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## **Human Activity Recognition necessity**

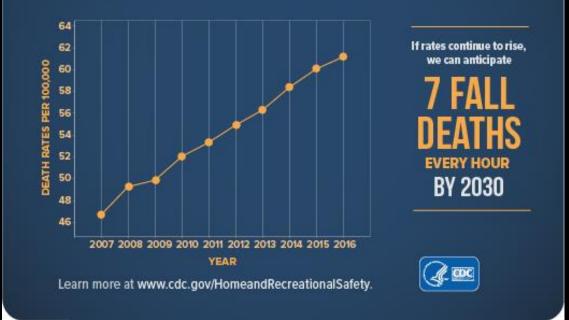
#### Falls Are Serious and Costly

•Each year, 3 million older people are treated in emergency departments for fall injuries.

•Over 800,000 patients a year are hospitalized because of a fall injury.

•Falls are the most common cause of traumatic brain injuries (TBI).

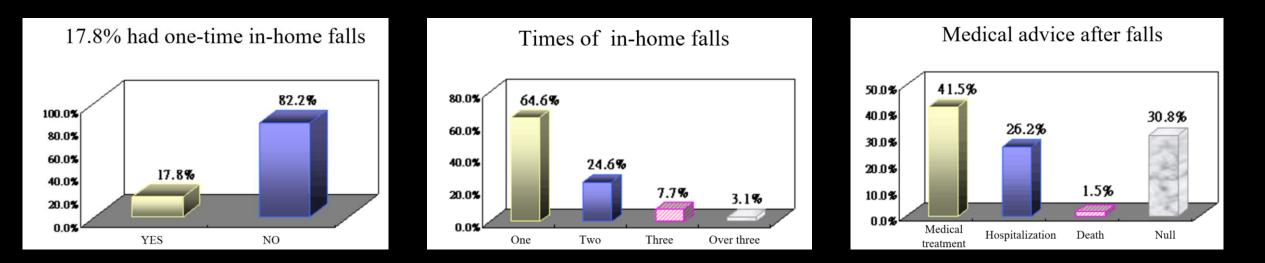
## Fall Death Rates in the U.S. INCREASED 30%



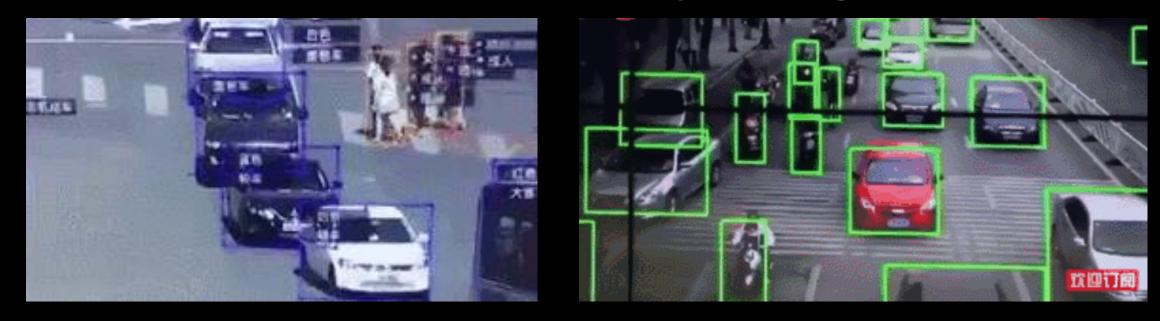
Bergen G, Stevens MR, Burns ER. Falls and Fall Injuries Among Adults Aged ≥65 Years — United States, 2018. MMWR Morb Mortal Wkly Rep 2016; 65:993–998. DOI: http://dx.doi.org/10.15585/mmwr.mm6537a2

## Human Activity Recognition necessity

- 17.8% had one-time in-home falls
- Post fall medical outpatient was 41.5%
- 50% of the citizens do not deploy any preventive equipment at home



## **Camera-based Activity Recognition**

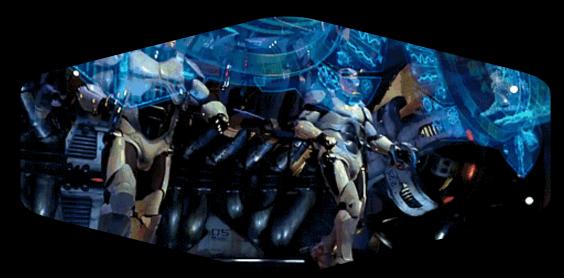


[1] Fang, Biyi, Xiao Zeng, and Mi Zhang. "Nestdnn: Resource-aware multi-tenant on-device deep learning for continuous mobile vision." In ACM MobiCom, 2018.
 [2] Xu, Mengwei, et al. "DeepCache: principled cache for mobile deep vision." Proceedings of the 24th Annual International Conference on Mobile Computing and Networking. ACM, 2018.

