with WiFi

- Comparison with Doppler-based methods



Advantages of statistical approaches:

- Works in NLOS
- Location and orientation independent
- Complete speed (thus more accurate)

Application: Fall Detection

Second leading cause

of accidental deaths worldwide

highest among adults over 60

646,000 deaths per year

80%+ in low/middle income areas

37.3M severe falls per year

Adults 65+ suffer the most

Fall detection is difficult!

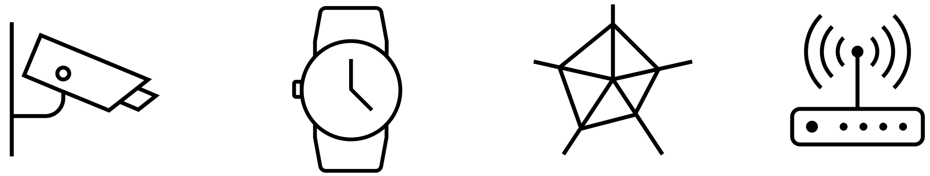
Cameras are privacy-intrusive

Wearables are inaccurate and unfavorable

UWB Radars have limited coverage

Existing WiFi methods need training

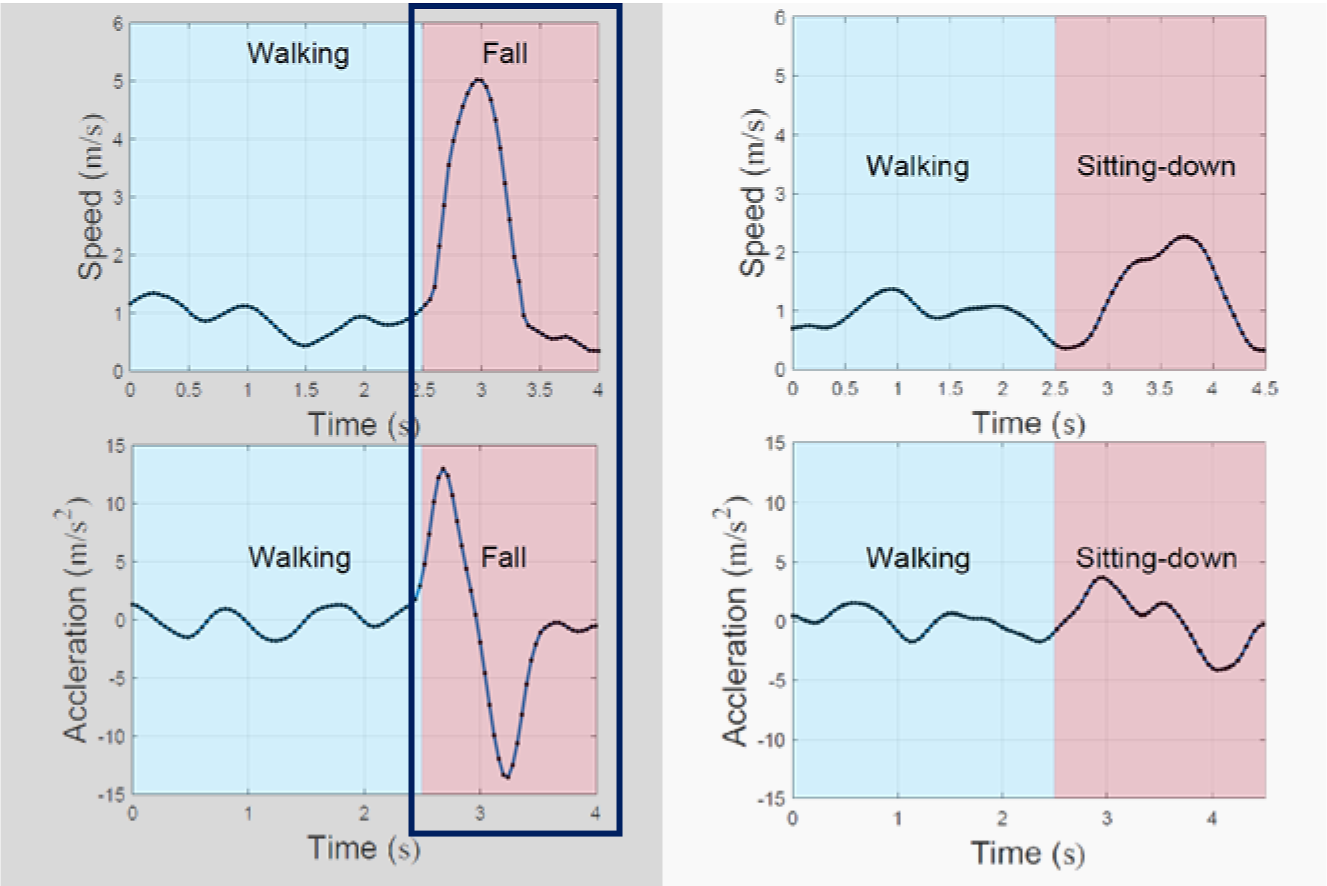
Low detection rate

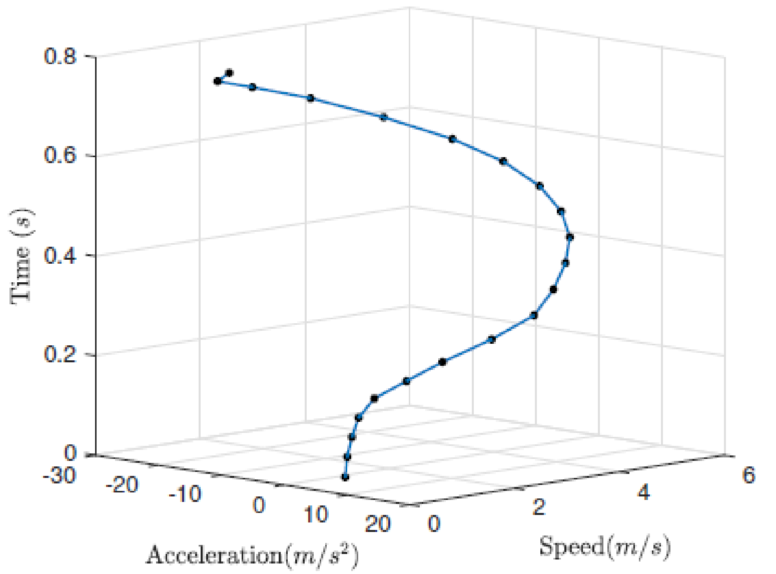


Hu, Y., Zhang, F., Wu, C., Wang, B., & Liu, K. R.. A WiFi-Based Passive Fall Detection System. IEEE ICASSP 2020.

Fall Detection by Speed

- Falls have distinct speed/acceleration patterns





Pattern Matching

Time series of speed & acceleration

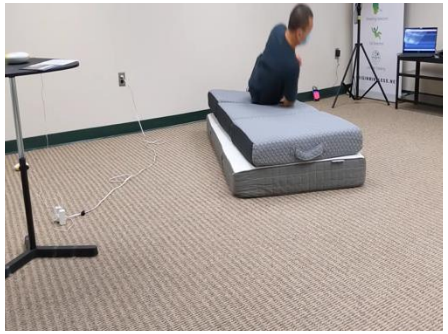
Evaluation

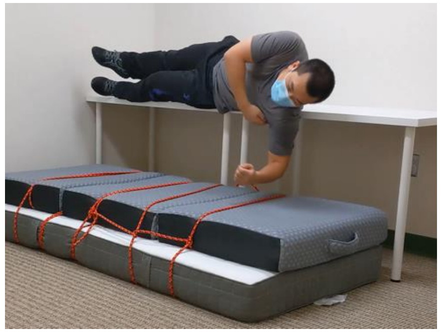
Offline Results

Activities	Features	Amount
Fall	LOS	518
	NLOS	328
Non-Fall	LOS	344
	NLOS	470

Methods	Features	Devices	Detection	False alarm
WiFall	Variance	3Tx/3Rx	87%	18%
RF-Fall	Spectrum	1Tx/2Rx	91%	11%
FallDeFi	Spectrum	2Tx/2Rx	95%/82%	15%/22%
DeFall	**Speed**	**1Tx/1Rx**	**96.0%**	**1.5%**

Real-time





138 / 140 falls detected

Application: Gait Recognition

Gait as a Vital Sign

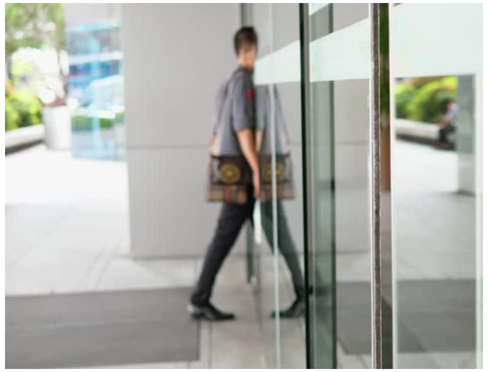
- Gait speed is termed as the sixth vital sign[1]
- Indicative and predictive for general health and functional status

5 SURPRISING WAYS YOUR WALKING SPEED REFLECTS YOUR HEALTH

[1] Stacy Fritz and Michelle Lusardi. 2009. White Paper: Walking Speed: the Sixth Vital Sign. Journal of Geriatric Physical Therapy 32, 2(2009), 2.

Gait as a Biometric Marker

- Walking is a complex function coordinating every body system
- Difficult to impersonate others' walking patterns



Wu, C., Zhang, F., Hu, Y., & Liu, K. R.. GaitWay: Monitoring and Recognizing Gait Speed Through the Walls. IEEE TMC 2020.

GaitWay: Gait Speed Recognition

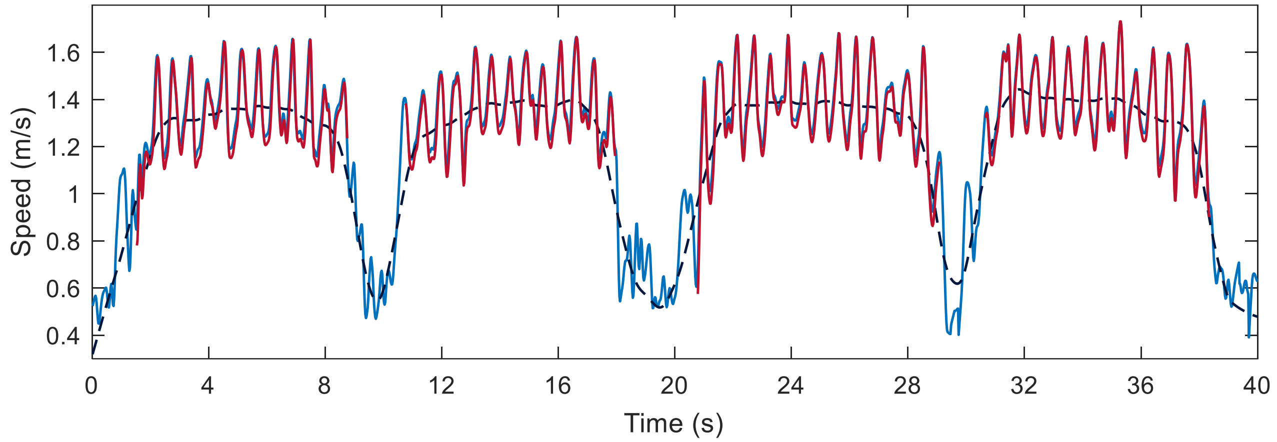
Speed Estimation

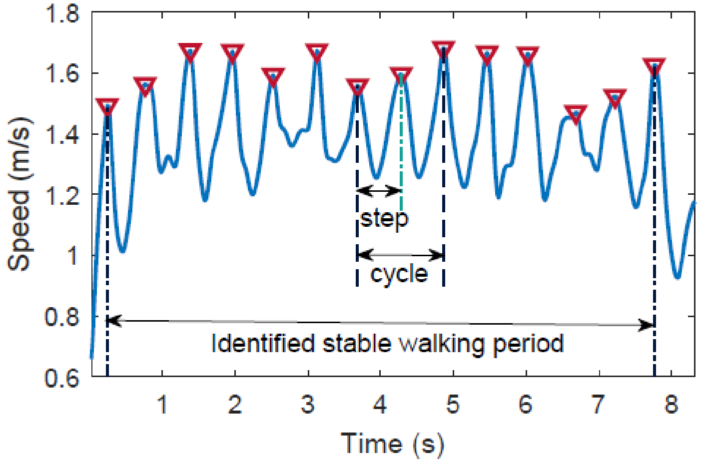
Stable Walking Extraction

Gait Cycle Extraction

Gait Feature Extraction

Gait Recognition (SVM)





Extract physically explainable and environmentally independent features

symmetry, smoothness, variability, periodicity, etc.

