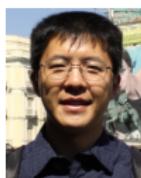


Understanding and Modeling of WiFi Signal Based Human Activity Recognition



Wei Wang[†], Alex X. Liu^{†‡}, Muhammad Shahzad[‡], Kang Ling[†], Sanglu Lu[†]

[†]Nanjing University, [‡]Michigan State University

September 8, 2015



Motivation

- WiFi signals are available almost everywhere and they are able to monitor surrounding activities.





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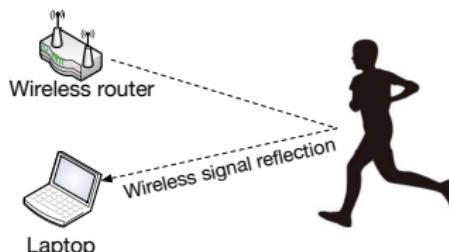




Problem Statement

WiFi based Activity Recognition

- Using commercial WiFi devices to recognize human activities.



Advantages

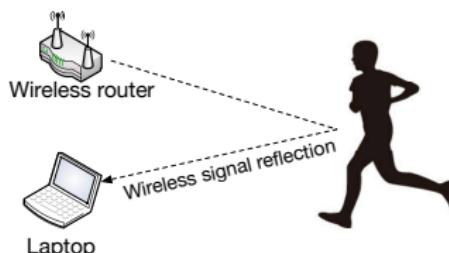
- ✓ Work in dark
- ✓ Better coverage
- ✓ Less intrusive to user privacy
- ✓ No need to wear sensors



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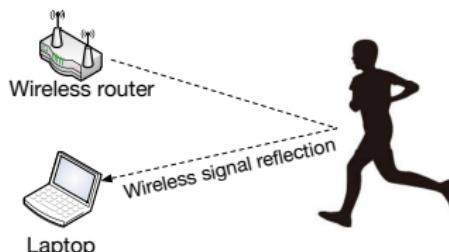




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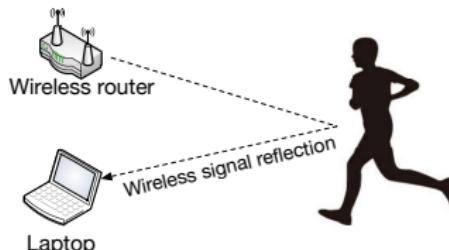




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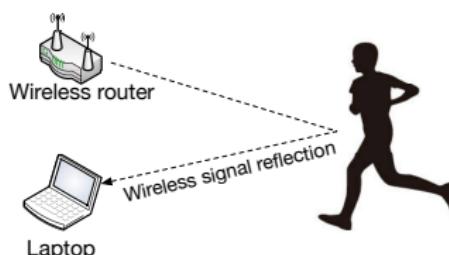




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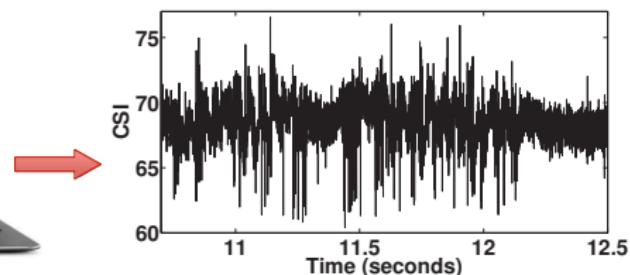
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Challenges

- Measurement from commercial devices are **noisy** and have **unpredictable** carrier frequency offsets
- Needs **robust** and **accurate** models to extract useful information from measurements