## Privacy concern, LoS dependent

## Wearable sensor-based Activity Recognition





[1] Han Ding, Longfei Shangguan, Zheng Yang, Jinsong Han, Zimu Zhou, Panlong Yang, Wei Xi, and Jizhong Zhao. Femo: A platform for free-weight exercise monitoring with rfids. In ACM SenSys, 2015.

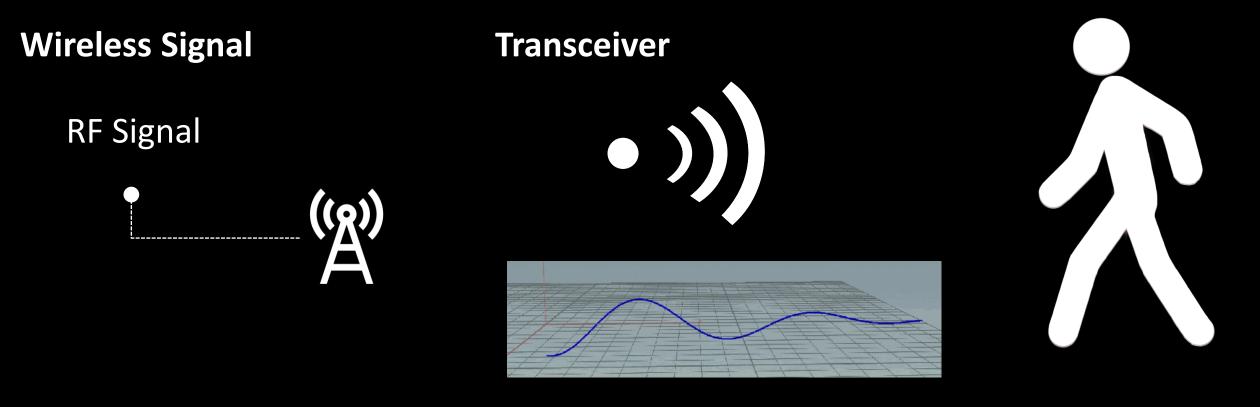
[2] Yuxiao Hou, Yanwen Wang, and Yuanqing Zheng. TagBreathe: Monitor Breathing with Commodity RFID Systems. In IEEE ICDCS, 2017.

- Direct body contact
- Inconvenience
- High cognitive load

# Wireless signal-based Activity Recognition

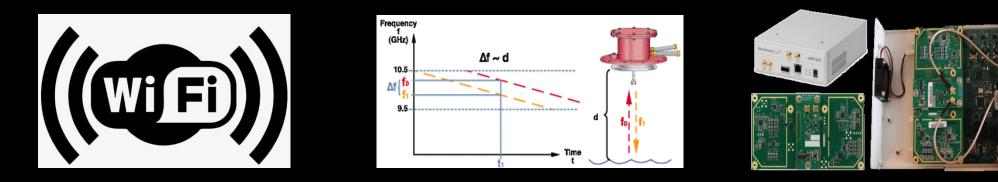
Introduction

01



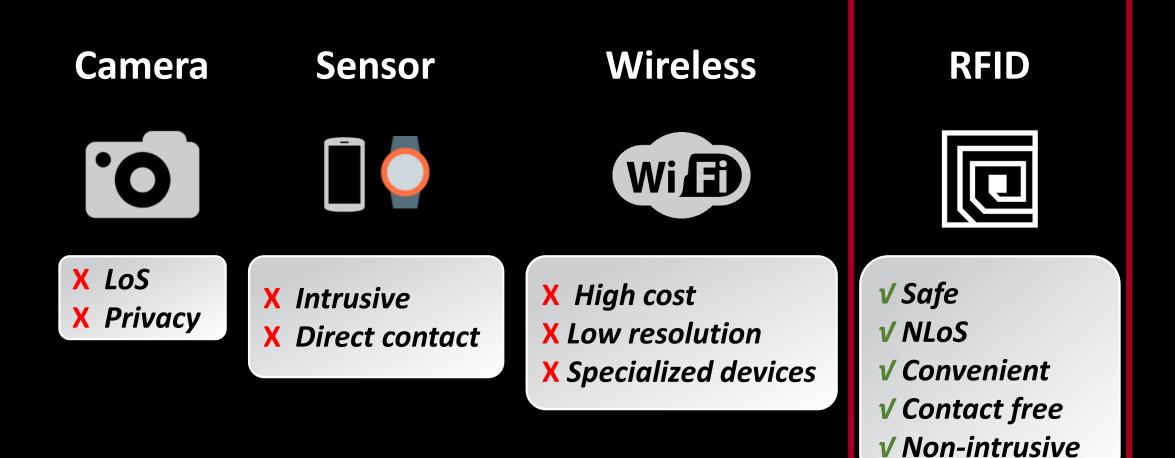


## Wireless signal-based Activity Recognition



Wi-Fi	FMCW	USRP		
Low resolution	Specialized devices High cost	Specialized devices High cost		