Whole-Home Motion Detection

Home Security
Intruder detection

Activity Monitoring
Occupancy detection

Home Automation
Presence detection

Infrared
LOS coverage

Cameras
False alarms
Privacy!

Vibration
Inaccurate
Deployment

Pressure
Confined coverage

Mission Impossible?
I (1996) →
← IV (2011)

Whole-Home Motion Sensing

- Recall ACF of $G(t, f)$:

$$\rho_G(\tau, f) = \frac{E_d^2(f)}{E_d^2(f) + \sigma^2(f)} \rho_\mu(\tau, f) + \frac{\sigma^2(f)}{E_d^2 + \sigma^2(f)} \delta(\tau)$$

If motion $\lim_{\tau \to 0} \rho_G(\tau, f) = \lim_{\tau \to 0} \frac{E_d^2(f)}{E_d^2(f) + \sigma^2(f)} \rho_\mu(\tau, f) > 0$

If no motion $\lim_{\tau \to 0} \rho_G(\tau, f) = 0$

Photo courtesy: Origin Wireless

Motion Statistic:

$$\hat{\phi}(f) \triangleq \hat{\rho}_G\left(\tau = \frac{1}{F_s}, f\right)$$

What's the statistical intuition?

Zhang, F., Wu, C., Wang, B., Lai, H. Q., Han, Y., & Liu, K. R.. WiDetect: Robust Motion Detection with a Statistical Electromagnetic Model. ACM IMWUT 2019

Statistical Motion Detection

- When motion presents ($\mathcal{H}_1$ hypothesis):

$$\lim_{\tau \to 0} \rho_G(\tau, f) = \lim_{\tau \to 0} \frac{E_d^2(f)}{E_d^2(f) + \sigma^2(f)} \rho_\mu(\tau, f) > 0$$

- When no motion presents ($\mathcal{H}_0$ hypothesis):

$$\lim_{\tau \to 0} \rho_G(\tau, f) = 0$$

- Define ***motion statistic*** on subcarrier *f* as:

$$\hat{\phi}(f) \triangleq \hat{\rho}_G\left(\tau = \frac{1}{F_s}, f\right)$$

Statistical Motion Detection

- Statistical Distributions of the ***Motion Statistic***

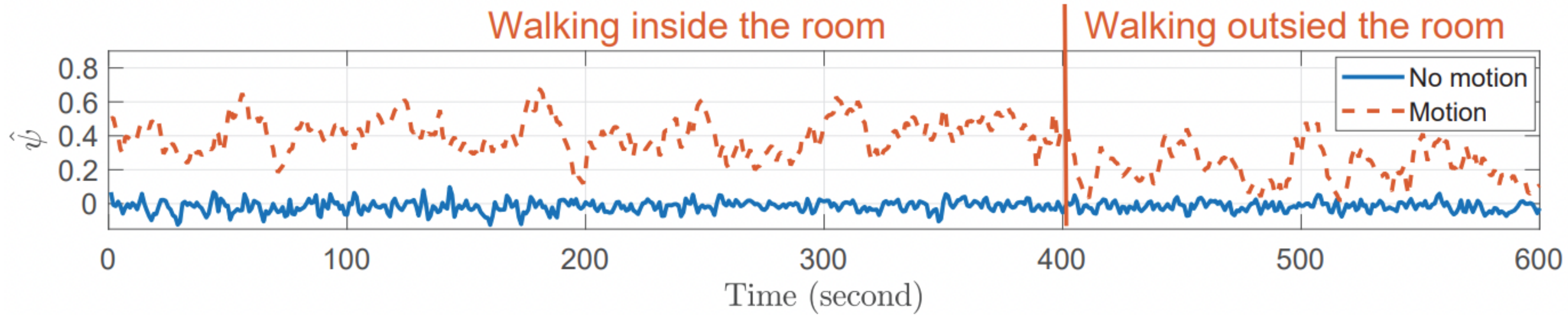
$$\mathcal{H}_0: \quad \hat{\phi}(f) \sim \mathcal{N}(-\frac{1}{T}, \frac{1}{T}), \ \forall f \in \mathcal{F}, \quad \text{where } T \text{ is the number of samples.}$$

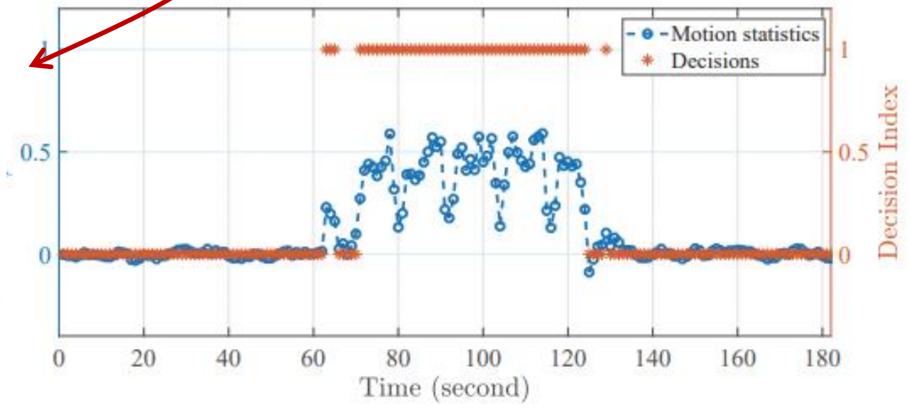
$$\mathcal{H}_1: \quad \hat{\phi}(f) \to \frac{E_d^2(f) + E_s^2(f)}{E_d^2(f) + E_s^2(f) + \sigma^2(f)} > 0, \ \forall f \in \mathcal{F}$$

- Detection Rule (Average over all subcarriers)

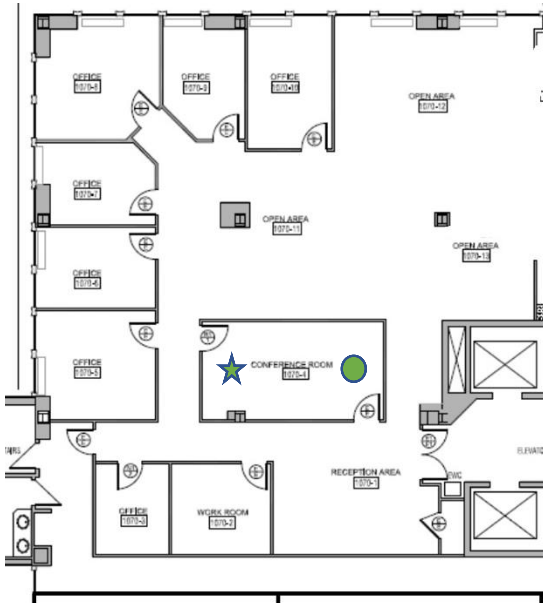
$$\boxed{\text{Reject } \mathcal{H}_0 \text{ iff } \hat{\psi} \triangleq \frac{1}{F}\sum_{f \in \mathcal{F}} \hat{\phi}(f) > \eta}$$

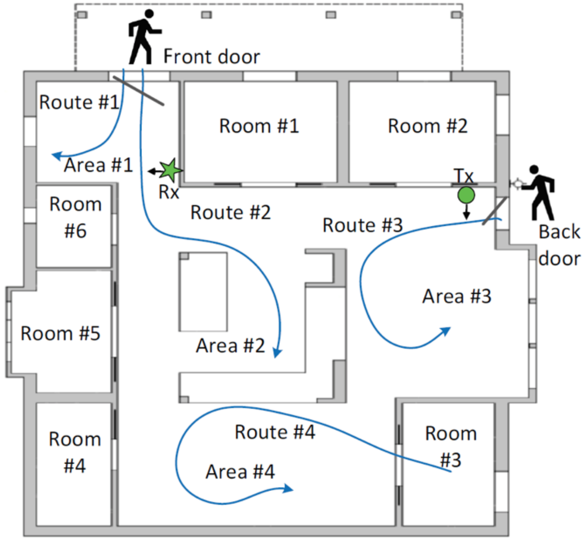
Motion indicator & Motion strength indicator





Experiments



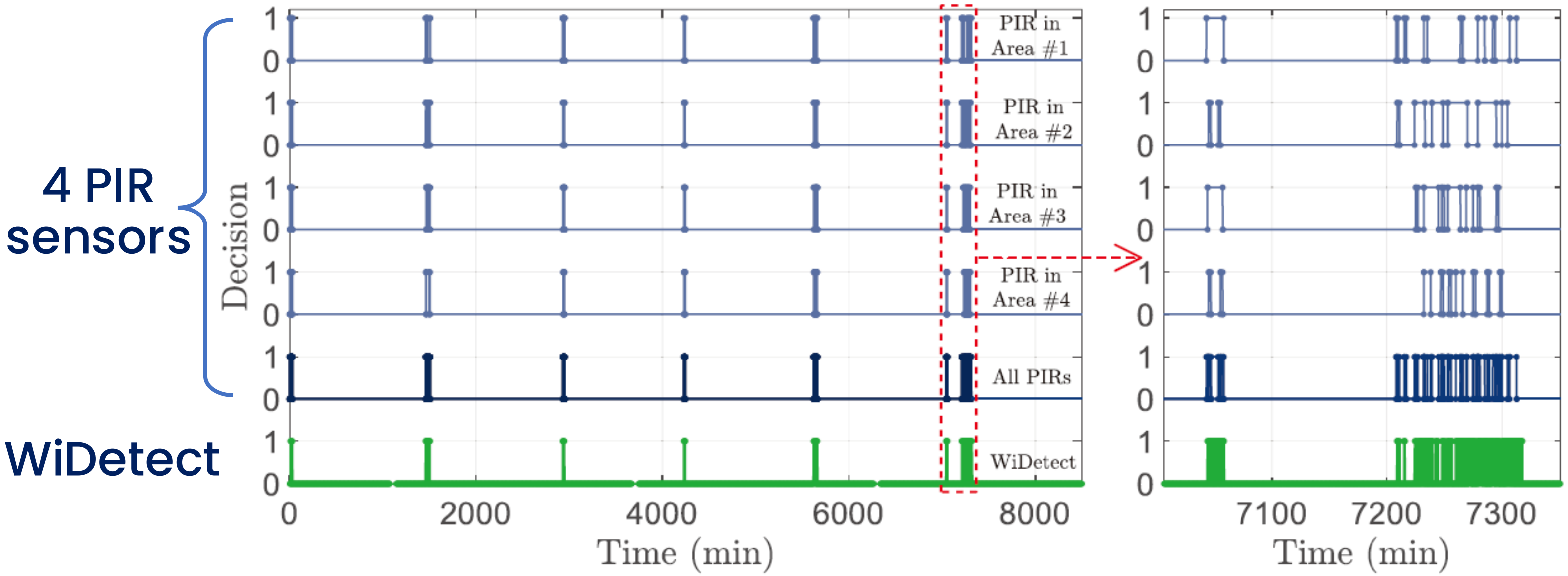


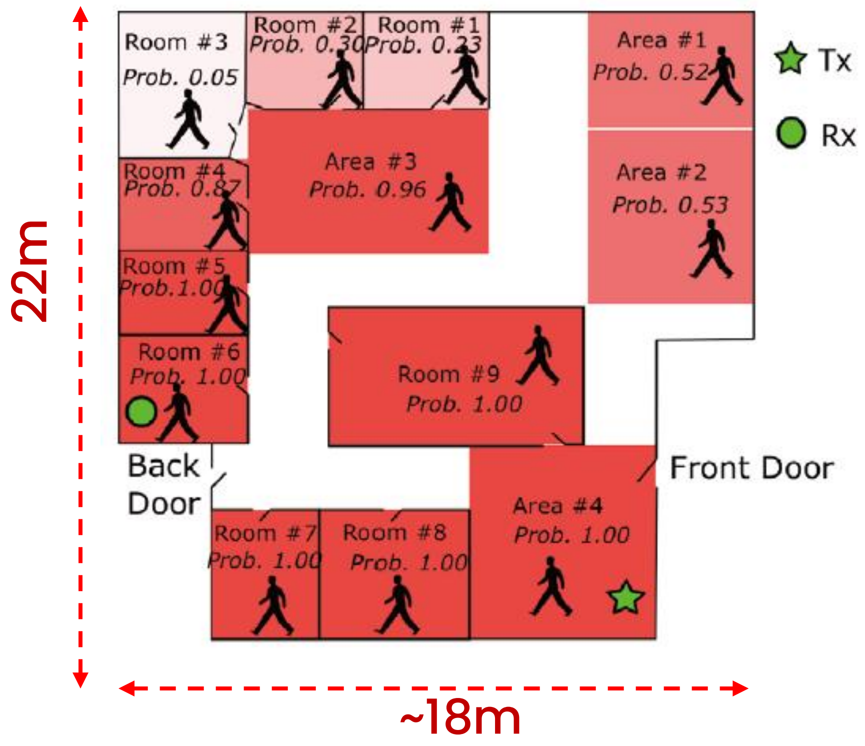
3x3 MIMO WiFi, **5.8GHz** channel, **30-180Hz** rate

