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iRadar: Synthesizing Millimeter-Waves from Wearable Inertial Inputs for Human Gesture Sensing

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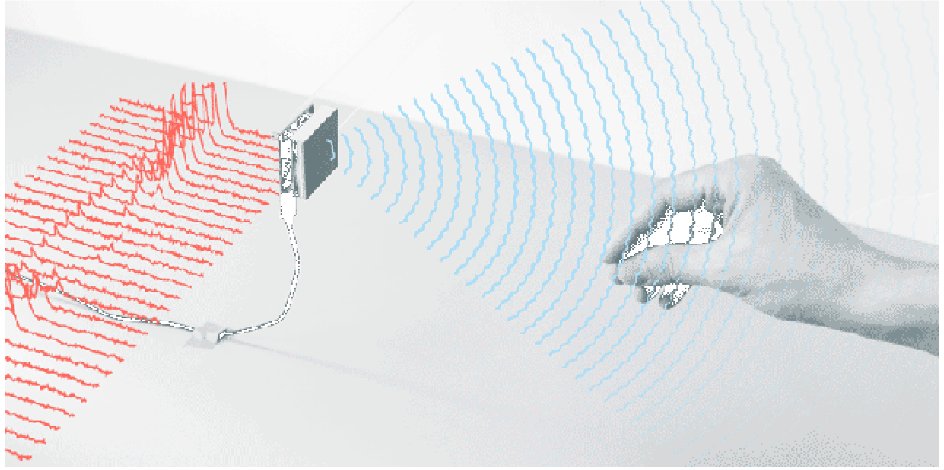
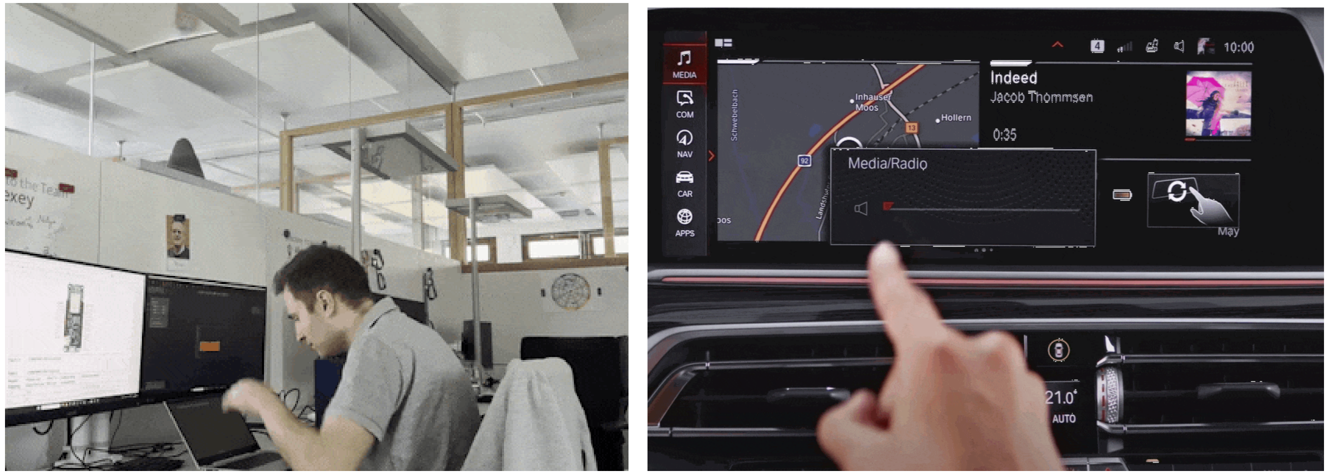
Background

❑ Radio Frequency (RF)–based gesture recognition

- ❖ Contactless and device-free human-machine interaction
- ❖ Each gesture has a unique pattern, and RF signals can capture these differences
- ❖ Applications like smart homes, autonomous driving, and interactive gaming