- Low resolution
- High deployment cost

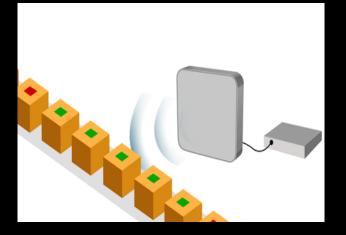


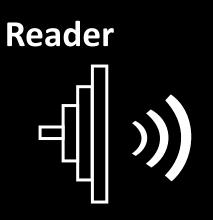
#### RFID

### **Contact-free**

Signal reflection model

## **RFID System**





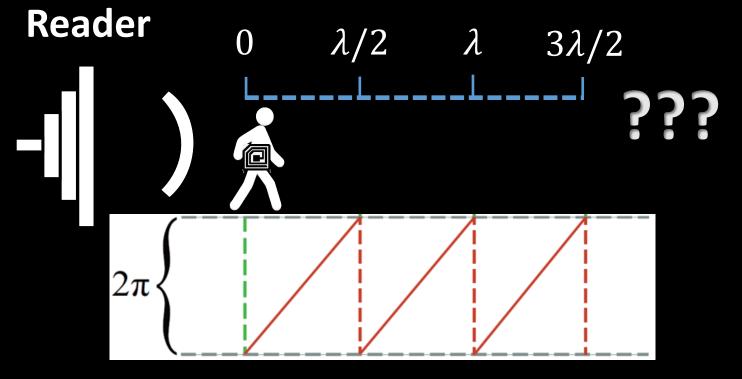








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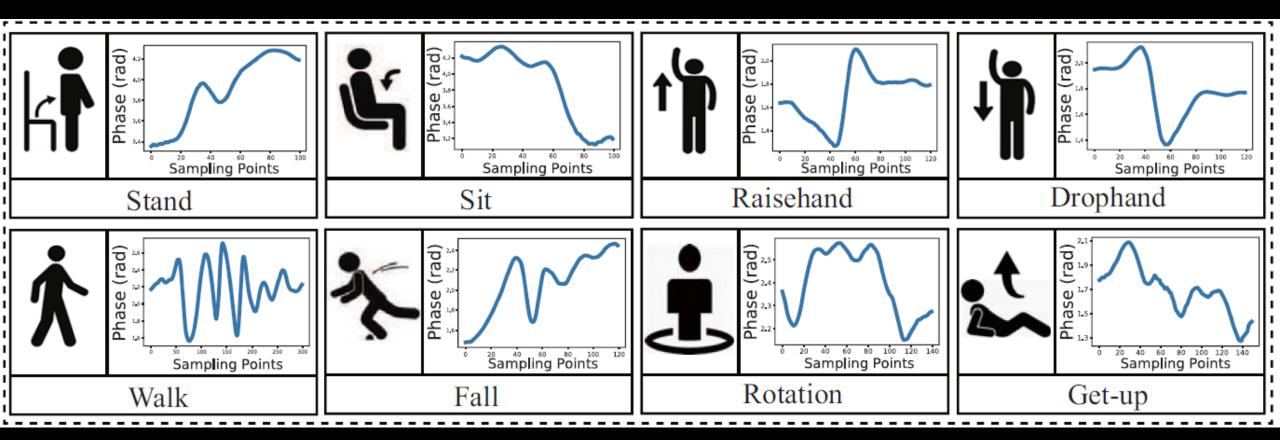
Phase change of the signal

 If the signal propagation distance changes continuously, the signal phase will change from [0,2π]

 If the signal propagation distance changes one wavelength, the signal phase will change 2π

If RFID tags are attached on human body (clothes), one may infer the type of human activity

## Contact-free Activity Recognition -----The **TACT** System



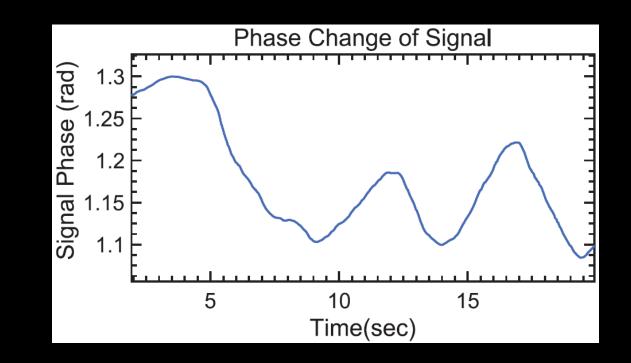
## **Reflection model for contact-free activity recognition**