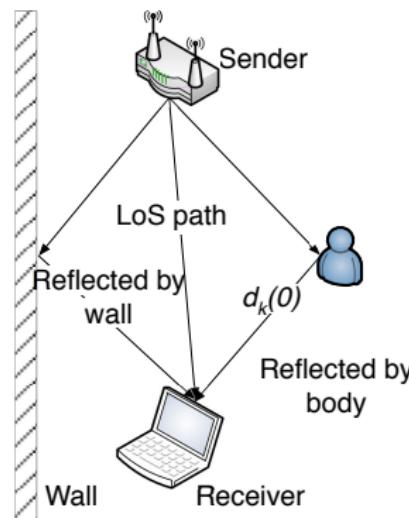




Understanding Multipath

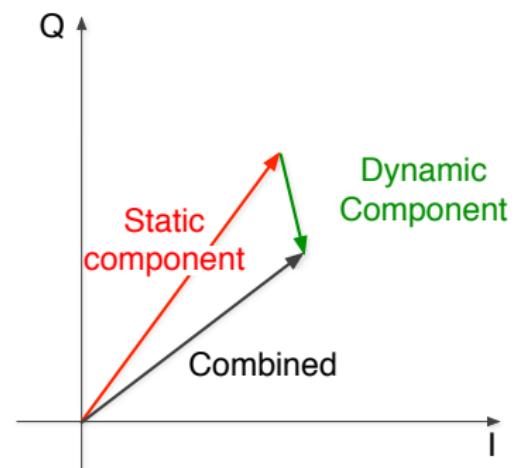
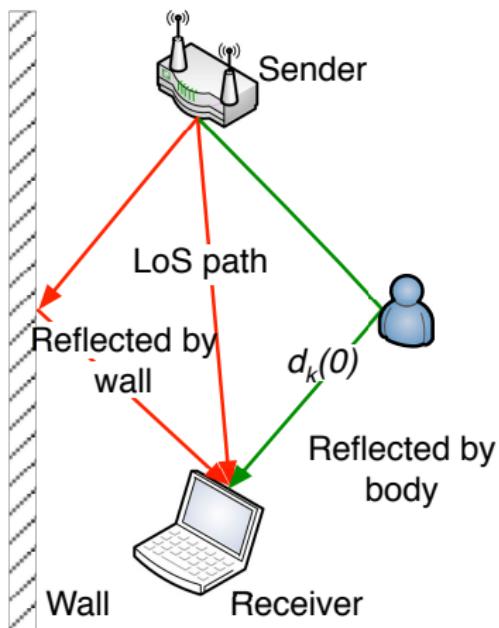
Key observations

- Multipaths contain both static component and dynamic component
- Each path has different phase
- Phases determine the amplitude of the combined signal



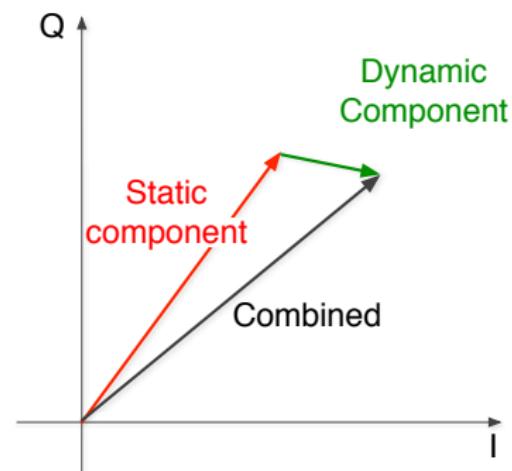
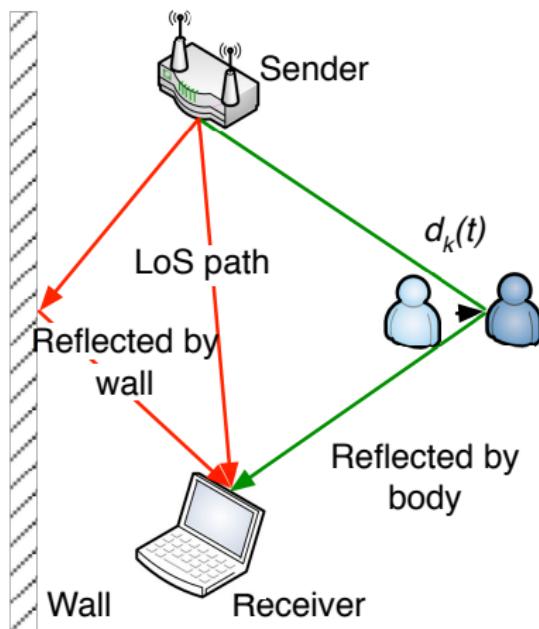