Principle of RF-based gesture recognition



Applications

Background

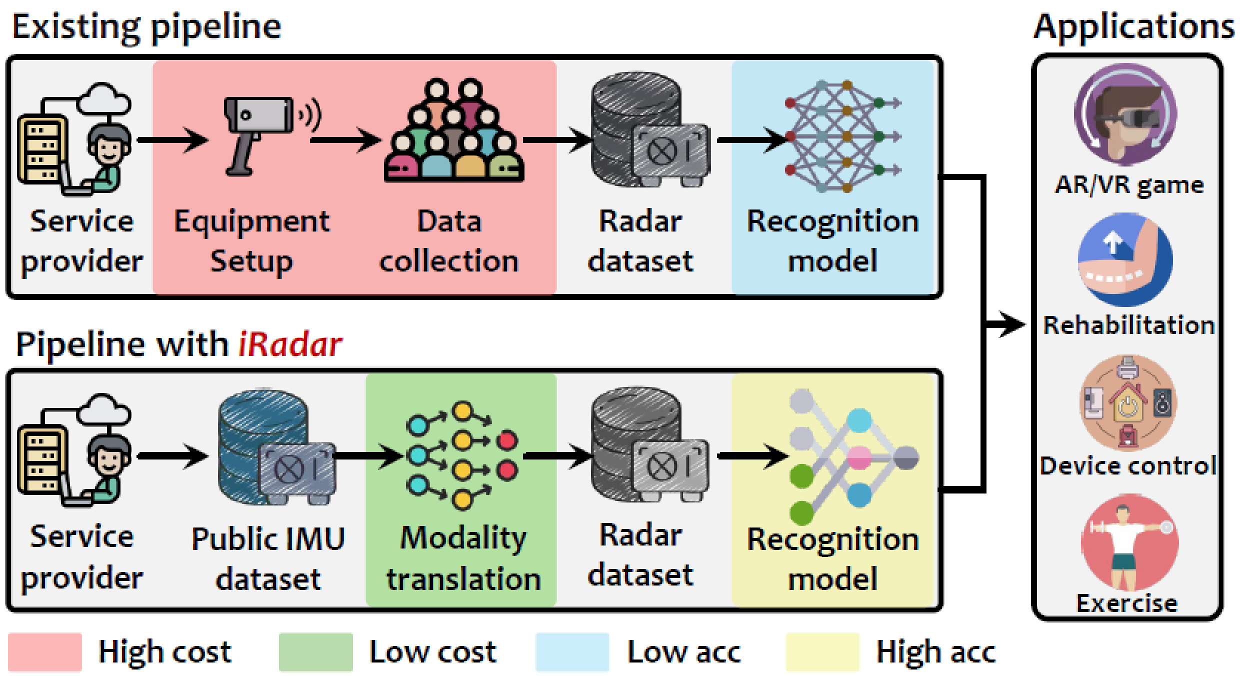
❑ Existing RF-based gesture recognition

- ❖ Uses millimeter-wave (mmWave) signals from frequency-modulated continuous-wave (FMCW) radar to capture the gestures
- ❖ **Limitation 1 :** Deployment of mmWave devices in the data collection area.
- ❖ **Limitation 2 :** The pre-collection of numerous gesture instances.

Redundant data collection process

Our solution

- **iRadar: synthesizing millimeter-waves from wearable inertial inputs**
  - Leverage the Inertial Measurement Unit (IMU) signal in modern mobile devices to simulate the mmWave of different gestures.
  - Eliminate the need for prior mmWave data collection.