1) **Office**: parameter study
2) Single **house**: coverage and PIR comparison
3) 1B1B **apartment**: 1-month deployment

Methods	Claimed FN	Claimed FP	Calibration
RASID	4.7%	3.8%	Yes
PILOT	10.0%	10.0%	Yes
E-Eyes	10.0%	1.0%	Yes
Omni-PHD	8.0%	7.0%	Yes
DeMan	5.9%	1.5%	Yes
CARM	2.0%	1.4 per hour	Yes
SIED	6.4%	2.0%	Yes
FreeSense	1.4%	0.5%	Yes
WiDetect	**0.3%**	**0.0%**	**NO**

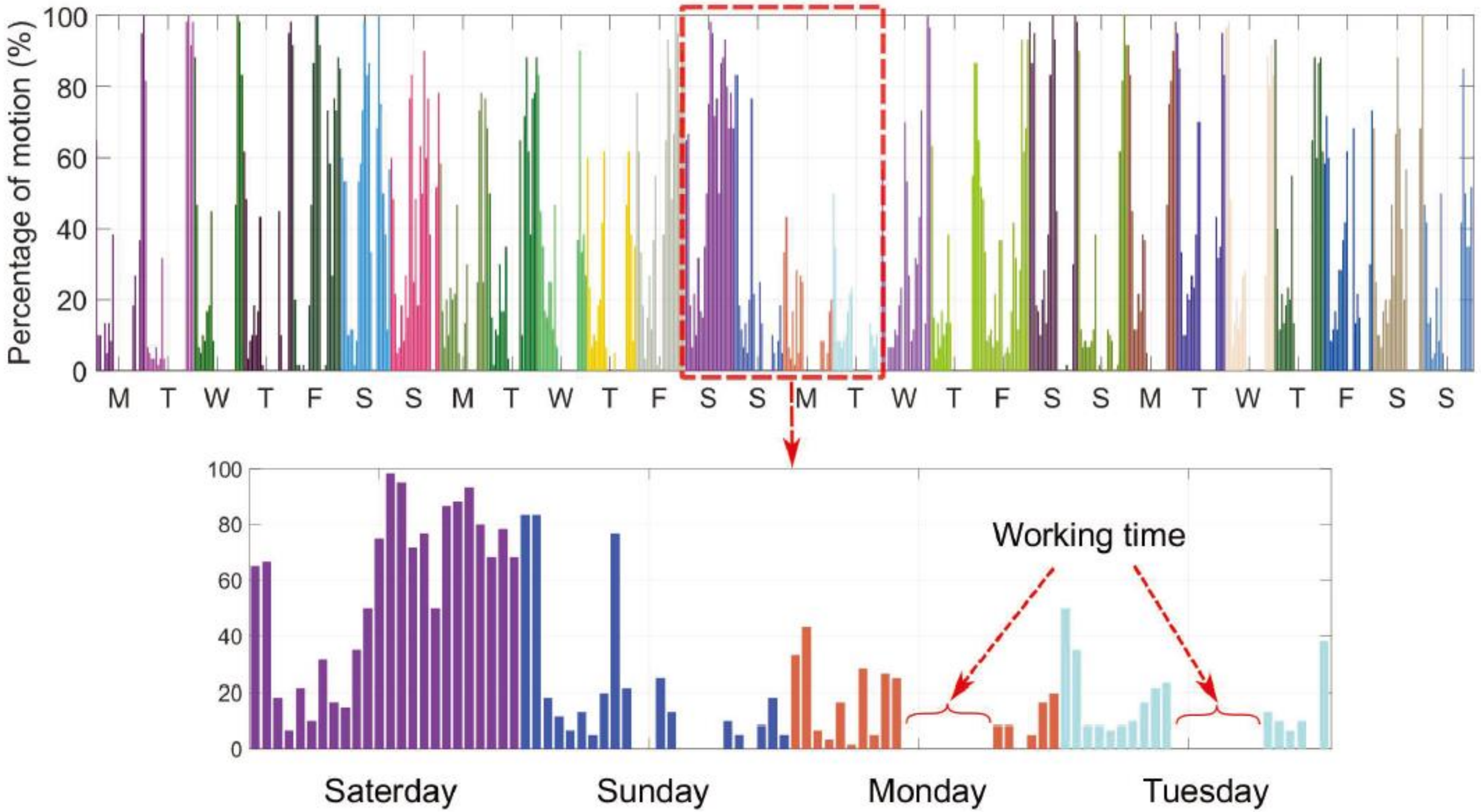
Experiments: Long-term & Coverage





Mission Impossible!

A false alarm of **10^{-6}** for a total of **4** weeks of data collected in **4** facilities!



Real-World Case Study

Activity of Daily Living Monitoring

Sleep Monitoring

Sleep is vital

Mentally & physically

10% suffer from chronic insomnia

1/3 of Americans short of sleep

Polysomnography(PSG)

$1300/night, too invasive

Pressure mat

inaccurate

UWB Radar

Inaccurate

short range

Wearables

Inaccurate

SMARS

Sleep Monitoring via Ambient Radio Signals

Photo courtesy: Origin Wireless

Breathing + Motion

Zhang, F., Wu, C., Wang, B., Wu, M., Bugos, D., Zhang, H., & Liu, K. R.. Smars: sleep monitoring via ambient radio signals. IEEE TMC 2019.

Breathing Signal

Photo courtesy: The Big Bang Theory

- Measurement of Breathing Signal Using CSI

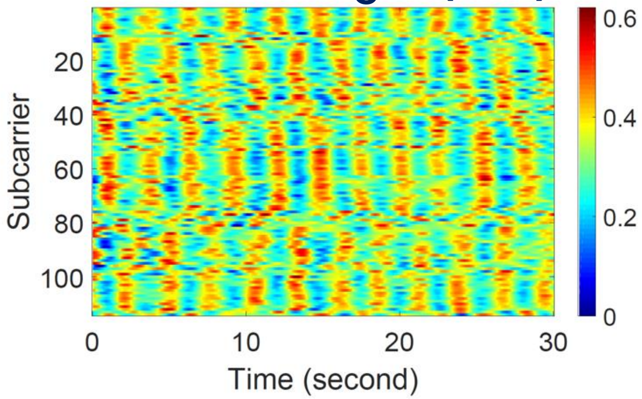
- Breathing is periodic

$$|H(t,f)|^2 = \underbrace{g(f)}_{\text{channel gain}}\underbrace{b(t-\Delta t_f)}_{\text{breathing signal}}$$

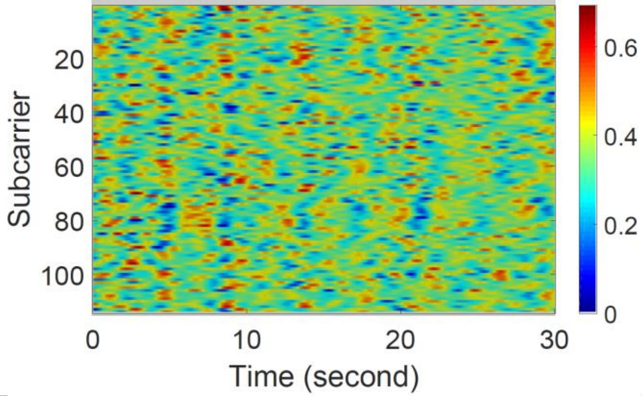
$$\hat{\rho}_G(\tau,f) \approx k(f)\underbrace{\rho_b(\tau)}_{\text{ACF of } b(t)} + n(\tau,f),$$

where $k(f) \triangleq \frac{g^2(f)}{g^2(f)+\sigma^2(f)}$, and $n(\tau,f) \sim \mathcal{N}(0,\frac{1}{N}),\ \forall f,\ \forall\tau$

Line-Of-Sight (LOS)



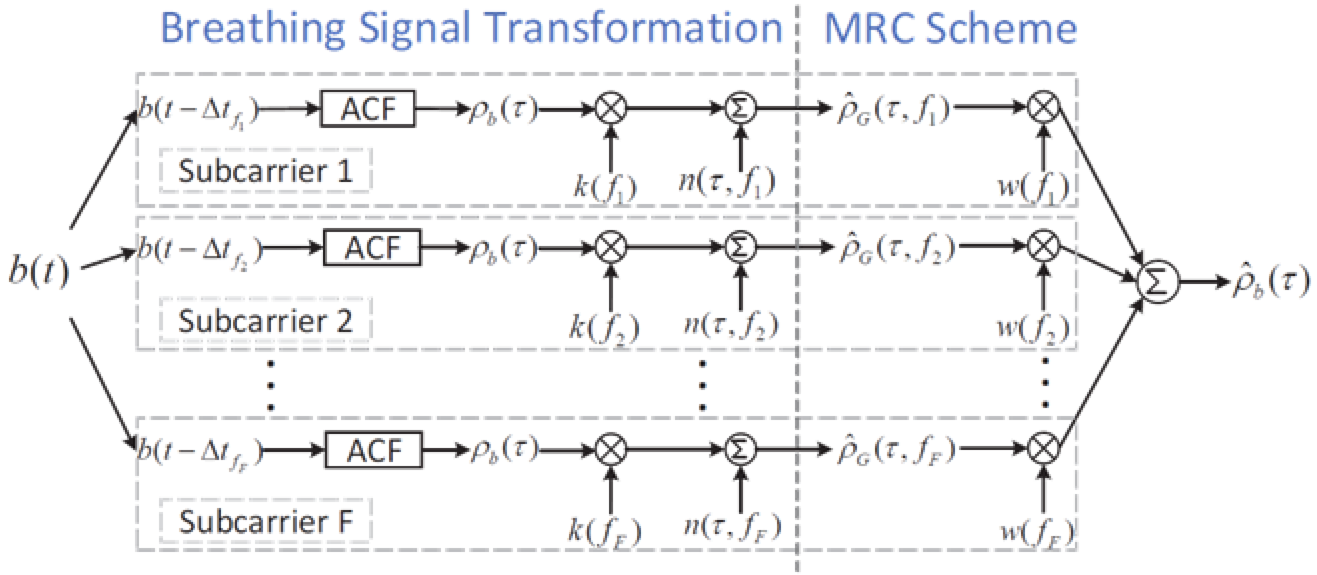
Non-Line-Of-Sight (NLOS)



Boosting Weak Breathing Signals

- Maximize Breathing Signal by Maximal Ratio Combining (MRC)
- Frequency diversity: frequency-selective fading

Maximal Ratio Combining (MRC)