Understanding Multipath



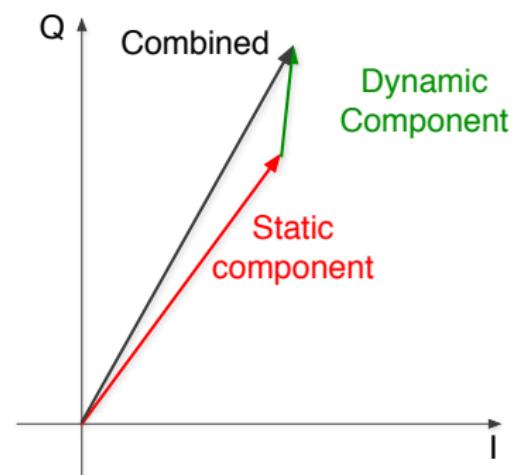
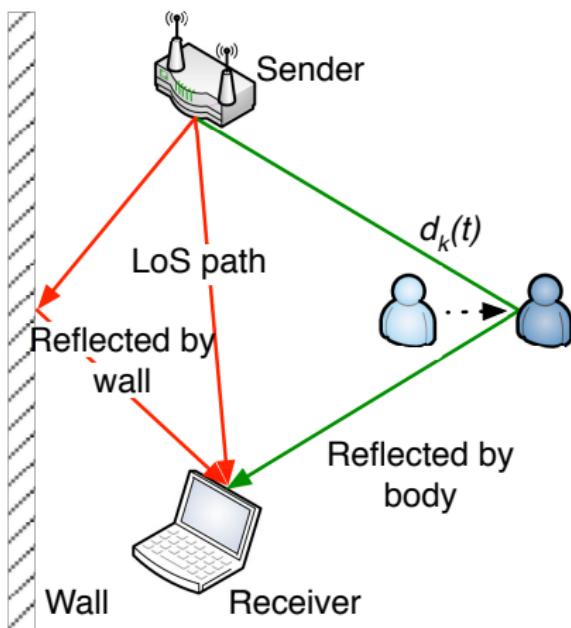


Understanding Multipath





Understanding Multipath

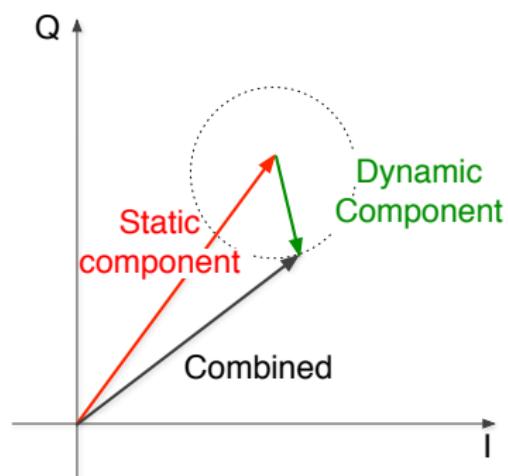




Understanding Multipath

Interpreting CSI amplitude

- Phases of paths are determined by path length
- Path length change of one wavelength gives phase change of 2π
- Frequency of amplitude change can be converted to movement speed

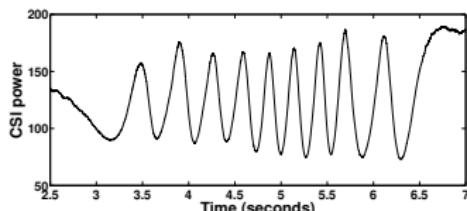




CSI-Speed Model

How accurate is it?

