Wireless Signal-based Human Activity Recognition using Deep Learning

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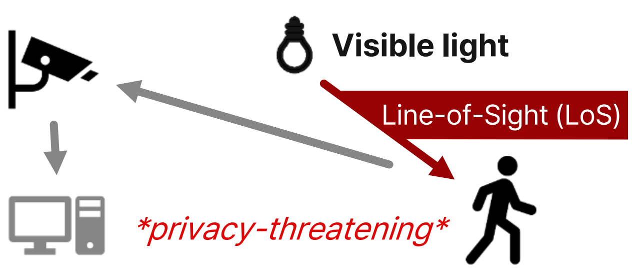
POSTECH

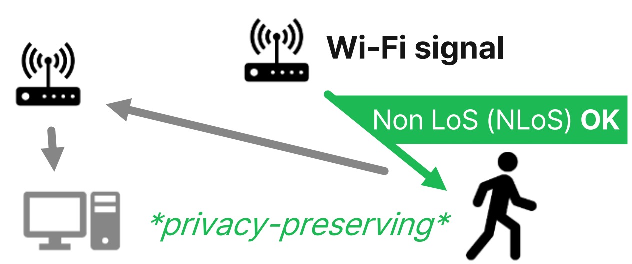
Human Activity Recognition (HAR)

HAR : “A form of human-computer interaction (HCI)”

Why Wi-Fi-based HAR?

	Vision-based	Wi-Fi-based
Coverage	line-of-sight of the camera	range of the Wi-Fi signal
Hardware Requirements	camera, light source, computer	Wi-Fi APs, computer **(may already exist)**
Lighting Requirements	visible lights	-
Privacy	**quite risky**	**pretty good** (only carries small information of the room)

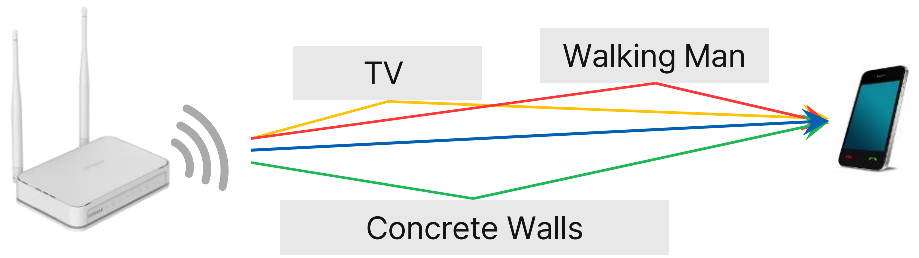




Channel State Information (CSI)

In Wi-Fi-based HAR, CSI is extracted from Wi-Fi signals

Channel A route that signal propagates

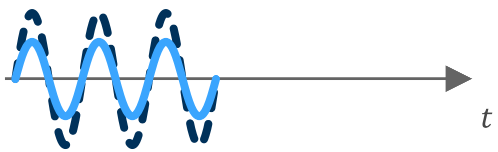


Multi-path signals are piled up at the receiver

- Channel affects signal in two ways

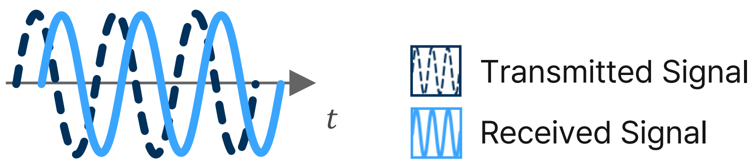
Amplitude Attenuation

: Reduction in the strength



Phase Shift

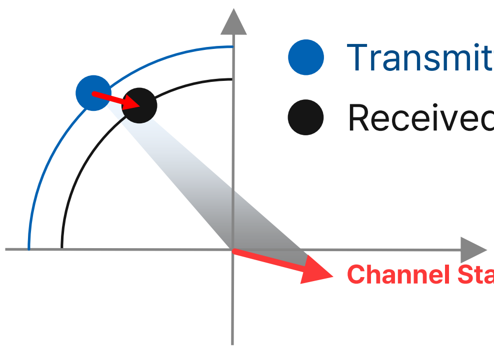
: Multi-path effects and Doppler effects



Channel State Information (CSI)