## **Understanding the Reflection of RFID Signal**

- Preliminary experiments
  - motionless reader

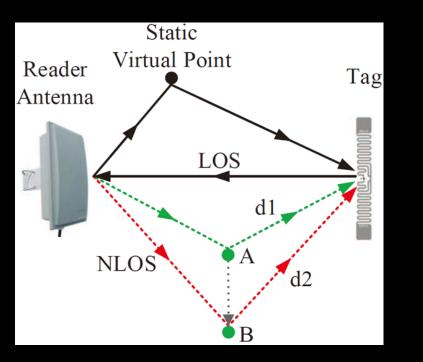
motionless tag

Signal propagation distance change



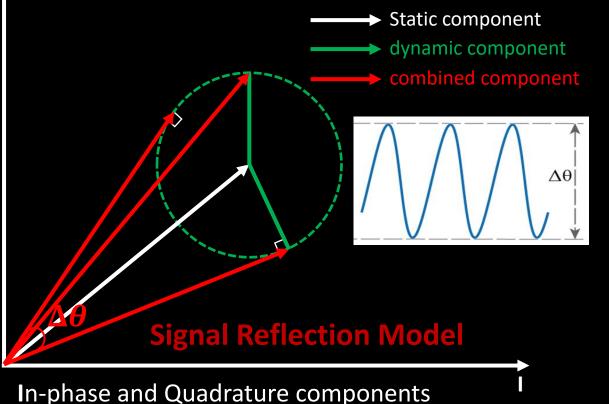
- The phase values continuously changed and exhibited a periodic pattern.
- > The range of phase values was only around 0.2, which was much smaller than  $2\pi$