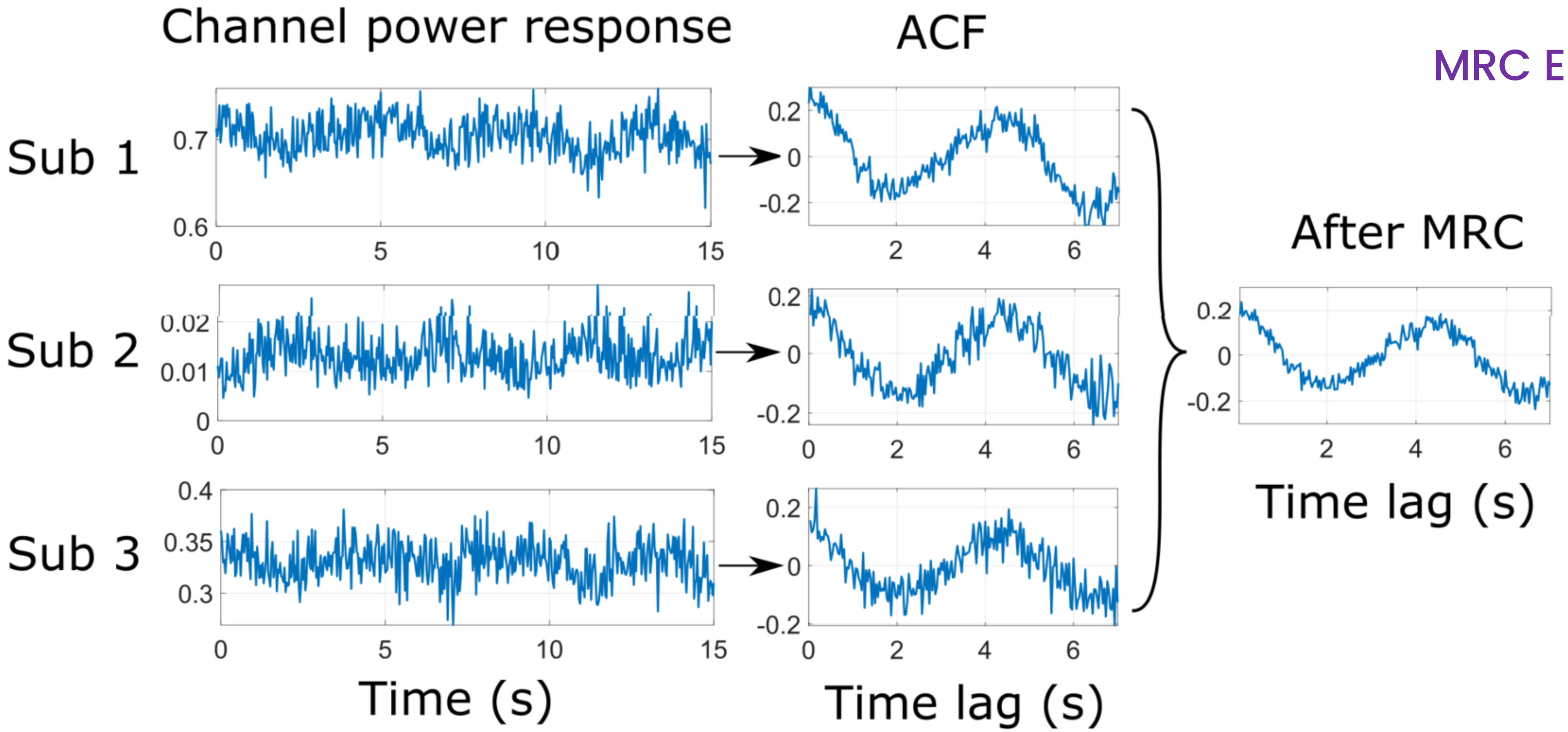


$$w(f) = \hat{k}(f) = \hat{\rho}_G\left(\tau = \frac{1}{F_s}, f\right)$$

$$\begin{aligned}\hat{\rho}_b(\tau) &= \sum_{f\in\mathcal{F}} w^\star(f)\hat{\rho}_G(\tau, f) \\ &= \sum_{f\in\mathcal{F}} \hat{\rho}_G(\tau = 1/F_s, f)\hat{\rho}_G(\tau, f).\end{aligned}$$

Boosting Weak Breathing Signals

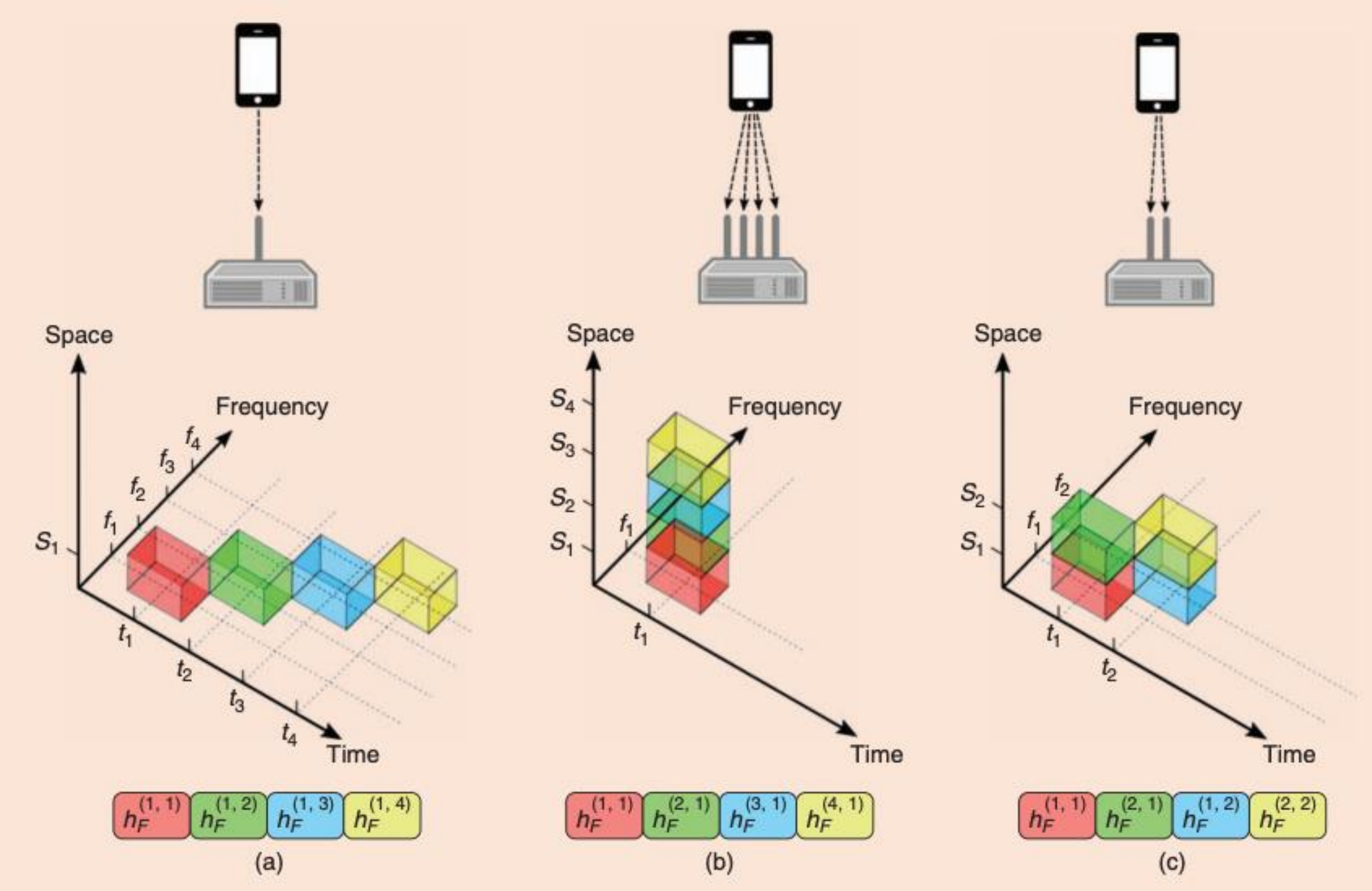
- Breathing Signal Maximization Using MRC



MRC Enhances SNR!

Diversity

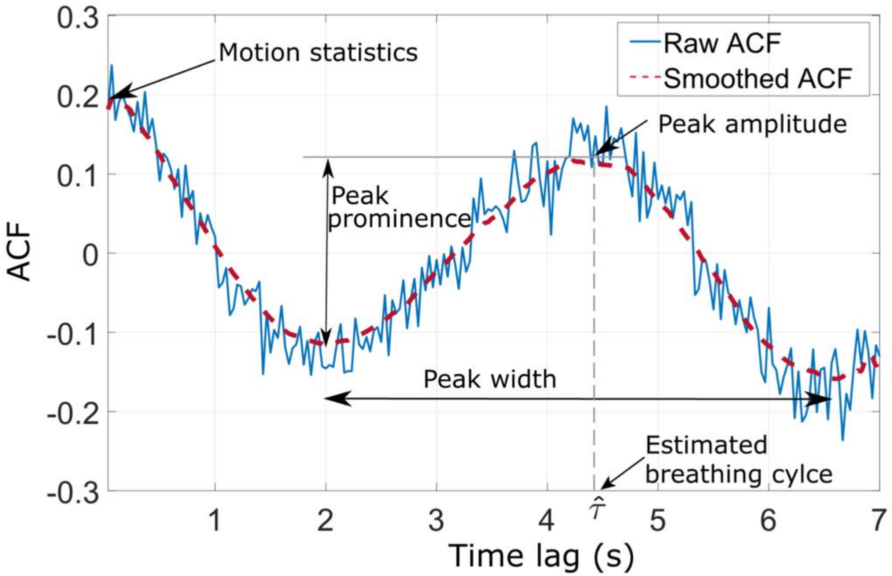
- Frequency diversity
- Space diversity
- Time diversity



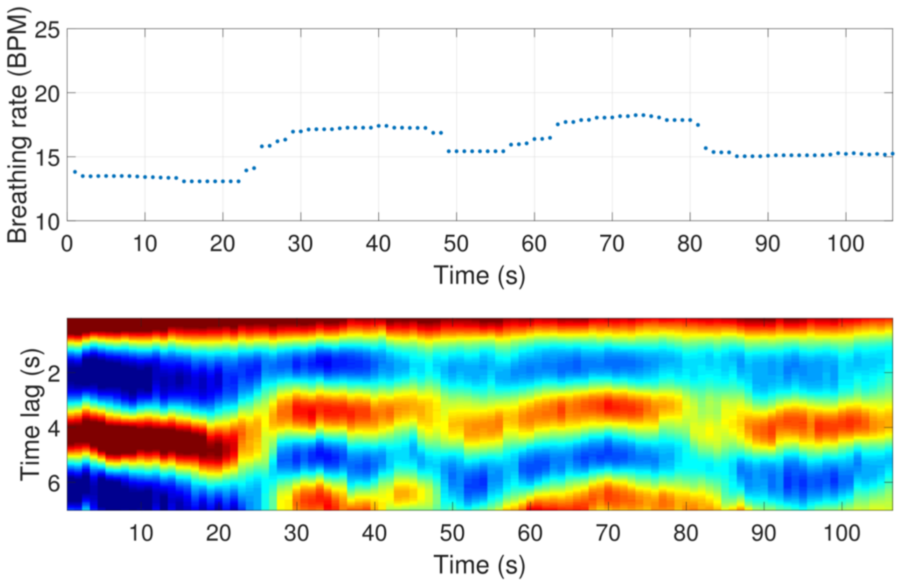
Wang, Beibei, et al. "The promise of radio analytics: A future paradigm of wireless positioning, tracking, and sensing." IEEE Signal Processing Magazine 35.3 (2018): 59-80.