- Wave length $\rightarrow 5 \sim 6\text{cm}$ in 5 GHz band



Waveform with regular moving speed

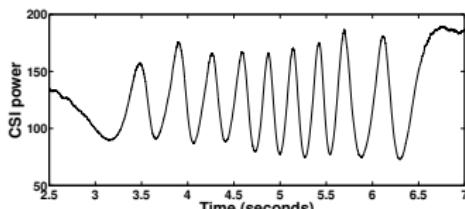
CSI amplitude changes are close to sinusoids



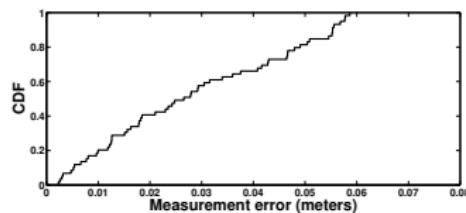
CSI-Speed Model

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Waveform with regular moving speed



Moving distance measurement error

CSI amplitude changes are close to sinusoids

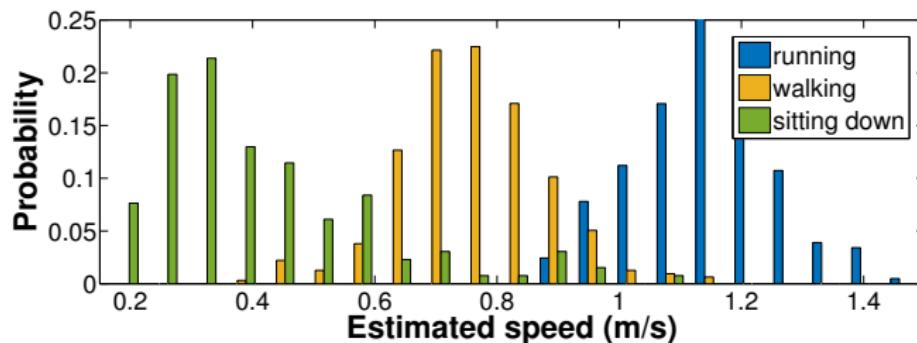
Average distance measurement error of **2.86 cm**



CSI-Speed Model

How robust is it?

- Robust over different multipath conditions and movement directions
- Linear combination of multipath do not change frequency



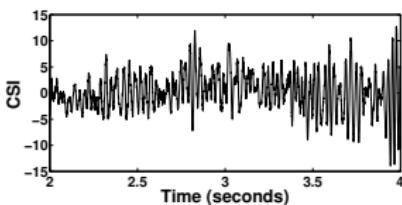
Speed distribution of different activities in different environments



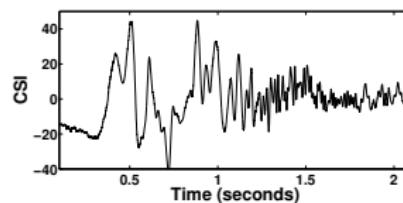
CSI-Activity Model

Activities are characterized by

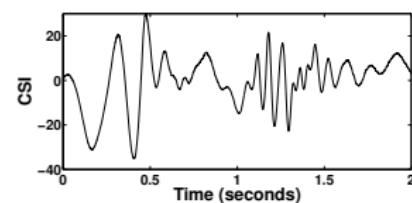
- Movement speeds
- Change in movement speeds
- Speeds of different body components