#### 02 Methodology Signal Reflection model



#### Phase Change of Signal

Q

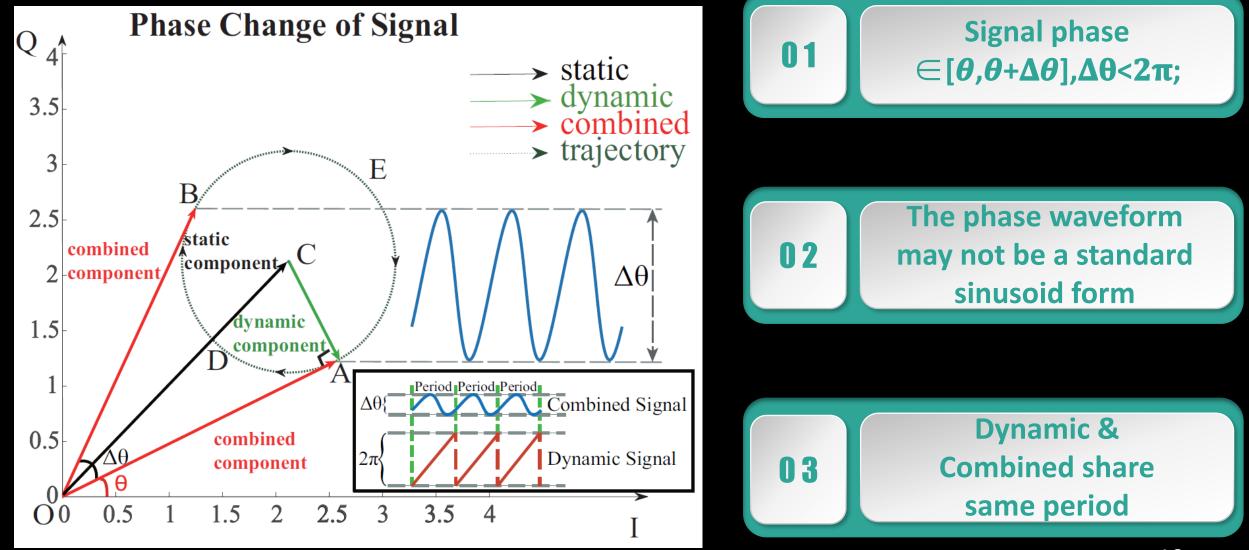


**Static Virtual Point:** All the signal reflected from static objects & LoS

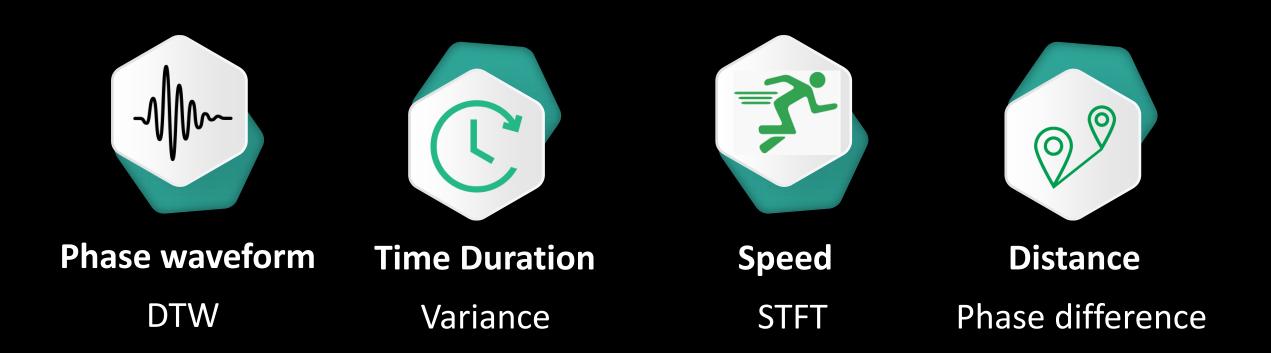
**Object moving:** Moving from A to B

- When the object moves, the dynamic component rotates
- The combined phase reaches maximum and minimum at two tangent points
- The combined phase periodically changes
- The combined phase range is  $\Delta \theta$

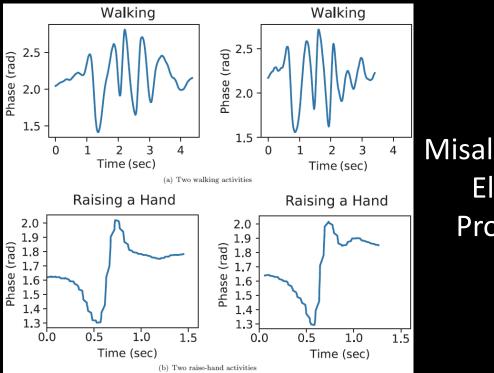
#### 02 Methodology Signal Reflection model



#### 02 Methodology Feature Extraction

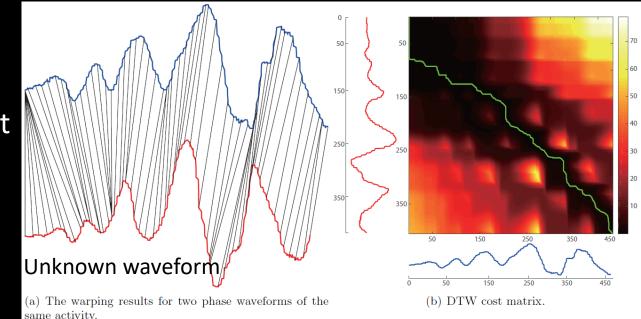


#### Phase waveform



Misalignment Elastic Property

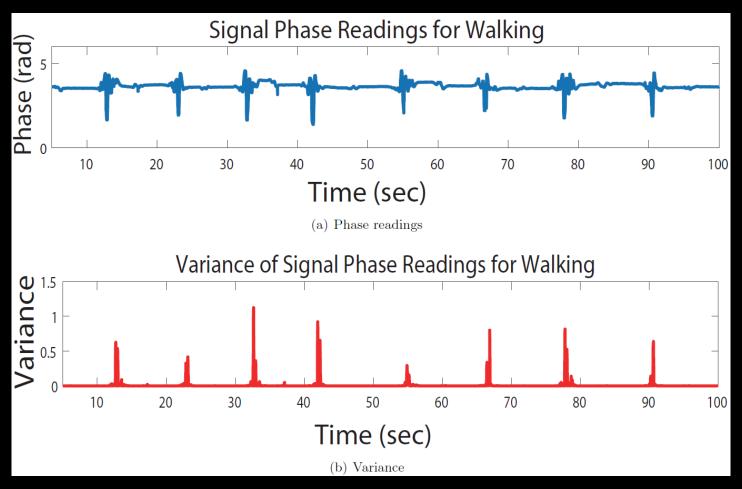
#### **Dynamic Time Warping (DTW)**



Different activities have different phase waveforms, while same activities share similar phase waveforms

#### **\*** Time Duration

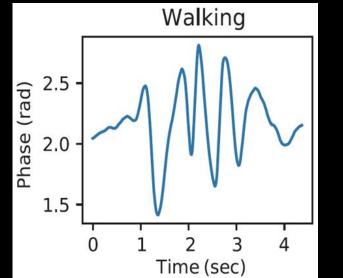
**Objective:** To segment the data corresponding to human activities



The **variance** of phase readings can serve as a good indicator for activity segmentation.