Instantaneous Breathing Estimation

- Features for Breathing Estimation



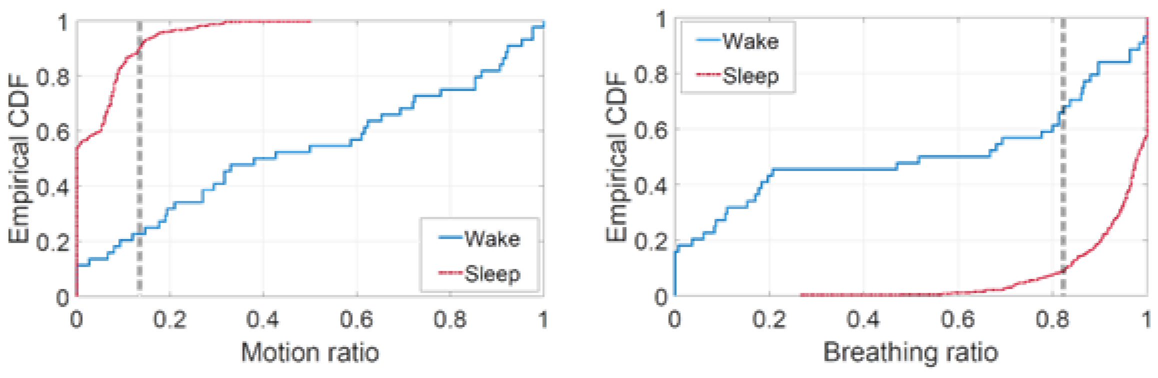
- Example of Breathing Estimation



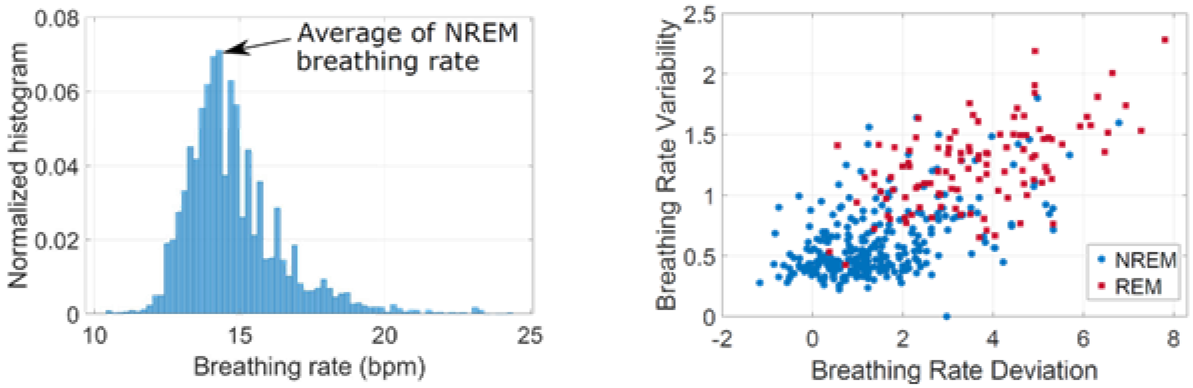
Motion & Breathing for Sleep Staging

- Sleep/Wake Classification
  - ***Motion ratio***: the percentage of time when the motion is detected;
  - ***Breathing ratio***: the percentage of time when breathing signal is detected.

- REM/NREM Classification
  - ***Breathing rate variability***: the variance of breathing estimates;
  - ***Breathing rate deviation***: the deviation of breathing estimates from average.

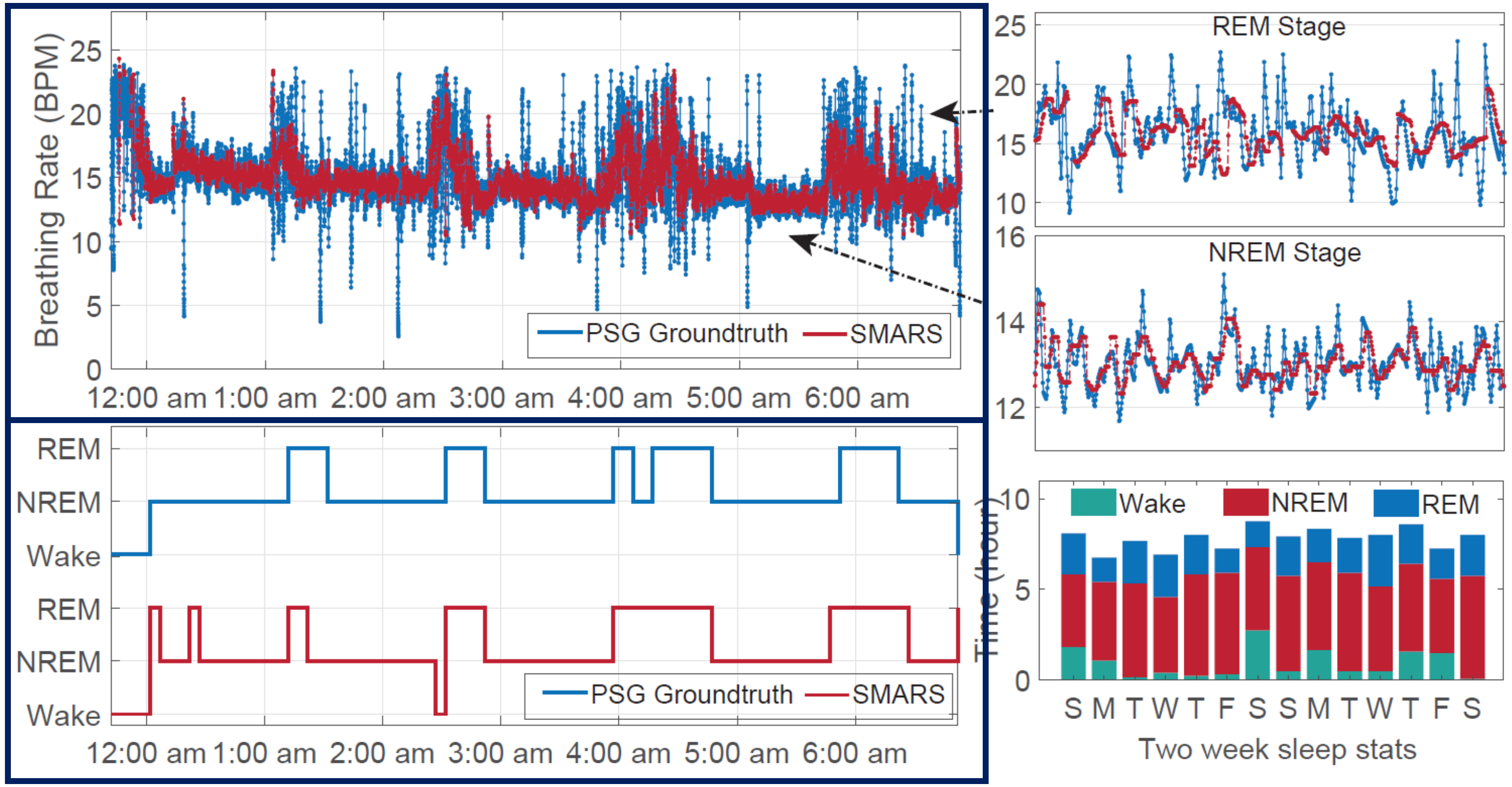


Wake/Sleep Classification



Rapid Eye Movement (REM)/Non-REM Staging

Sleep Monitoring Results



A Unified Framework

- All based on ACF
  - motion, speed, breathing
- A unified pipeline
  - A time series of CSI
  - Consider a specific window and calculate the ACF
  - Slide the window and continue to calculate the ACF
  - Find
    - The value of the first sample for motion
    - The first peak in the ACF for breathing or speed

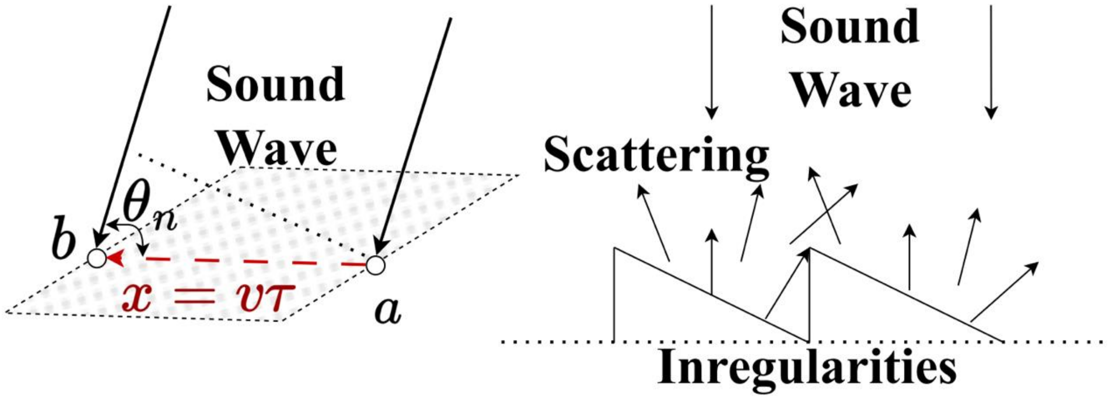
CSI Tools

- Intel 5300 NIC CSI Tool (2012, the first one)
  - Intel WiFi Wireless Link 5300 802.11n
  - 30 subcarriers
- Atheros CSI Tool (2015)
  - Qualcomm Atheros series
- Nexmon (2017)
  - Broadcom Wi-Fi Chips, can support measurement on phones!
- PicoScenes (2019)
  - 802.11ac/ax
  - Qualcomm Atheros AR9300 (QCA9300), Intel Wireless Link 5300 (IWL5300), Intel AX200 and Intel AX210.
- ESP32 CSI Tool
  - The only one commercially supported

Even holds with sound signals!

- Do the same/similar properties hold for acoustics?
  - WiFi: Electromagnetic waves
  - Sound: Mechanical waves

- Sound Diffusion Model in Room Acoustics

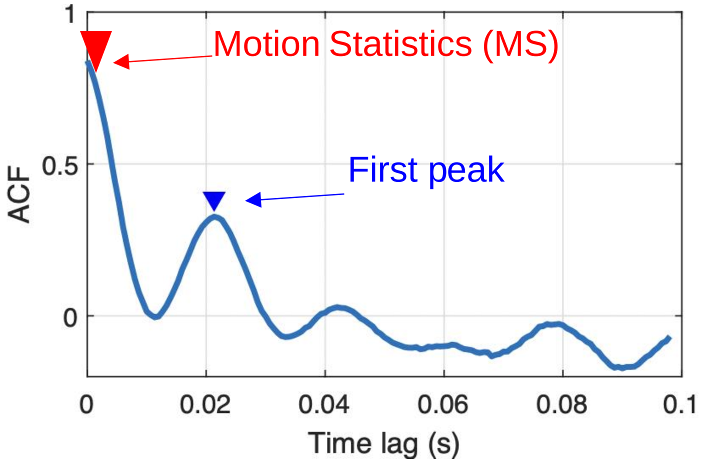


$$\psi_p(x) = \frac{1}{2\pi}\int_0^{2\pi} \psi(x,\theta)\, d\theta = J_0(kx)$$

$$J_0(x) = \frac{1}{2\pi}\int_0^{2\pi} \cos(x\cos\theta)d\theta$$

Y. Zhang, W. Hou, Z. Yang, C. Wu, VeCare: Statistical Acoustic Sensing for Automotive In-Cabin Monitoring, NSDI'23

Statistical Acoustic Sensing (SAS)



ACF of CSI resembles 0th-order Bessel function of its first kind.

A function of speed *v*, independent of moving directions and locations.