Channel State

- Degree of distortions that occurred in signals on a channel
- Estimated by WLAN processor to revert received signal to the original one



Mathematical Expression of Channel Effects

- Channel varies by the signal frequency and time

↓ Received signal ↓ Transmitted signal

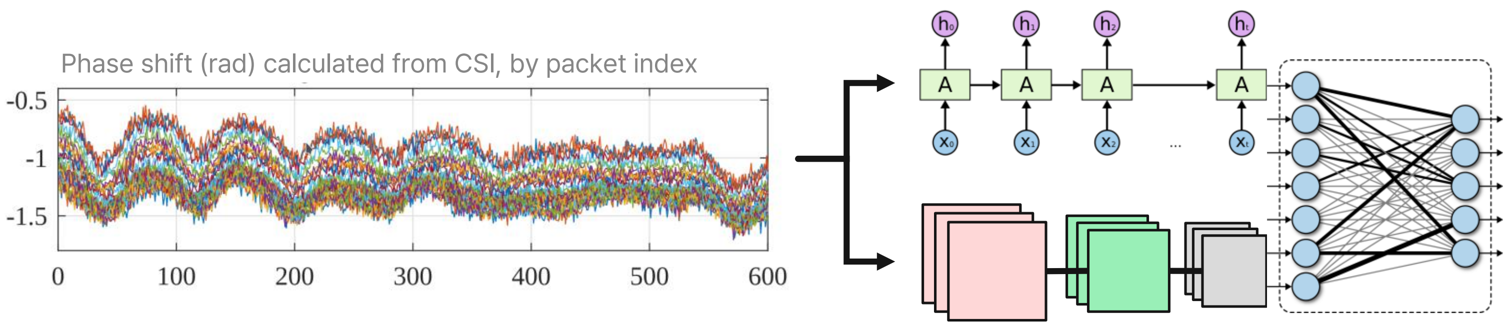
$$y(f,t) = \boldsymbol{H}(f,t) \cdot x(f,t) + \boldsymbol{N}(f,t)$$

↑ Channel State ↑ Noise (AWGN)

- Channel state can be expressed as a matrix whose columns and rows represent the Tx and Rx antennas

Wi-Fi-based HAR Meets Deep Learning

CSI has high usability as an input of deep learning model



Desired outputs by purposes

- CSI data can be trained for various applications including
  - Fire detection, smoke detection
  - Head noding (sleep) detection, breathing detection
  - People counting, Home security
  - **Hand gesture recognition, human activity recognition**

HAR USING WIRELESS SIGNAL **PT. 1**

Human Activity Recognition

To cope with generalization problem

Challenges to Wi-Fi-based HAR

High Environmental & Personal Dependency

- Everything on the signal propagation path affects Wi-Fi CSI
  - Signals are scattered, attenuated, reflected and refracted
  - Multipath and mobility of transceivers induce phase shift
- Each person has different personal behavioral habits
  - Traind model might include personal habits of experiment participants

Channel Congestion

- CSI can be extracted only when medium access is available (i.e., sending packets)
- Stable and periodic CSI measurement is hard on congested channels

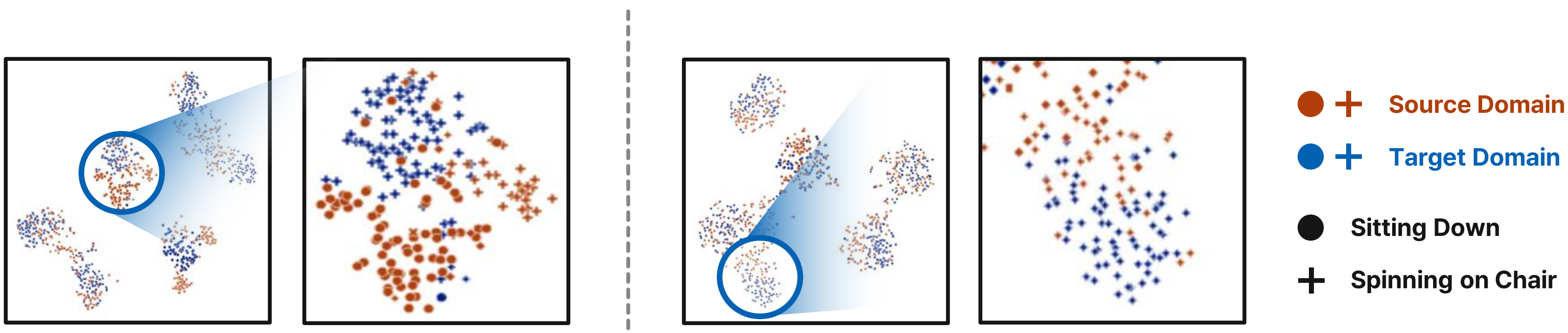
Channel congestion is often occurred when too many devices try to send a lot of packets