#### Moving speed

**Objective:** To measure the moving speed of different activities.

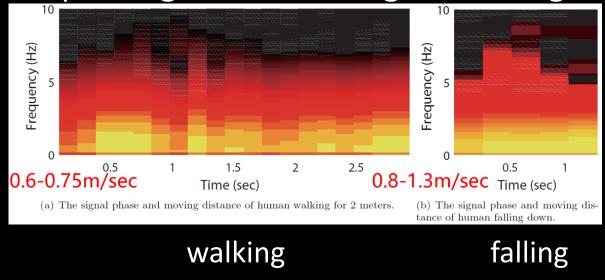


A faster movement results in more rapid fluctuation of phase waveform --- the frequency of phase waveform.  $v = f \times \lambda$ 

# Method: Short-Time Fourier Transform (STFT)

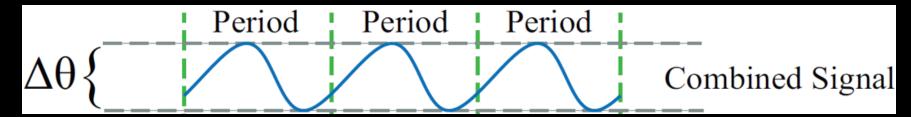
Instantaneously frequency

#### Spectrogram of walking and falling



#### Moving distance

**Objective:** To measure the moving distance of different activities.



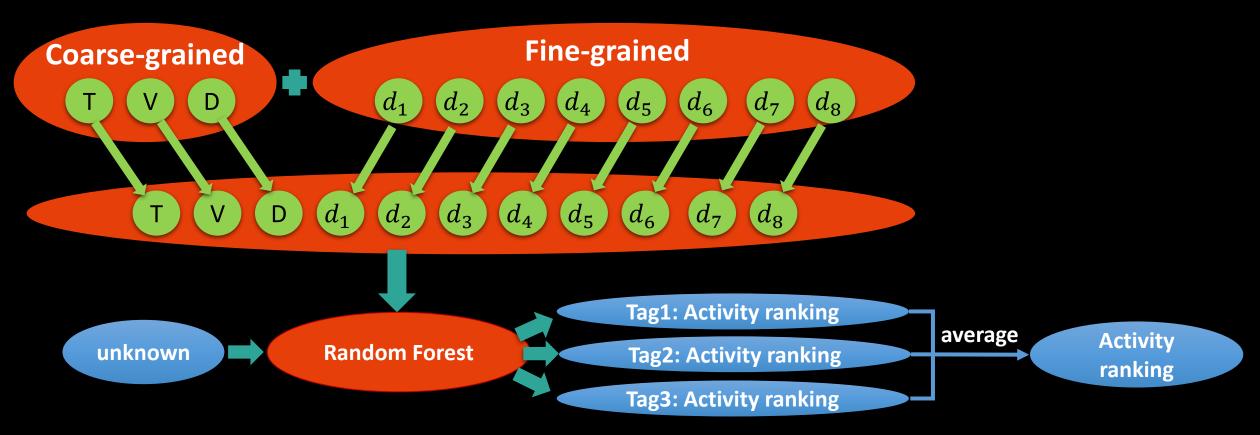
Extract distance from phase difference of 2 consecutive phases.

$$D = \sum_{i=1}^{N-1} \frac{\lambda}{2\pi} \times (|\theta_{i+1} - \theta_i|) \longrightarrow D = \sum_{i=1}^{N-1} \frac{\lambda}{2\Delta\theta} \times (|\theta_{i+1} - \theta_i|)$$

Classification

**Coarse-grained features:** duration of activity, speed, distance

Fine-grained features: phase waveform



## **Extracted Features**

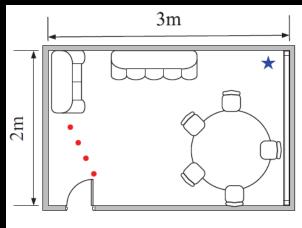
## System Performance

Robustness

## 03 Evaluation Experiment settings



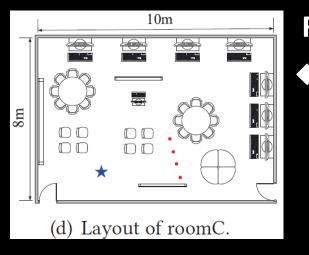
# COTS RFID System Impinj R420 Reader Commodity passive tags Directional Antenna



(b) Layout of roomA.