Acoustic Channel State Information (CSI)

$$H(f,t) = \sum_{i \in R_D} H_i(f,t) + \sum_{j \in R_S} H_j(f,t) + N(f,t)$$

Autocorrelation Function (ACF) of CSI

$$\rho(f,\tau) = \frac{\sum_{i \in R_D} 2\pi\sigma_i^2(f) + \sigma_N^2(f)\delta(\tau)}{\sum_{i \in R_D} 2\pi\sigma_i^2(f) + \sigma_N^2(f)} J_0(kv\tau)$$

$$\triangleq g(f) J_0(kv\tau), \quad \tau \neq 0$$

Motion: $g(f) = \lim_{\tau \to 0} \rho(f,\tau) = \tilde{\rho}\,(f, \tau = 1/F_s)$

The value of the first sample in ACF

Breath: $f_{breath} = 60/\boldsymbol{\tau_b}$

Find the delay of the first peak in ACF

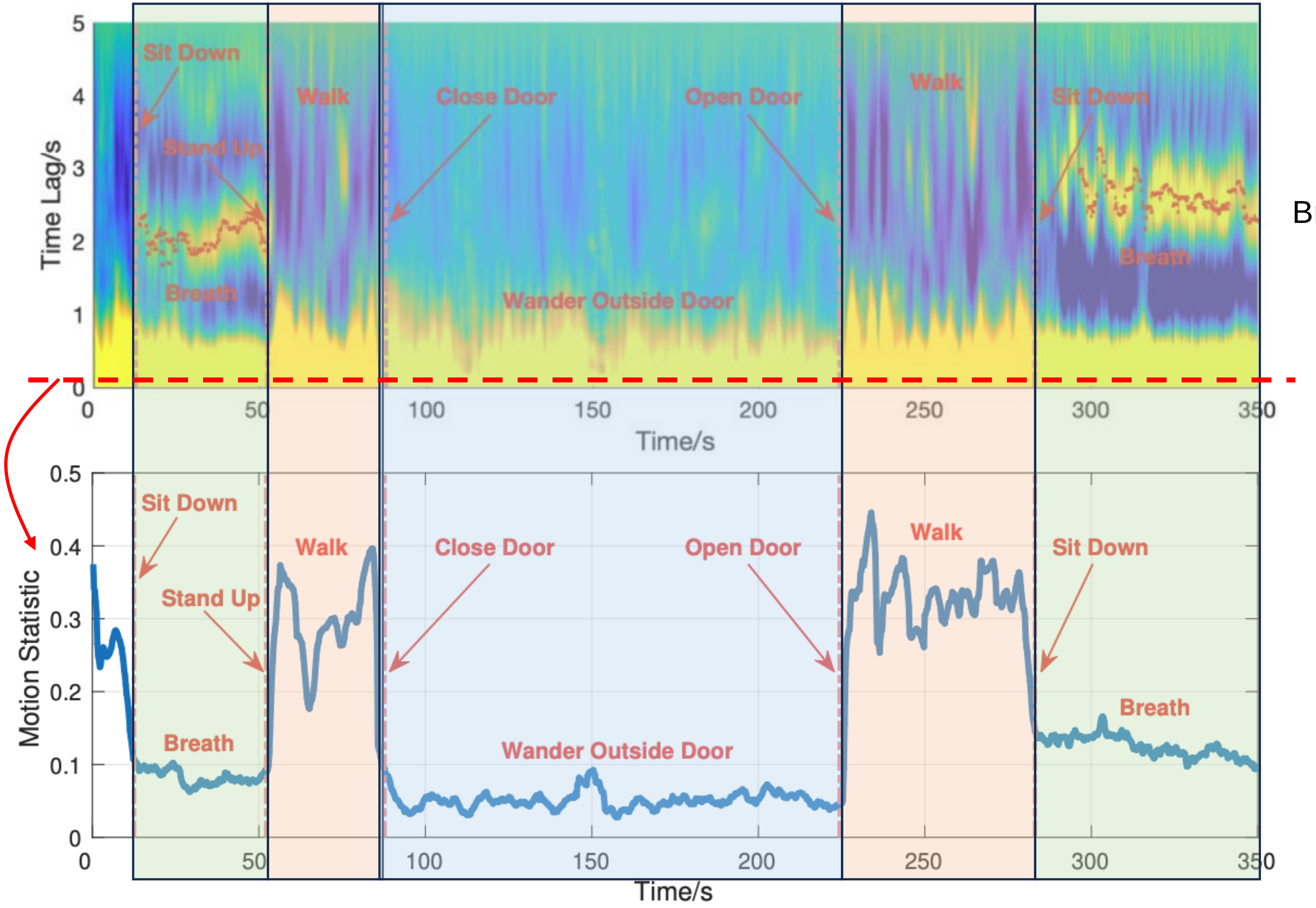
Speed: $v = \frac{x_0}{k\tau_s} = \frac{x_0\lambda}{2\pi\boldsymbol{\tau_s}}$

Find the delay of the first peak in ACF

Statistical Acoustic Sensing (SAS)

ACF Matrix

Motion Statistics



Breath@~24BPM

VeCare: In-Cabin AI with SAS

VeCare: A early attempt for Child Presence Detection using commodity in-car audio devices

Child Presence Detection

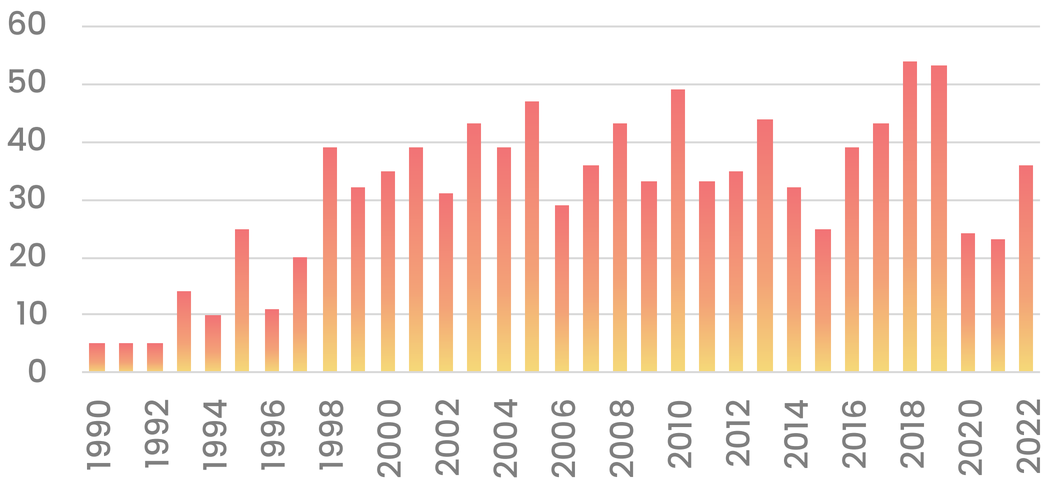
Detect unattended children left in a car to avoid heatstroke deaths

Child Vehicular Heatstroke Deaths

39 (one every 9 days) deaths per year,

1000+ children have died since 1990 **in US ***

*Data source: KidsAndCars.org



Y. Zhang, W. Hou, Z. Yang, C. Wu, VeCare: Statistical Acoustic Sensing for Automotive In-Cabin Monitoring, NSDI'23

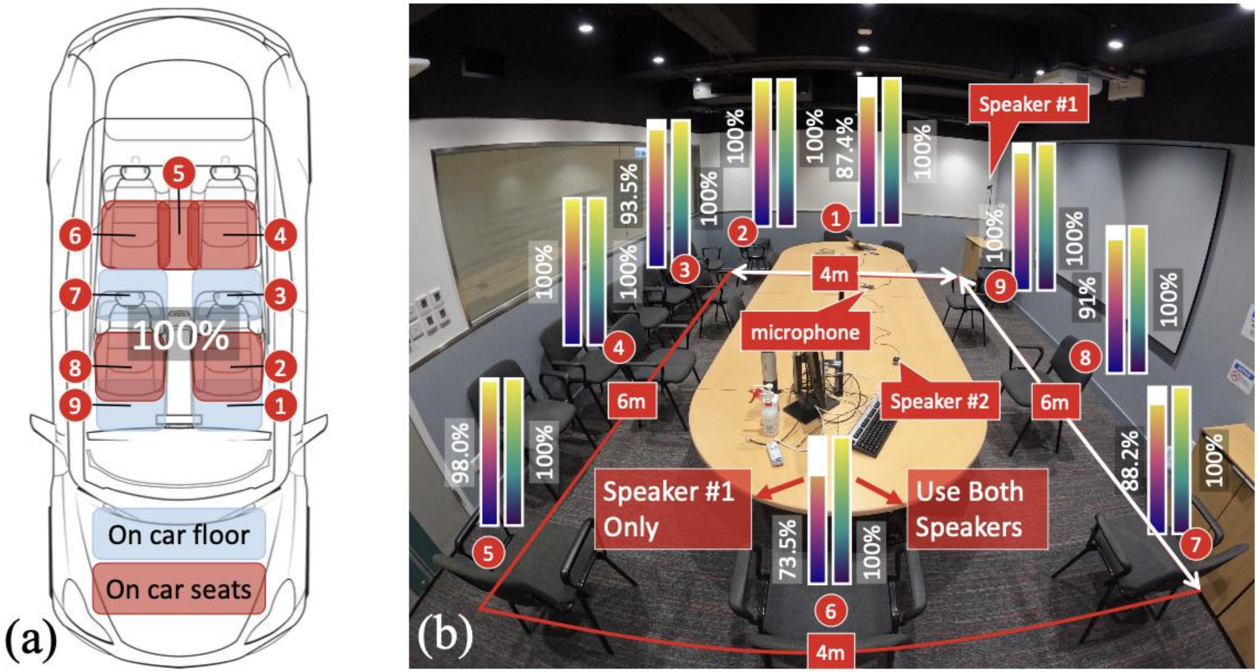
VeCare: In-Cabin AI with SAS

NO MORE

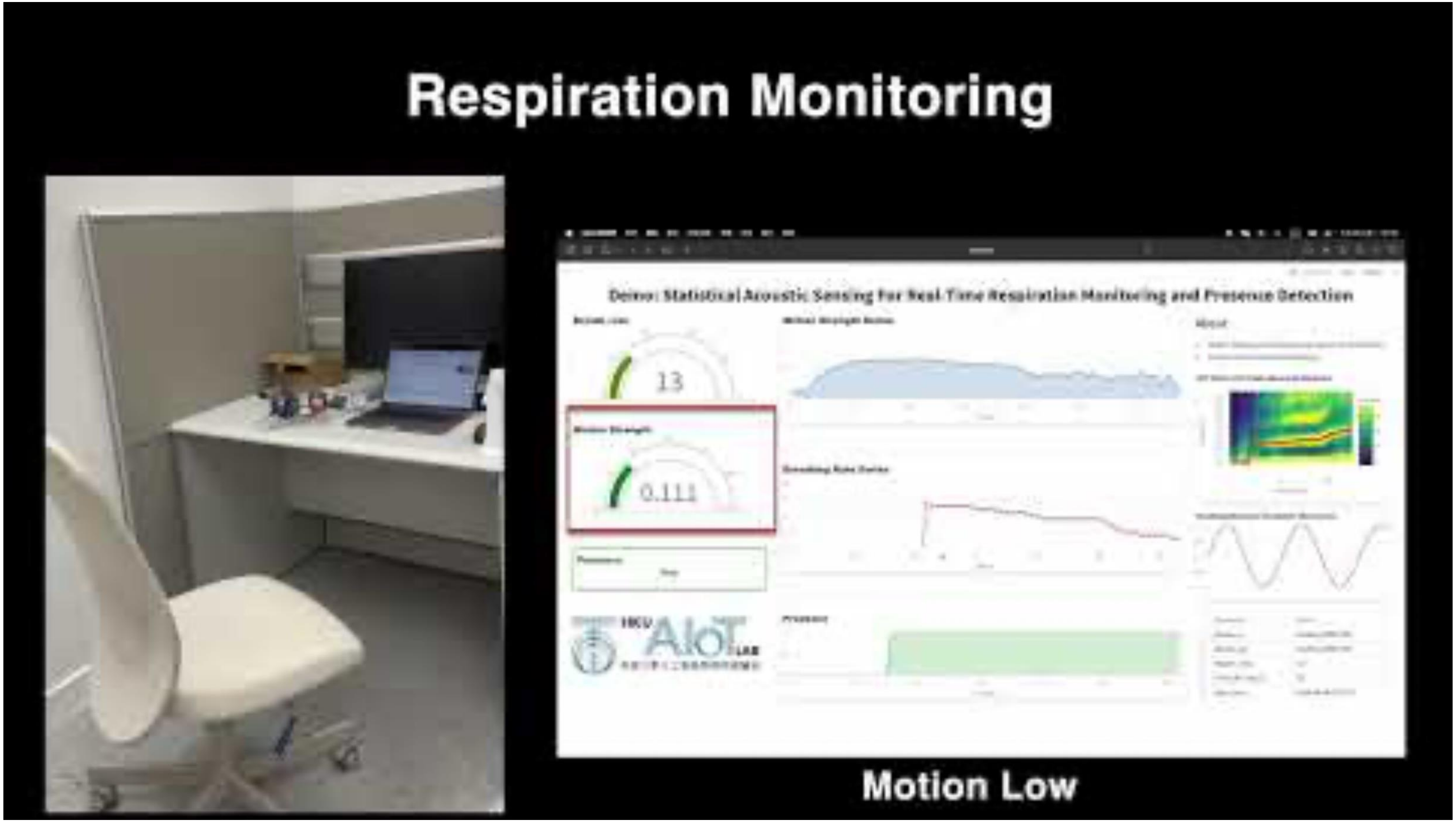
Hot Car Deaths!