How To Cope With Environmental Dependency

Domain adaptation (DA) is a typical method to get rid of some dependency
It is hard to collect good quality data a lot for unsupervised DA
Instead, trying few-shot DA may more powerful

- Unsupervised DA requires a huge amount of data
- Few-shot DA uses small labeled data, **without big performance degradation**

<Aligned Feature Space By DA Type>



Aligned by Unsupervised DA

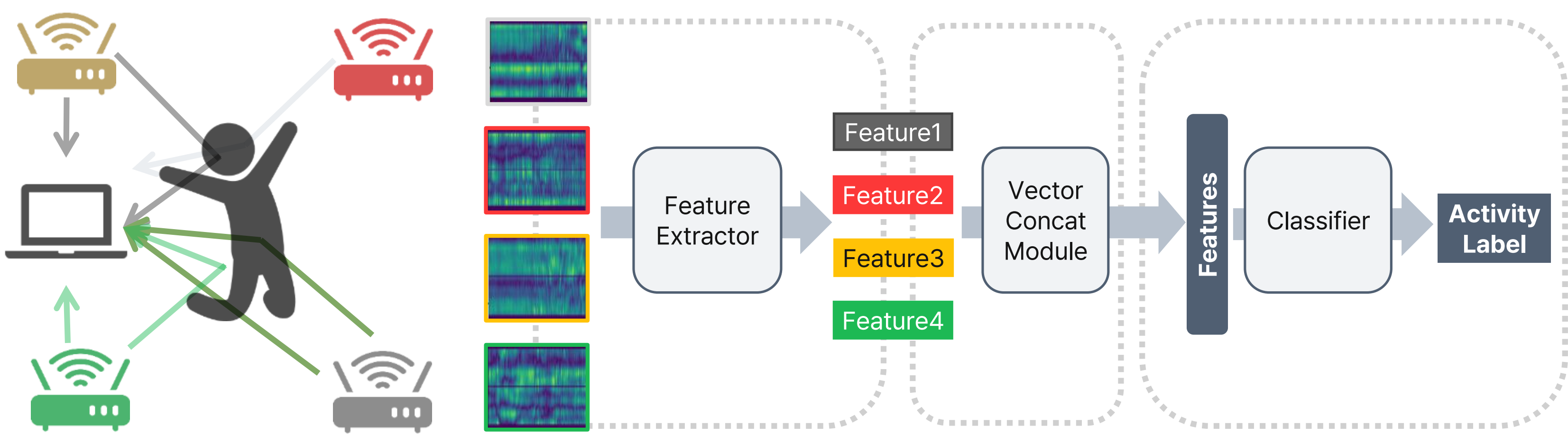
Aligned by Few-Shot DA

How To Avoid Band Congestion

Adding more Tx-Rx antenna pairs of different channels not only gets over the packet bursts but has the effect of using wider bandwidth

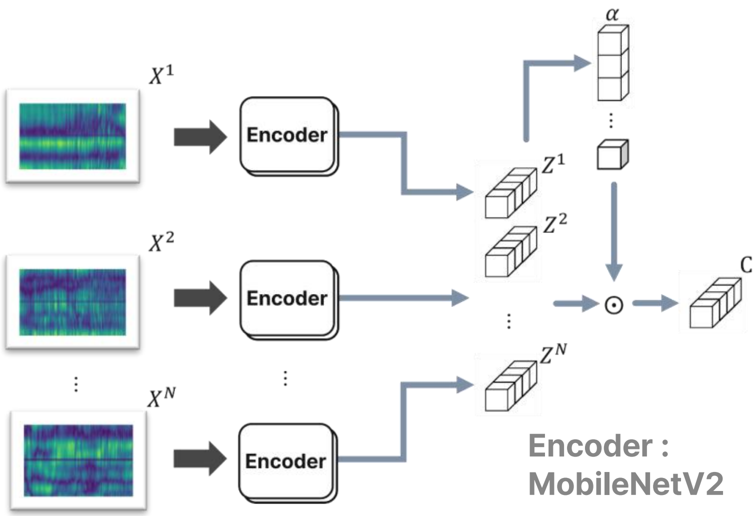
- CSI data from all pairs would share common properties of human activities
- This multi-view CSI fusion will effectively help extract essential features