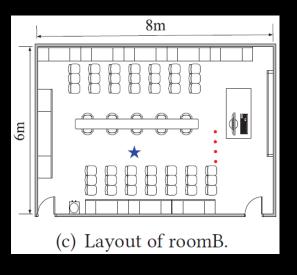
#### Room A

Small size with 3m\*2m



Room C

Large size with 10m\*8m



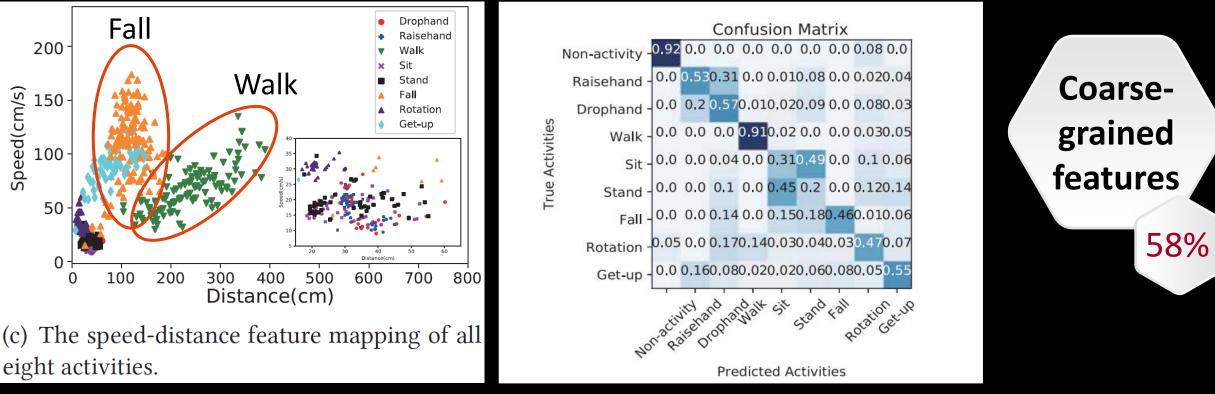
#### Room B

Median size with 8m\*6m



640 traces for training 1280 traces for evaluation 10-fold cross-validation

## **Extracted Features**



- The speeds of falling and walking significantly differ with other activities
- Walking has longer moving distances

**Evaluation** 

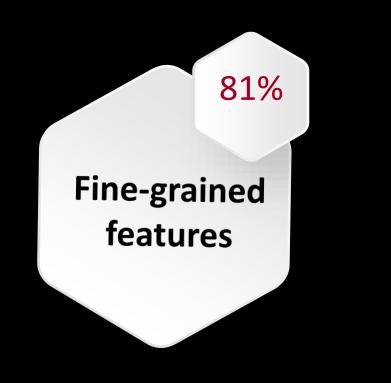
03

- Other activities are difficult to distinguish
- Only using coarse-grained feature may not work

## System Performance

#### **Fine-grained features**

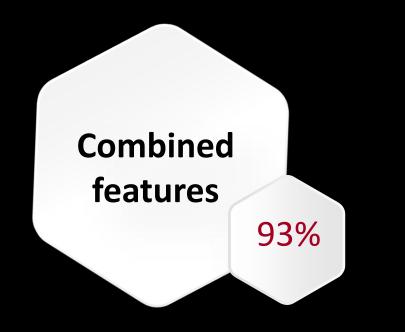
#### 8 DTW distances

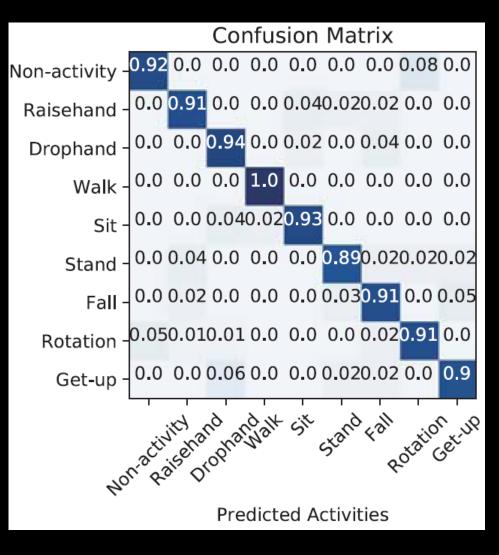


	Confusion Matrix								
Non-activity -									
Raisehand -	0.0	0.78	0.0	0.0	0.0	0.0	0.14	0.03	0.05
Drophand -	0.0	0.03	0.93	0.0	0.03	0.0	0.0	0.03	0.0
Walk -	0.0	0.0	0.02	0.8	0.02	0.0	0.15	0.0	0.02
Sit -	0.0	0.0	0.05	0.0	0.88	0.0	0.0	0.0	0.07
Stand -	0.0	0.0	0.0	0.0	0.0	0.45	0.47	0.05	0.03
- Walk Sit Stand Fall	0.0	0.08	0.0	0.0	0.0	0.06	0.78	0.04	0.04
Rotation -	0.05	0.04	0.0	0.0	0.02	0.04	0.05	0.76	0.04
	0.0	0 1 2	0.00	0.0	0.02	0 0 0	0.0	0.02	0.71
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NO	C 43	AND ON	.01				<b>\$</b>	~ `	-
•	on Raise Drophand all Sit Stand Fall Rotation Cet-up								