VeCare: SAS for Child Presence Detection

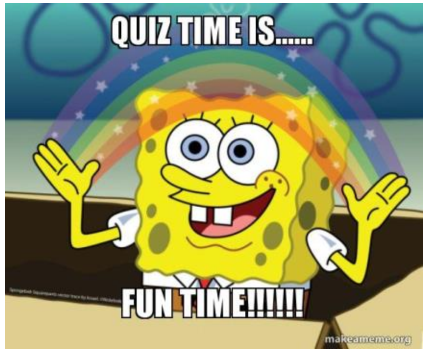
CPD with no blind spot!



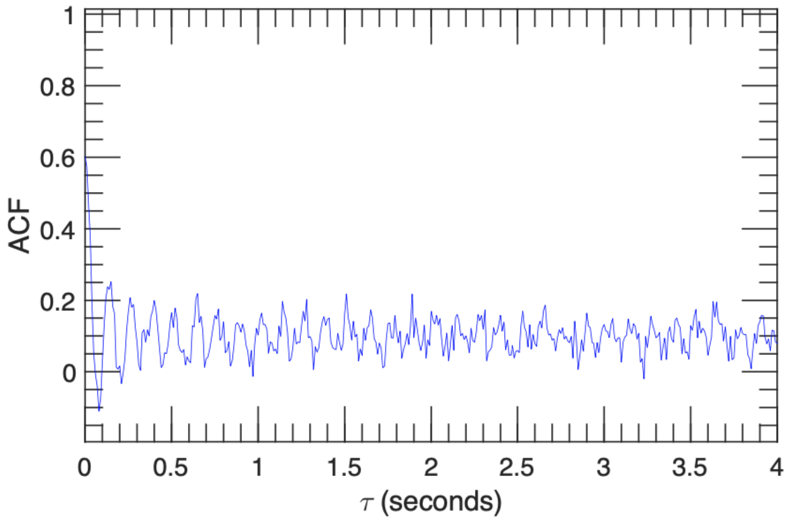
Y. Zhang, W. Hou, Z. Yang, C. Wu, VeCare: Statistical Acoustic Sensing for Automotive In-Cabin Monitoring, NSDI'23

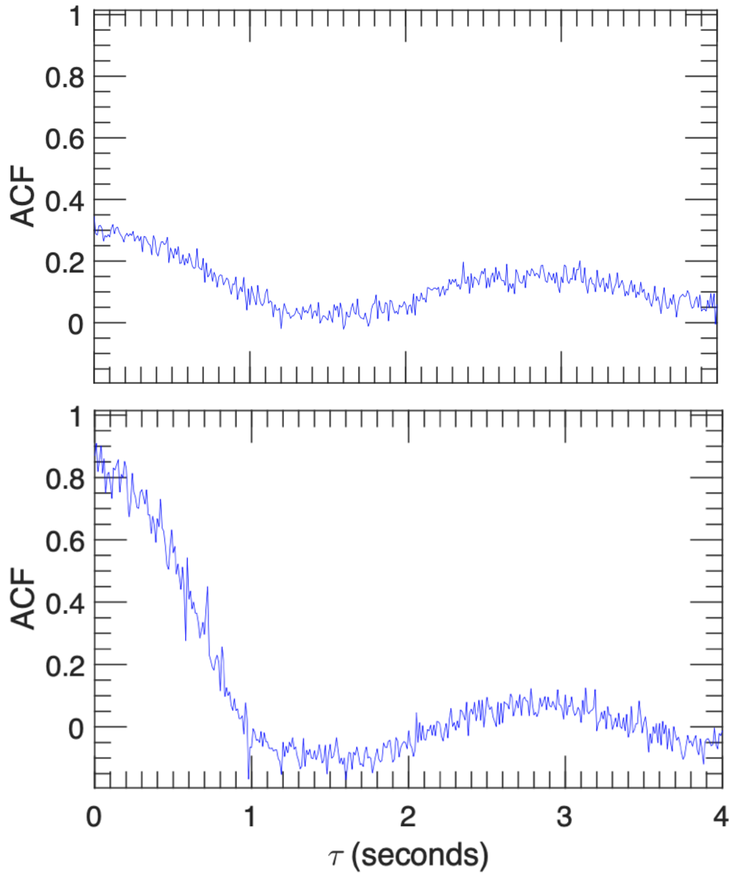

Respiration Monitoring
Demo: Statistical Acoustic Sensing For Real-Time Respiration Monitoring and Presence Detection
13
0.111
HKU
AIoT
LAB
Motion Low

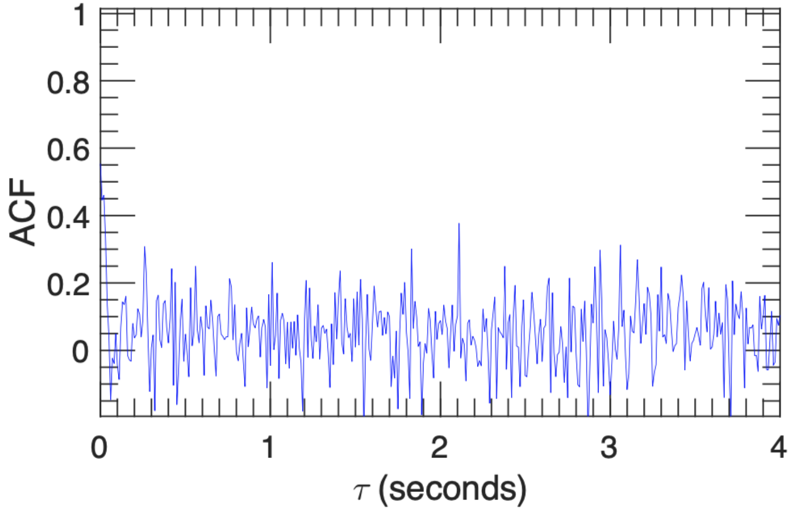
Quiz



- What is (most likely) going on given the following ACF of CSI?







Questions

- What windows should we use for calculation?
- How to determine whether it is breathing or speed?
- How much computation is needed?

More Questions

- Why not FFT?
  - FFT is a (more) common tool for finding frequency/periodicity.

- Why not Deep Learning?
  - DL is now a popular tool for finding X.
  - →→ Lecture on Deep Wireless Sensing

- Limitations of (current) WiFi sensing?

Contents

Person Re-ID

XModal-ID: Through-Wall Person Identification from Candidate Video Footage Using WiFi, MobiCom’19

WiFi Imaging and Pose

[MobiCom 2020] Towards 3D Human Pose Construction Using WiFi

WiFi Imaging

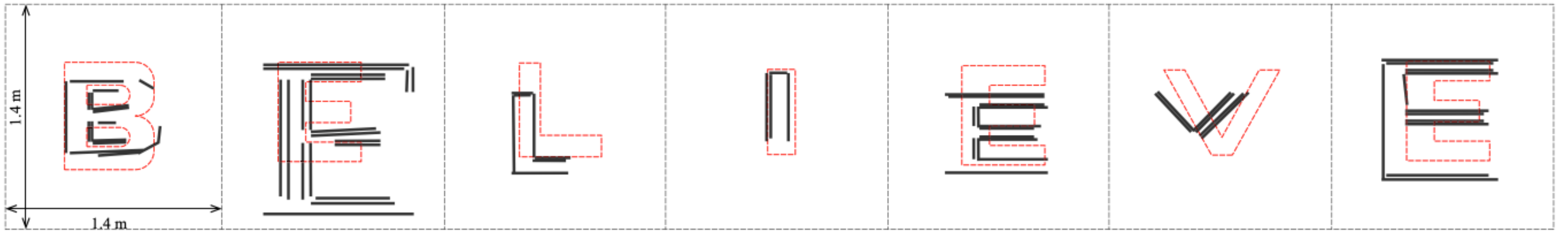
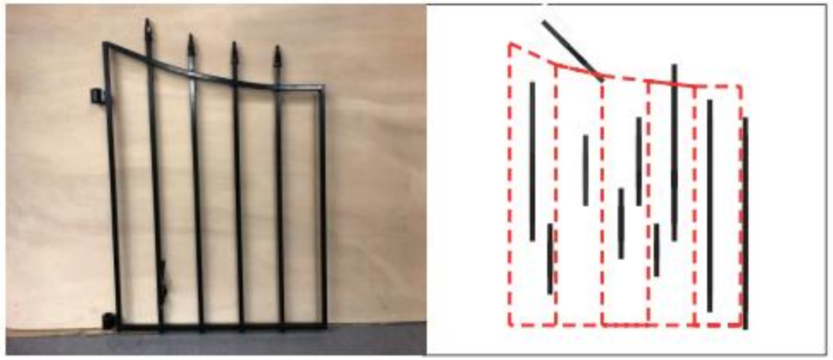
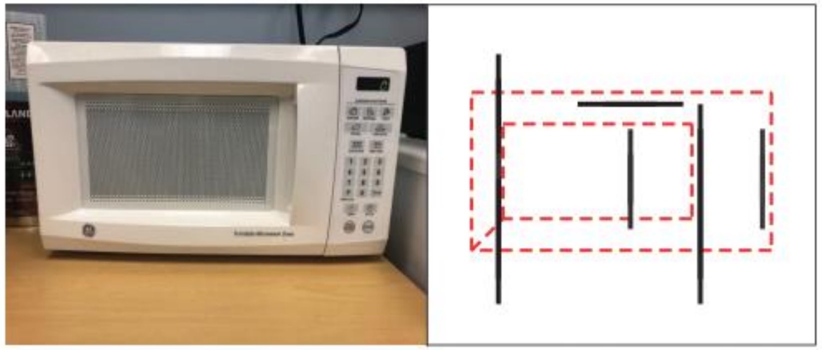


Figure 11: Through-wall reading: Wiffract enabling WiFi to image and read the letters of the word "BELIEVE" behind the wall of Area 3. The dashed lines represent the ground-truth while the solid lines represent our image.