<Multi-View Feature Training>

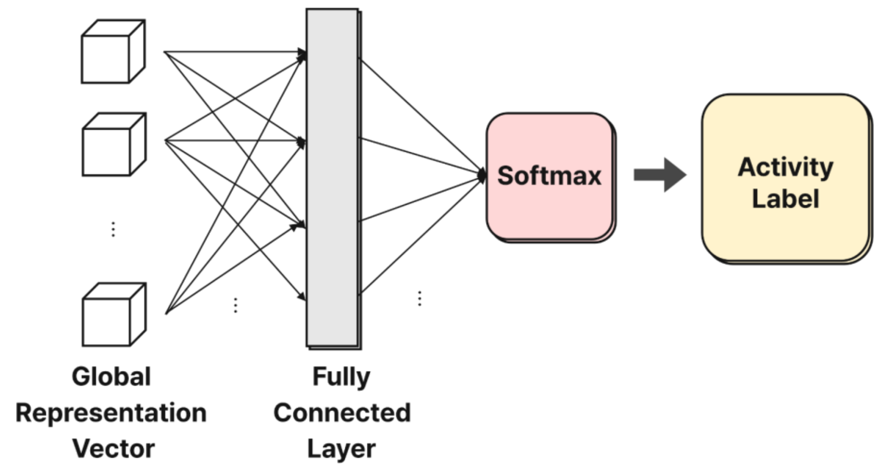


HAR Model Design

Feature Extractor



Activity Classifier



<Data Collection>

HAR Evaluation Results

Offline Evaluation Results

Single View	Source Only	CORAL (UDA)	Transfer Learning		Domain Adaptation	
			1-Shot	4-Shot	1-Shot	4-Shot
Source Accuracy	97.9%	91.6%	89.5%	88.5%	94.8%	**96.9%**
Target Accuracy	49.0%	30.2%	60.3%	81.4%	63.7%	**88.1%**

Impacts of Multi View Training

Training Methods	Source Only		1-Shot DA		4-Shot DA	
	Single View	Multi View	Single View	Multi View	Single View	Multi View
Source Accuracy	97.9%	95.8%	94.8%	95.8%	96.9%	**96.9%**
Target Accuracy	49.0%	60.4%	63.7%	70.9%	88.1%	**90.3%**

HAR USING WIRELESS SIGNAL **PT. 2**

Fall Detection

Towards real-time Wi-Fi-based HAR application

Fall Detection

Fall detection is one of the applications of CSI data

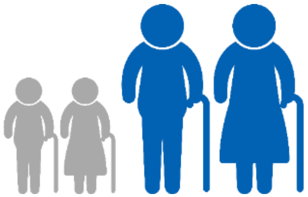
Especially important matter for elderly person living alone

⅓ Elders Experience Fall

⅓ of over-65 experience a fall once a year [1]

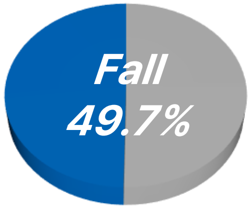
Pupulation Aging

The number of elders will be doubled in 10y [2]



Fall: Top Medical Accident

49.7% of medical accidents are fall [3]



- No prevention available other than exercising and continuous monitoring
- Fast follow-up diagnosis and cure is important to minimize sequellaes