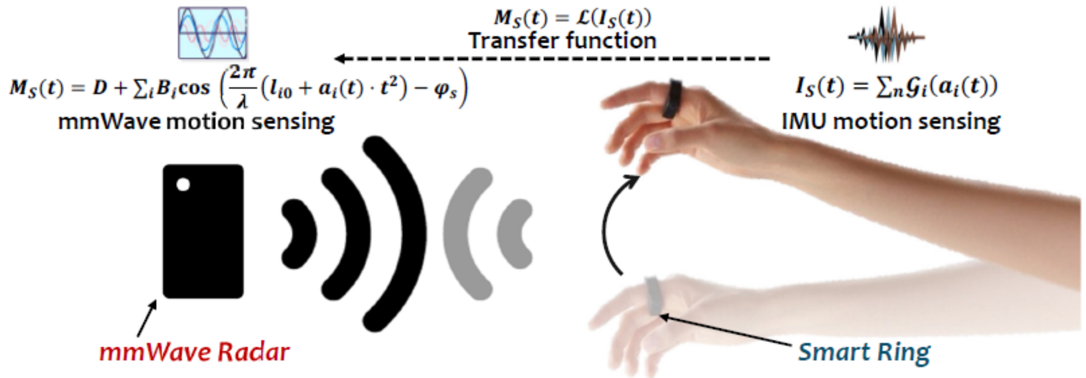


Motivation for iRadar

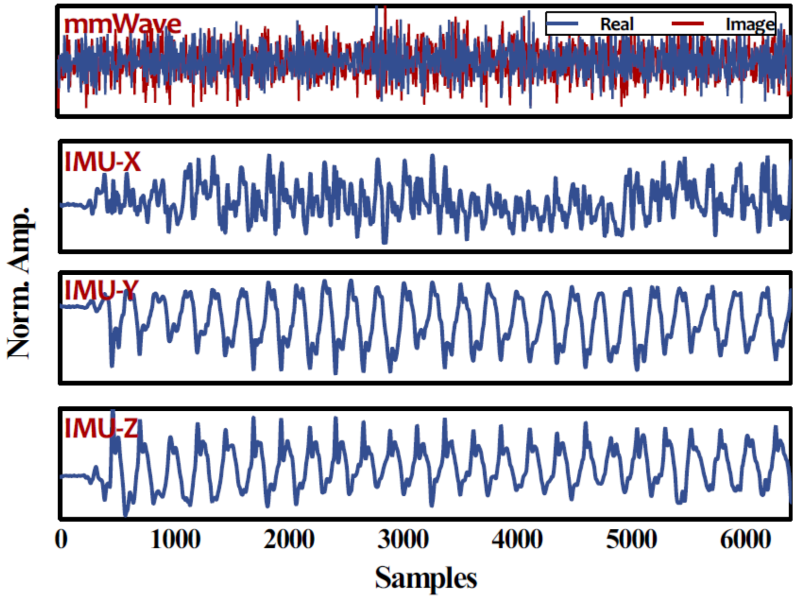
Challenges

❑ Intrinsic difference between IMU and mmWave signals

- ❖ Inertial forces and joint rotations on IMUs VS Reflection and scattering effects on mmWave signals
- ❖ Real numbers VS Complex numbers



Principle difference.

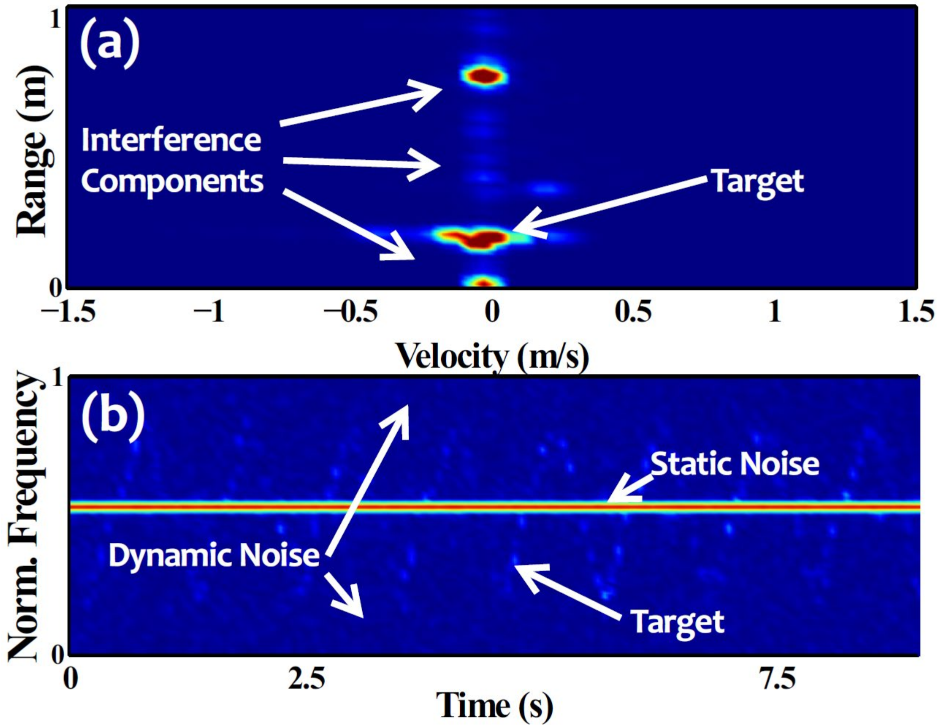


Signal difference.

Challenges

❑ Noisy gesture sensing in mmWave radar

- ❖ Range-Doppler Map (RDM) contains interference components (by different body parts)
- ❖ Time-Frequency map contains static and dynamic noises

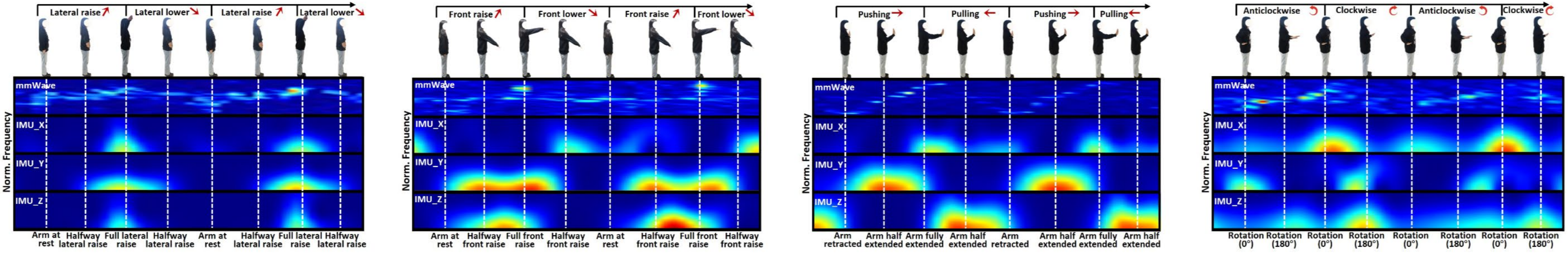


Noisy gesture sensing.