Walking



Falling

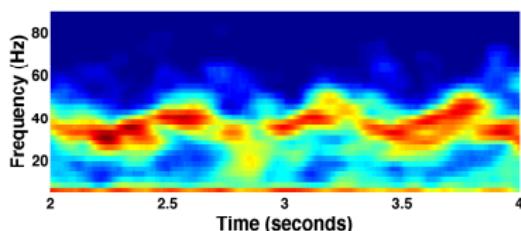


Sitting down

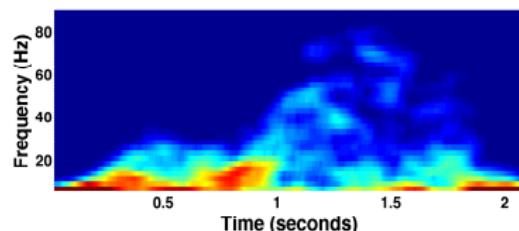


CSI-Activity Model

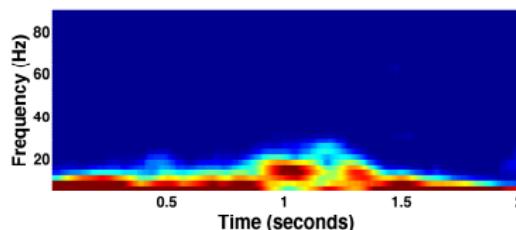
- Use time-frequency analysis to extract features
- Use HMM to characterize the state transitions of movements



Walking



Falling

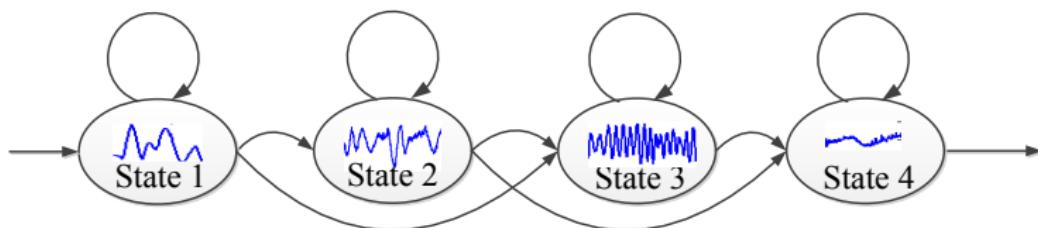


Sitting down



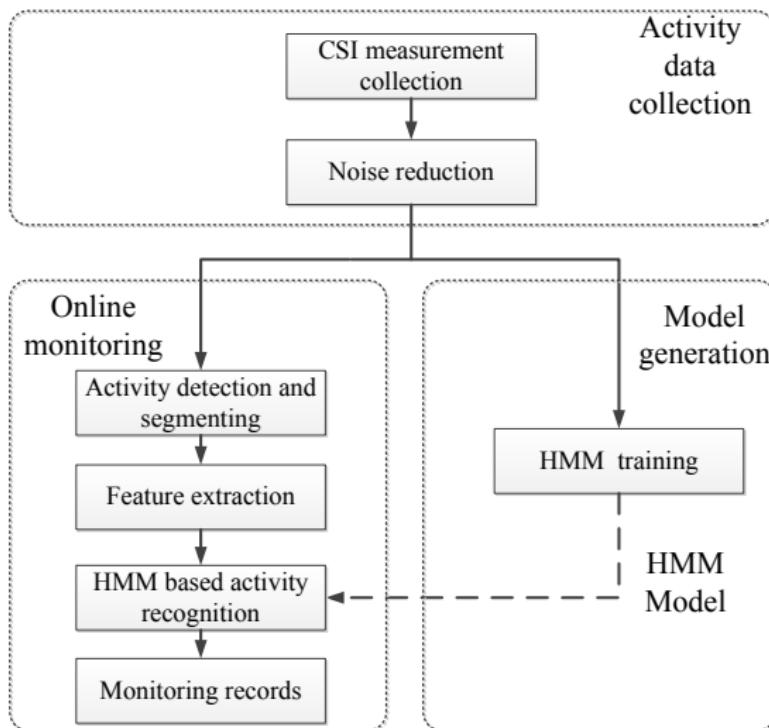
CSI-Activity Model

- Build one HMM model for each activity
- Determine states based on observations in waveform patterns
- State durations and relationships are captured by transition probabilities