→ **Highly accreditable real-time detection of fall is required**

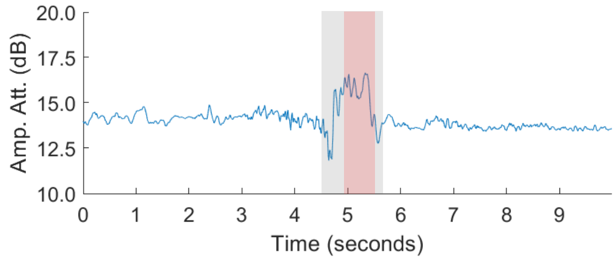
Source [1] : Tinetti ME, Speechley M, Ginter SF. Risk factors for falls among elderly persons living in the community. N Engl J Med. 1988 Dec 29;319(26):1701-7. doi: 10.1056/NEJM198812293192604.
Source [2] : Statistics Korea (KOSTAT), 2019
Source [3] : Korea Consumer Agency (KCA), Medical Management Negligence Report

Analyzing Fall CSI To Reduce Model

- Too many factors such as SFO, CFO change phase shift angle

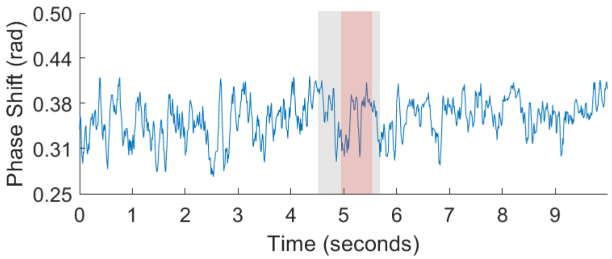
Amplitude on fall

Amplitude of a subcarrier during fall



Phase shift on fall

Phase shift of a subcarrier during fall

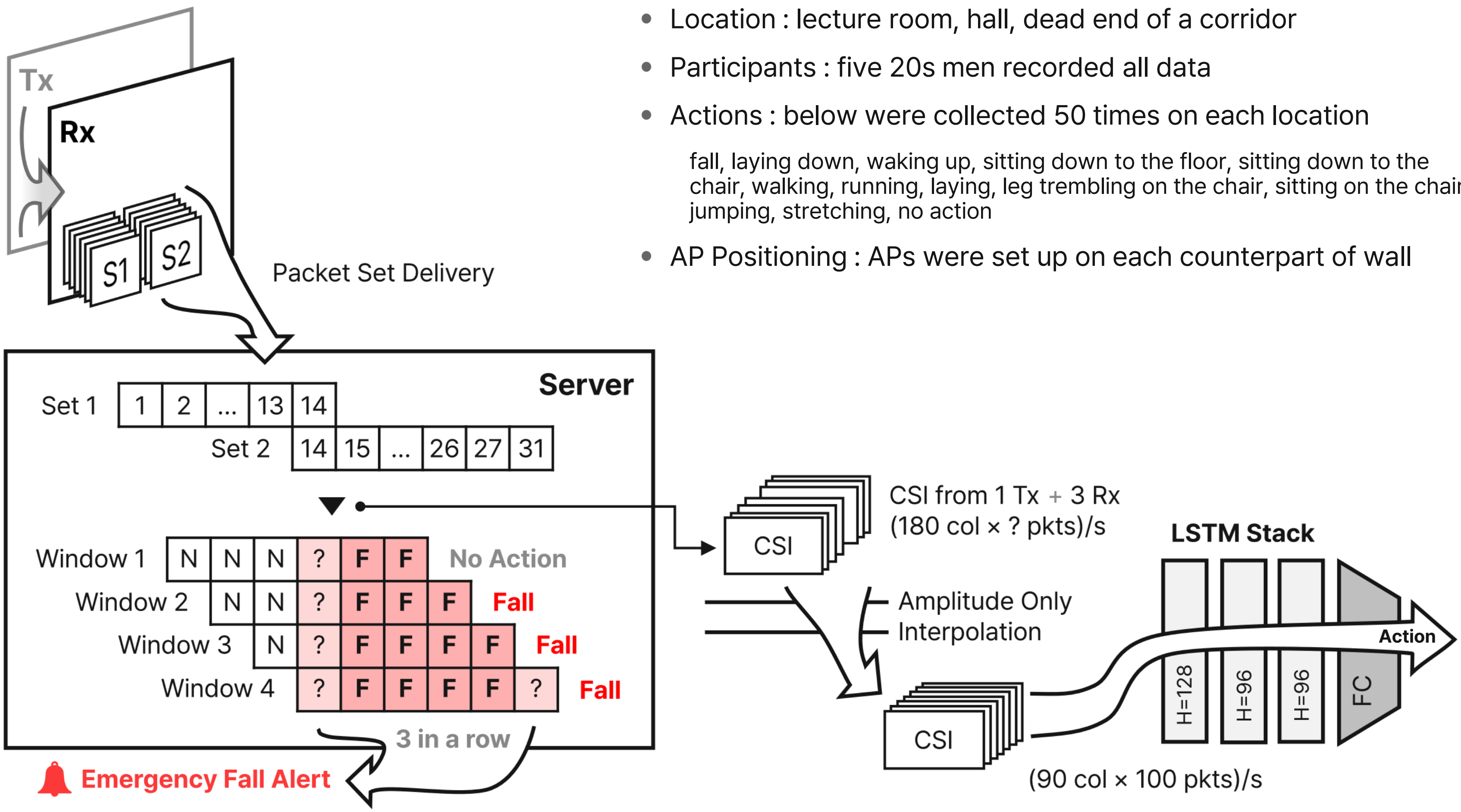


- Even after frequency offset removal in WLAN processor, there are still remaining phase shifts
- According to the t-SNE analysis result, phase shift and its trained hidden features were hard to use for activity classification/detection