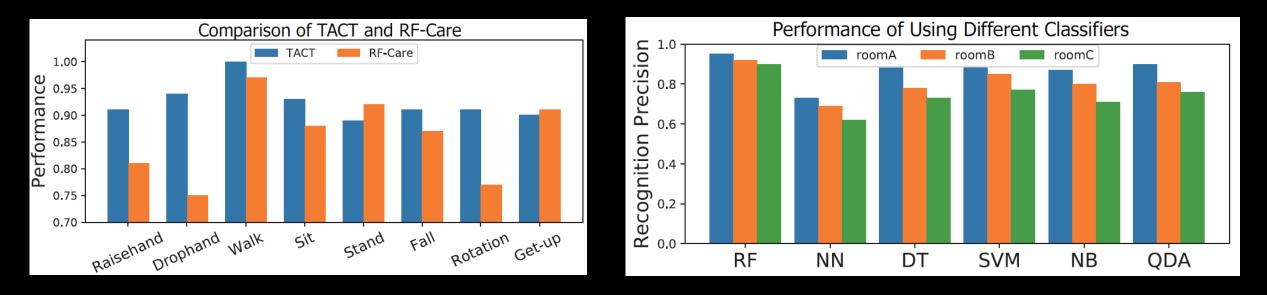
#### System Performance

#### **Fine-grained + Coarse-grained features**





## System Performance



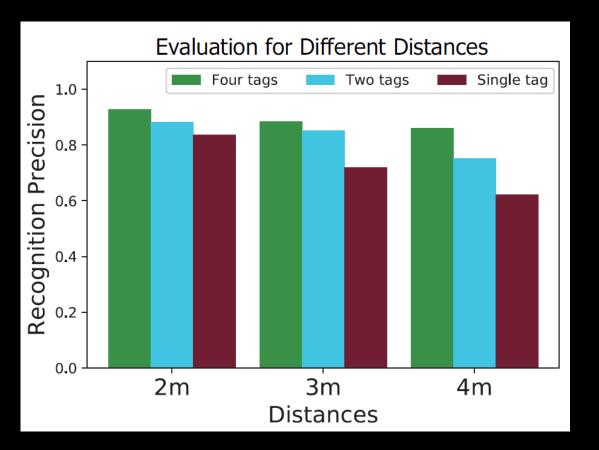
#### **Compare to existing work**

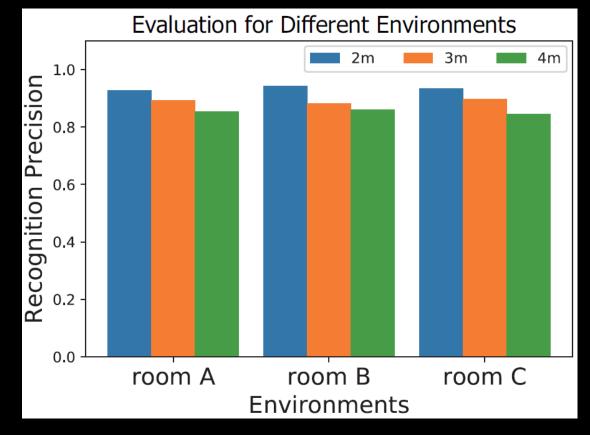
#### **Six classifiers**

# Our TACT system significantly outperforms RF-Care

**RF-Care**: Lina Yao, Quan Z. Sheng, Wenjie Ruan, Tao Gu, Xue Li, Nick Falkner, and Zhi Yang. 2015. RF-Care: Device-Free Posture Recognition for Elderly People Using A Passive RFID Tag Array. In proceedings of the 12th EAI International Conference on Mobile and Ubiquitous Systems: Computing, Networking and Services (MOBIQUITOUS'15).

## Robustness





## Deploying multiple tags indeed can improve the system performance

## Environment has relatively small impact on the performance

## Conclusion

#### 04 Conclusion

- Build a contact-free model which can be used to quantify the correlation between signal phase values and key features of human activities.
- Coarse-grained & Fine-grained features combination
- Implementation of the contact-free activity recognition system using RFID technology
- Extensive evaluation under different settings, and the average recognition precision -- up to 93.5%.



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