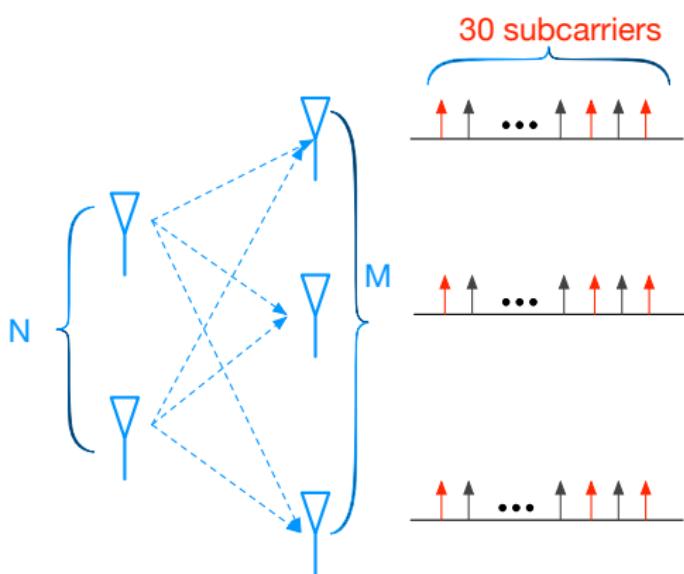


System Architecture

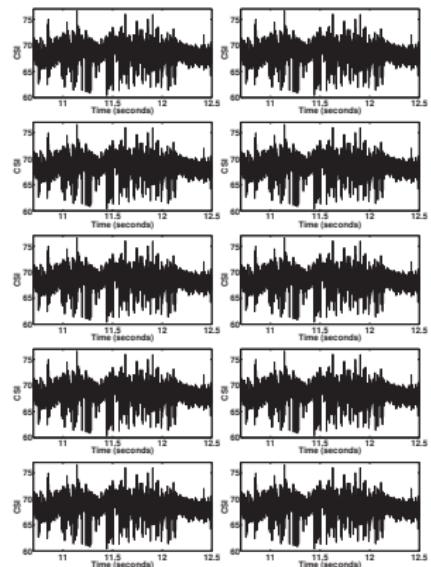




Data Collection



$N \times M \times 30$ CSI streams

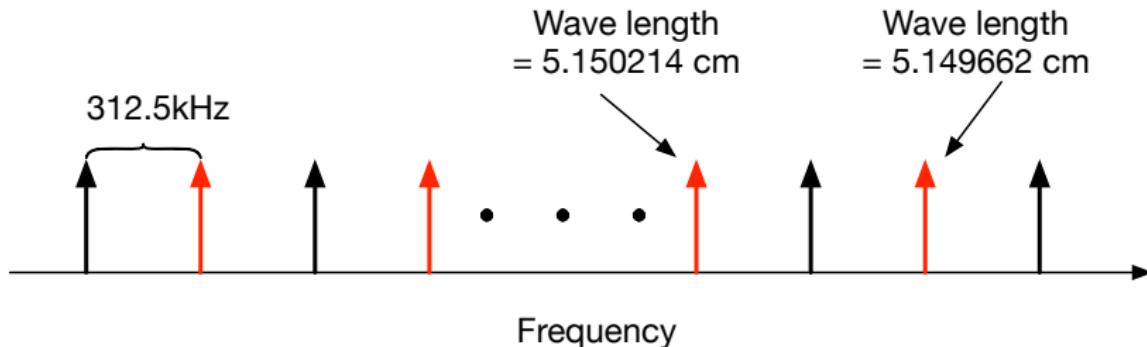




Noise Reduction

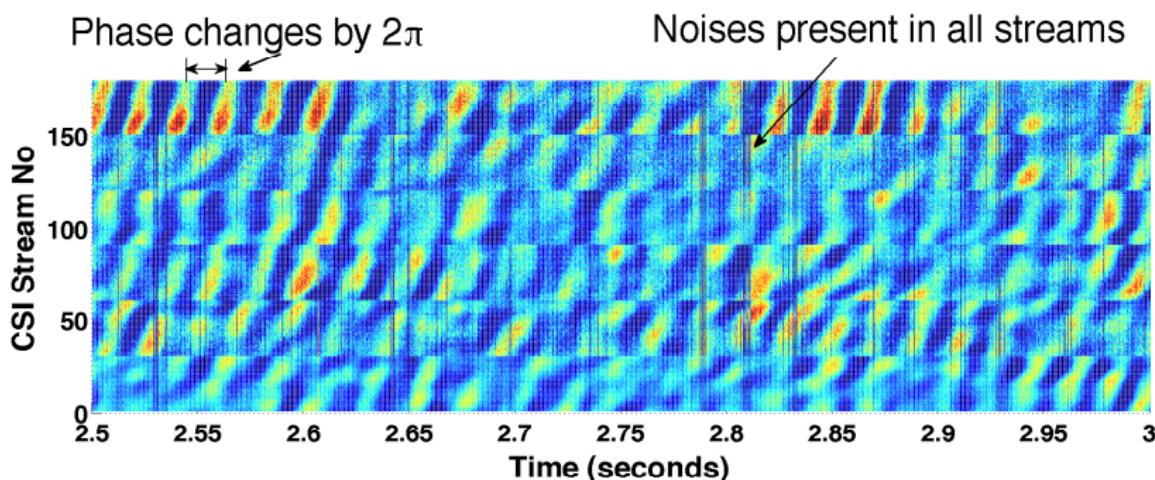
Correlation of CSI on different subcarriers

- Subcarriers only differ slightly in wavelength
- Subcarriers have the same set of paths, with different phases





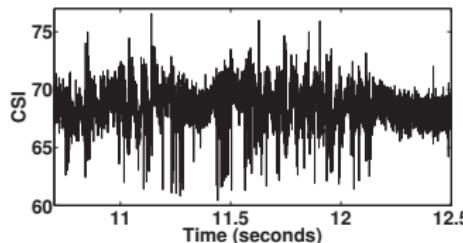
Correlation in CSI Streams



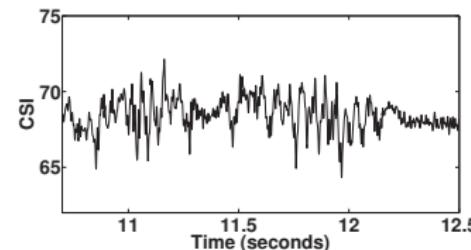


Noise Reduction

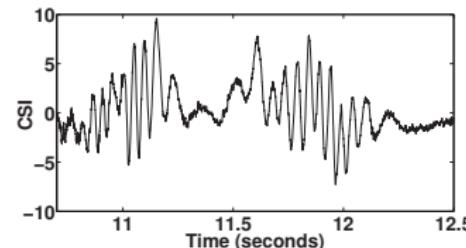
Combines $N \times M \times 30$ subcarriers using **PCA** to detect time-varying correlations in signal



Original



Low-pass filter



PCA



Real-time Recognition

- Activity detection
 - Use both the signal variance and correlation to detect presence of activities
- Feature extraction
 - Time-frequency analysis (DWT)
- HMM model building
 - Eight activities
Walking, running, falling, brushing teeth, sitting down, opening refrigerator, pushing, boxing
 - More than 1,400 samples from 25 persons as the training set



Evaluation Setup

- Commercial hardware with no modification
 - Transmitter: NetGEAR JR6100 Wireless Router
 - Receiver: Thinkpad X200 with Intel 5300 NIC
- A single communicating pair is enough to monitor $450\ m^2$ open area
- Measurement on UDP packets sent between the pair
- Sampling rate 2,500 samples per second