→ It's more efficient to use only amplitude information

Designing Fall Detection System

System Architecture



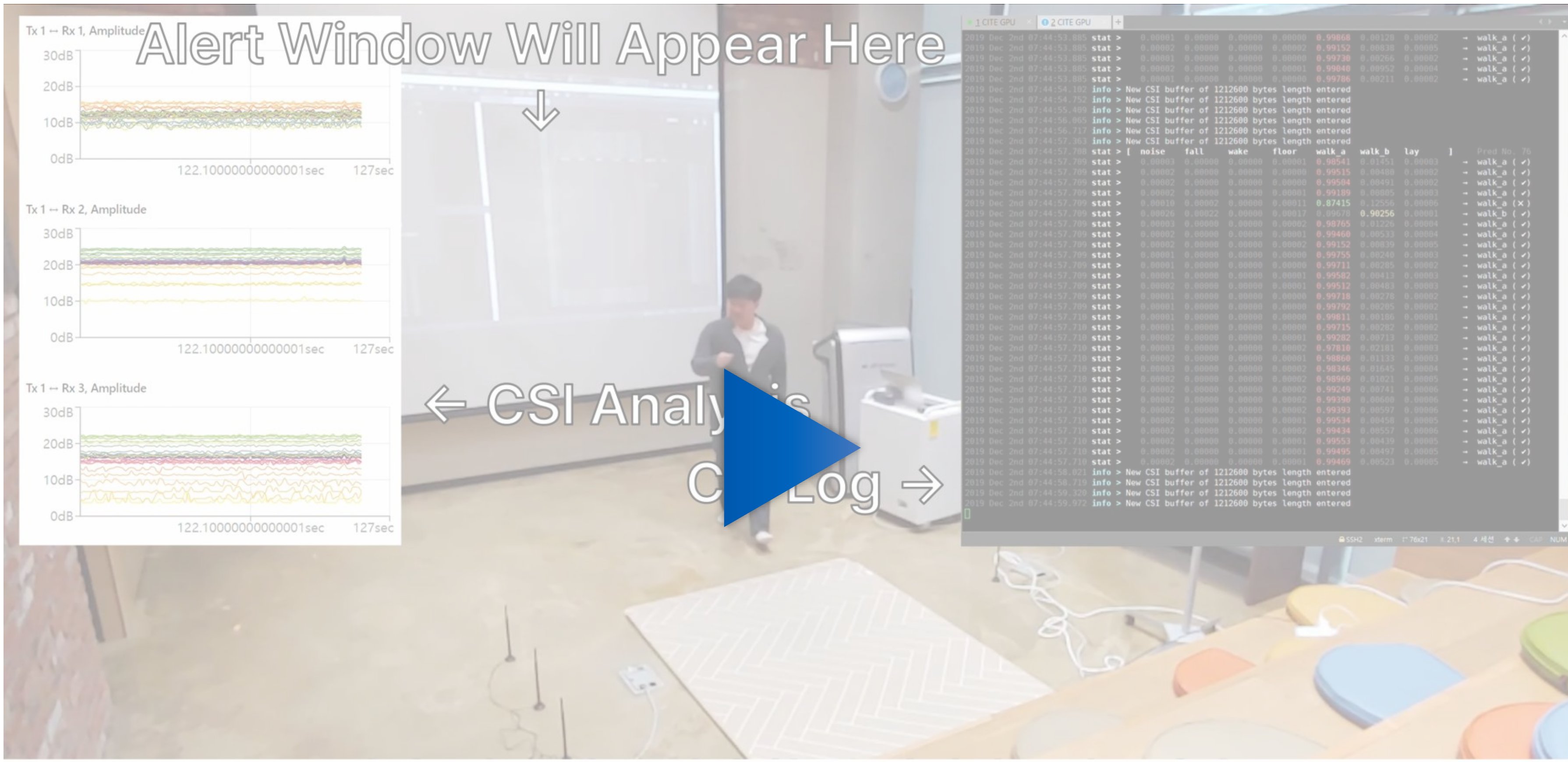
Dataset

- Location : lecture room, hall, dead end of a corridor
- Participants : five 20s men recorded all data
- Actions : below were collected 50 times on each location

  fall, laying down, waking up, sitting down to the floor, sitting down to the chair, walking, running, laying, leg trembling on the chair, sitting on the chair, jumping, stretching, no action

- AP Positioning : APs were set up on each counterpart of wall

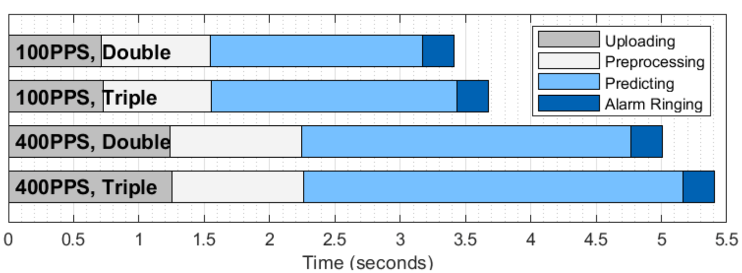
Fall Detection Demonstration



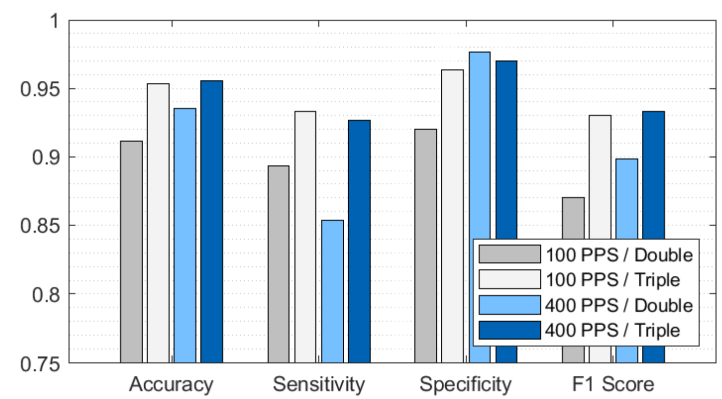
Fall Detection Performance

- **Control Variables**
  - Packets-per-second (PPS) : 100 PPS (19.2kbps) or 400 PPS (76.8kbps)
  - LSTM stack level : 2 LSTM (double) or 3 LSTM (triple)
- **Got high F1 score of 0.9329 in 5.5 seconds, with very light model**

<Alarm Delay Analysis>



<Performance>



Actual Result

Prediction		Fall	Non−Fall
	Fall	*True Positive (TP)*	*False Positive (FP)*
	Non−Fall	*False Negative (FN)*	*True Negative (TN)*

$$\text{Accuracy} = \frac{TP + FP}{All} \quad \text{Sensitivity} = \frac{TP}{TP + FP} \quad \text{Specificity} = \frac{TN}{FP + TN} \quad \text{F1 Score} = \frac{2 \times TP}{2 \times TP + FP + FN}$$

Conclusion

- Due to the increasing use of mobile devices HAR using wireless signals is actively studied
- Wireless signals based HAR has many advantages over other HAR techniques including camera-based HAR
- HAR technology with deep learning techniques may increase the detection performance

Thank you for listening

End of document.