Garden fence



Microwave oven



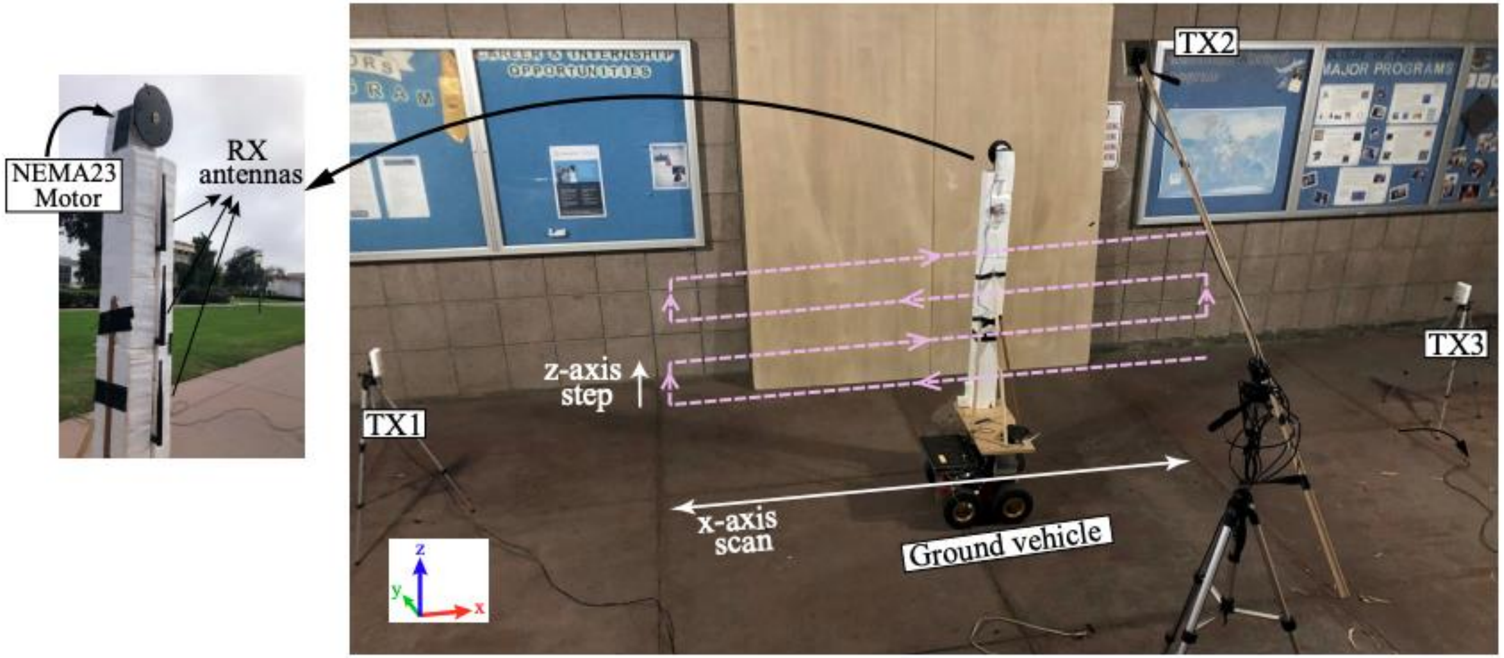
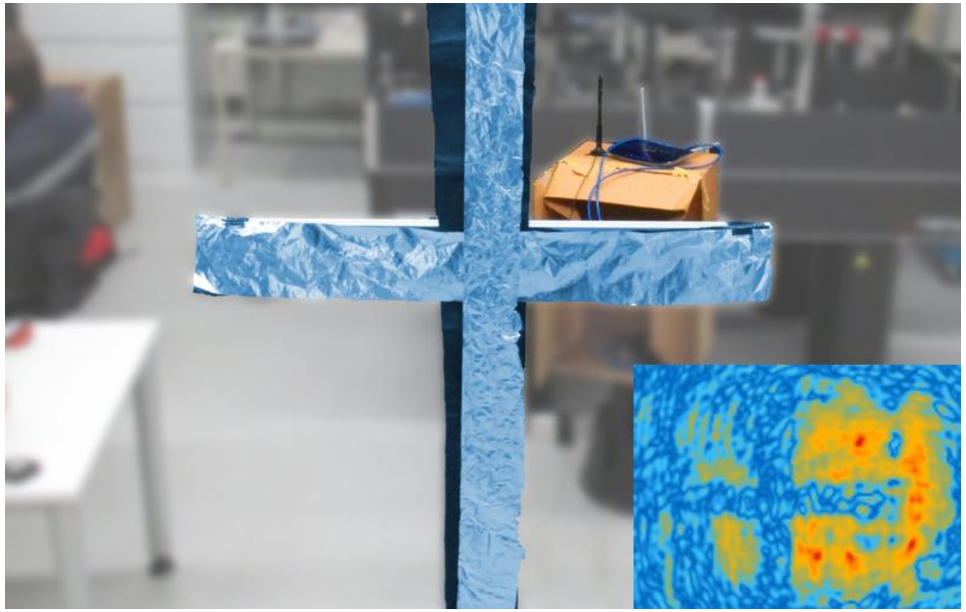
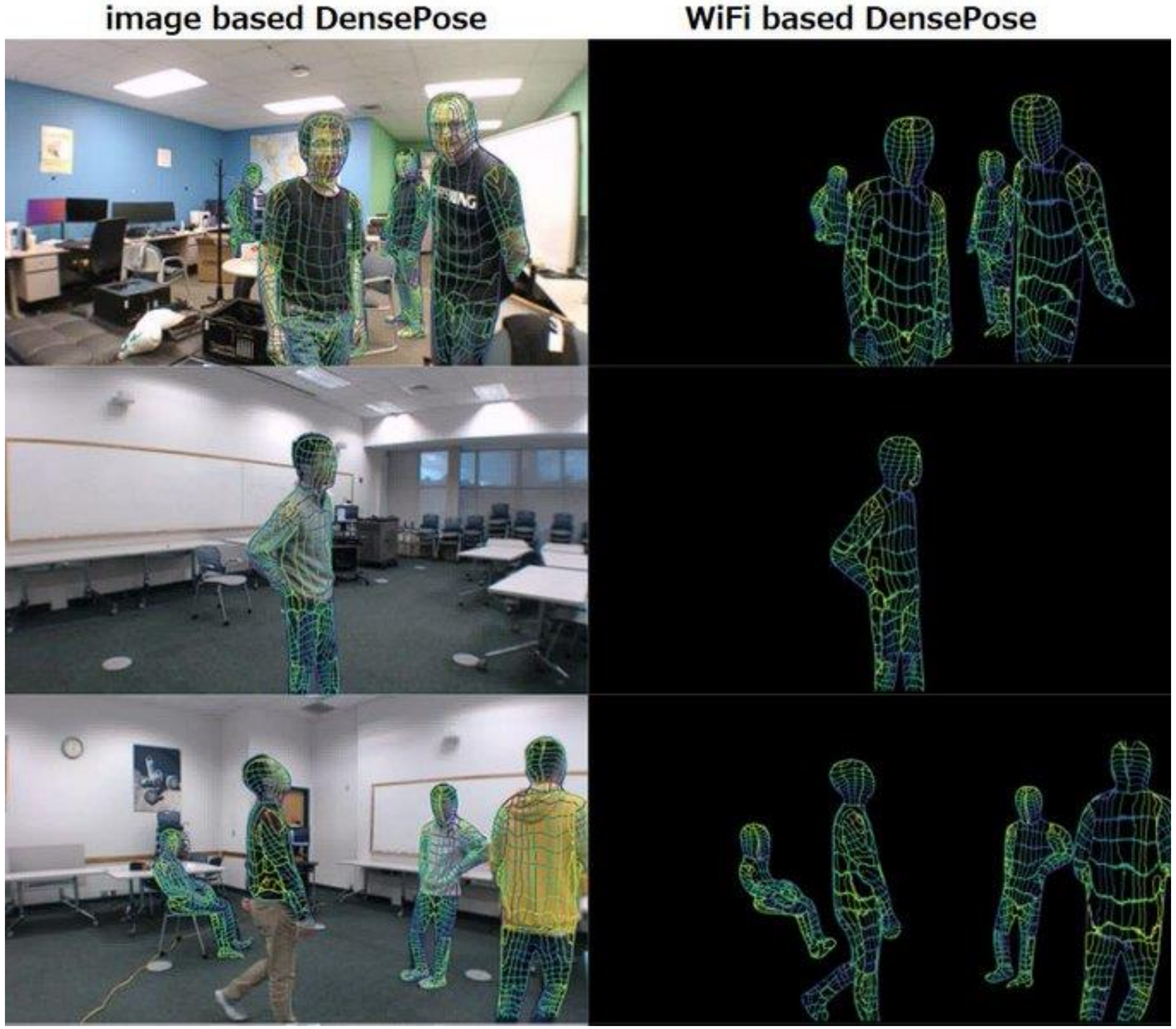


Figure 5: Sample experimental setup: 6 antennas of two laptops serve as receivers while a WiFi card of one laptop is used for transmission. A vertical structure carrying the RX antennas is mounted on a ground robot to synthesize an RX grid in the x-z plane, on which we measure WiFi CSI power measurements from three TX antennas (of one WiFi card) simultaneously.

Wiffract: A New Foundation for RF Imaging via Edge Tracing, MobiCom'22

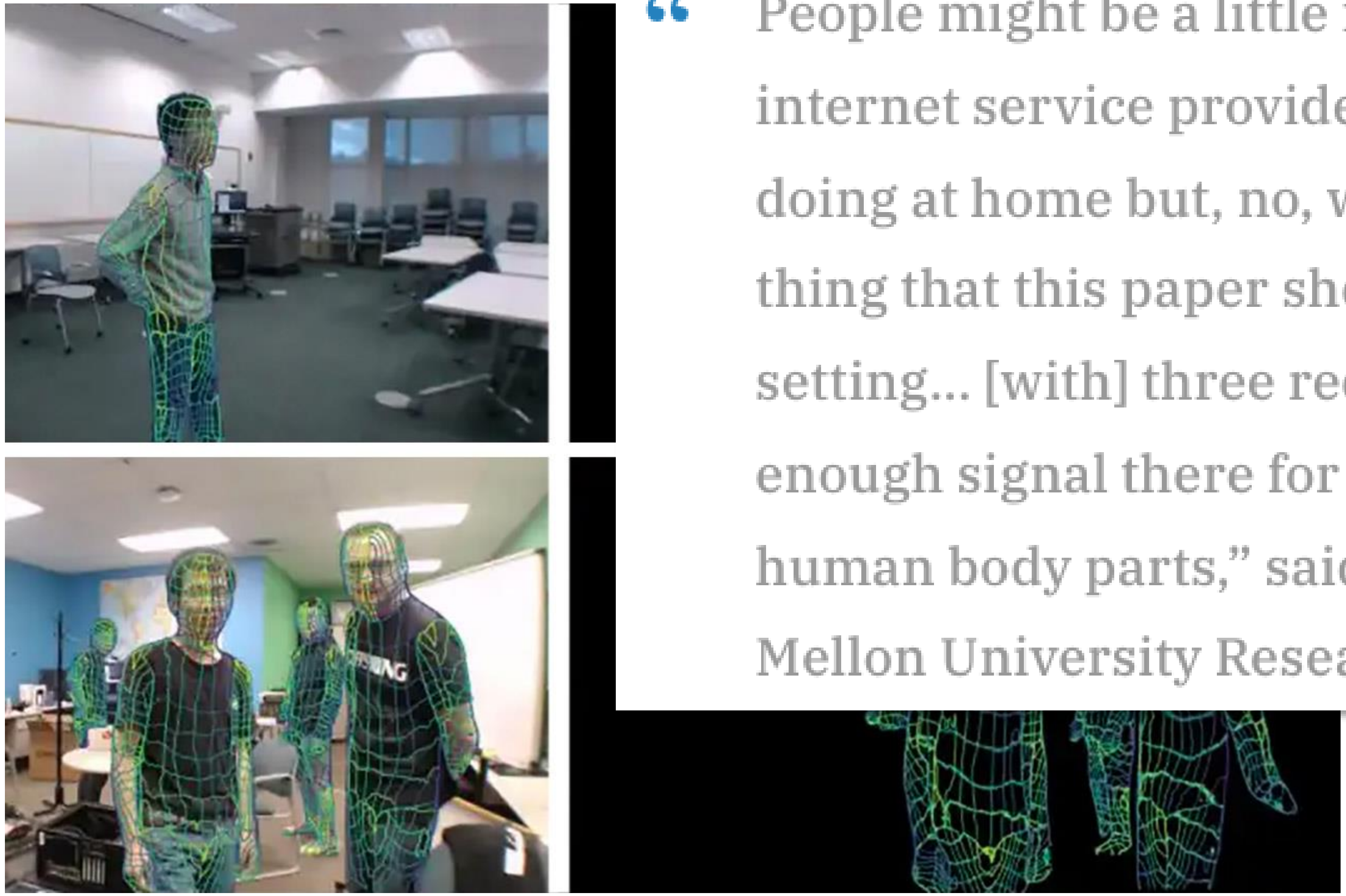
WiFi Imaging and Pose





Holography of Wi-fi Radiation, Physical Review Letters, 2017
Wiffract: A New Foundation for RF Imaging via Edge Tracing, MobiCom'22
DensePose From WiFi, arXiv:2301.00250v1

WiFi does more, but not everything



> “People might be a little freaked out now, in the sense that internet service providers might locate what people are doing at home but, no, we are still not there. The only thing that this paper shows is that, in a very constrained setting... [with] three receivers of Wi-Fi signal, there is enough signal there for the fine-grained detection of human body parts,” said Fernando De la Torre, Carnegie Mellon University Researcher.

Sensing in 5G/6G

- Massive MIMO is standard
  - Many antennas!!
- Large bandwidths
  - e.g., 400MHz
- ISAC waveform design
  - Radar mode + comm mode


Wellbeing Monitoring
Home Automation
Gesture Control
Motion Detection
Gait Recognition
Proximity Detection
Sleep Monitoring
Passive Tracking
Fall Detection
WiFi Only
The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it.
-- Mark Weiser (1991)

Multipath: Foes or Friends?

Foes

Classical Communications

Frenemy

Prior Wireless Sensing

Friends

Wireless AI

#WiFiCanDoMore

- Reading material
  - C. Wu, B. Wang, O. C. Au and K. J. R. Liu, "Wi-Fi Can Do More: Toward Ubiquitous Wireless Sensing," in *IEEE Communications Standards Magazine*, vol. 6, no. 2, pp. 42-49, June 2022, doi: 10.1109/MCOMSTD.0001.2100111.

Questions?

- Thank you!