Evaluation Results

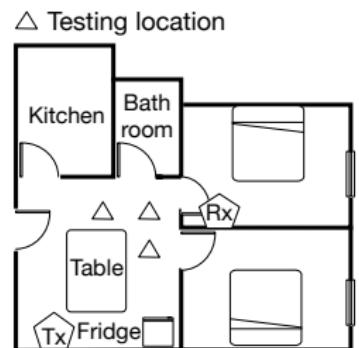
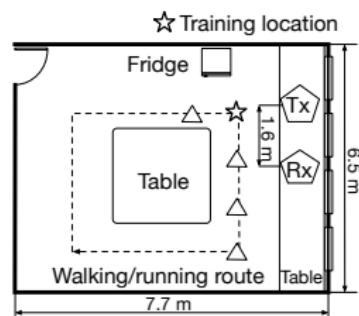
	Activity recognized									
	R	W	S	O	F	B	P	T	E	
True activity	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Running	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Walking	0.000	1.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sitting	0.000	0.000	0.947	0.030	0.011	0.000	0.012	0.000	0.000	0.000
Opening	0.000	0.005	0.150	0.803	0.042	0.000	0.000	0.000	0.000	0.000
Falling	0.000	0.010	0.041	0.010	0.939	0.000	0.000	0.000	0.000	0.000
Boxing	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000	0.000
Pushing	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000
Brushing	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000	0.000	0.000
Empty	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000

- Ten-fold validation accuracy: 96.5%
- Detects human movements at 14 meters
- Real-time recognition on laptops
- Packet sending rate can be as low as 800 frames per second



Evaluation on Robustness

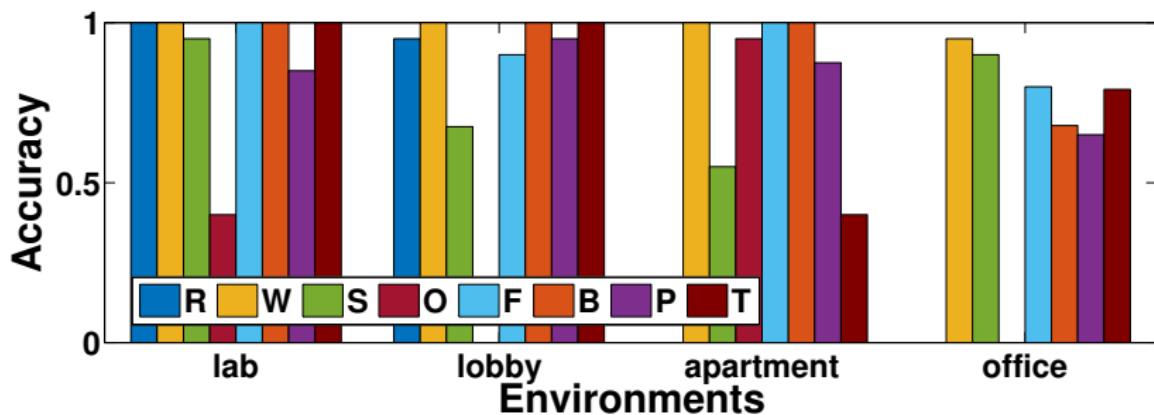
- Models are robust to environment changes
- Train once, apply to different scenarios
- Training use database collected in lab with different users
- Test in with users not in the training set
 - Open lobby
 - Apartment (NLOS)
 - Small office





Evaluation on Robustness

- Consistent performance in unknown environments, with more than 80% average accuracy





Conclusions

- CSI measurements contains fine-grained movement informations
- CSI-Speed model
 - quantifies the correlation between CSI value dynamics and human movement speeds
- CSI-Activity model
 - quantifies the correlation between the movement speeds of different human body parts and a specific human activity
- Our models are robust to environment changes



Q & A

Thank you!

Questions?