Feasibility study

❑ Correlation model

- ❖ Different gestures induce correlated changes in mmWave and IMU spectrograms.
- ❖ There exists a possibility of converting IMU data into mmWave data through a non-linear function.

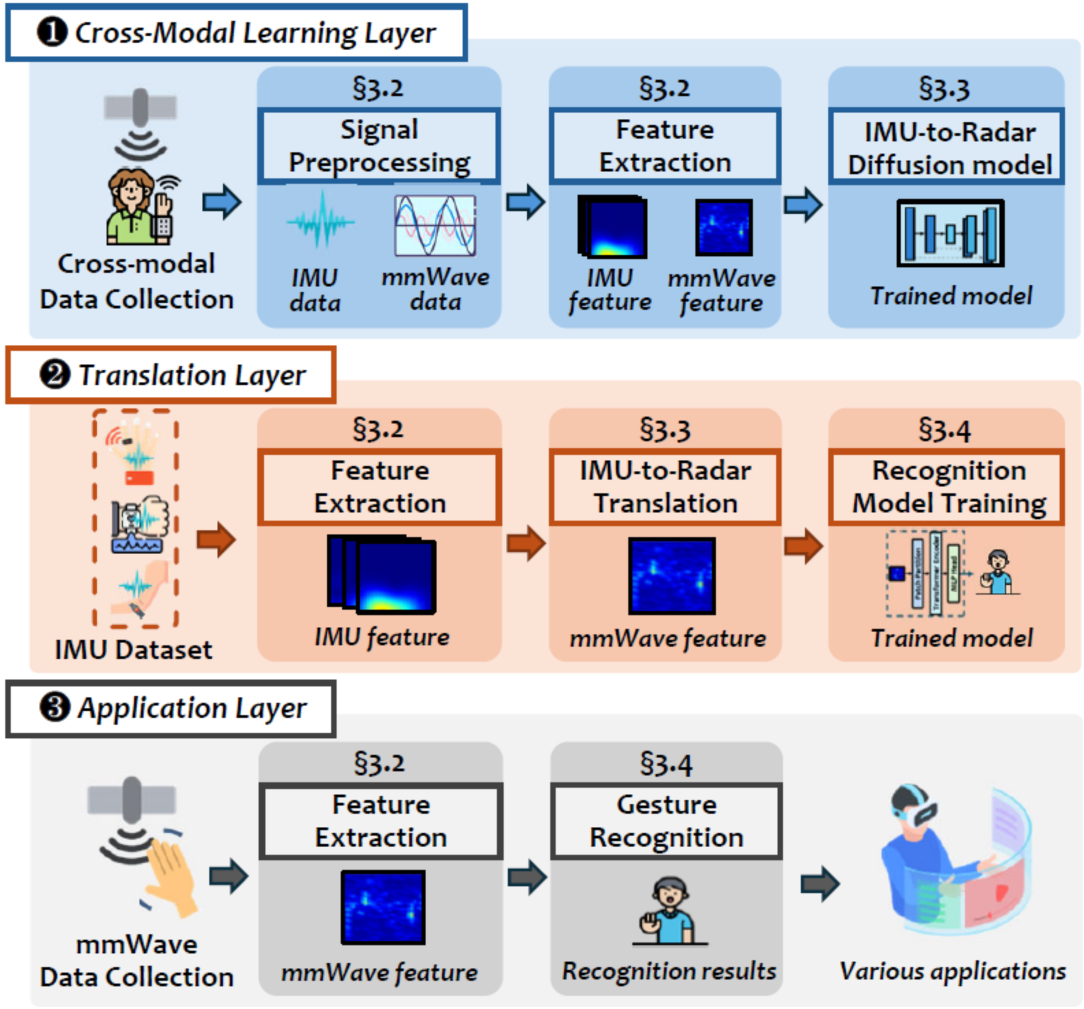


(a) Lateral raises. (b) Front raises. (c) Pushes. (d) Horizontal rotations.

Gesture cycles with corresponding IMU and mmWave features.

System design

- ❑ iRadar workflow

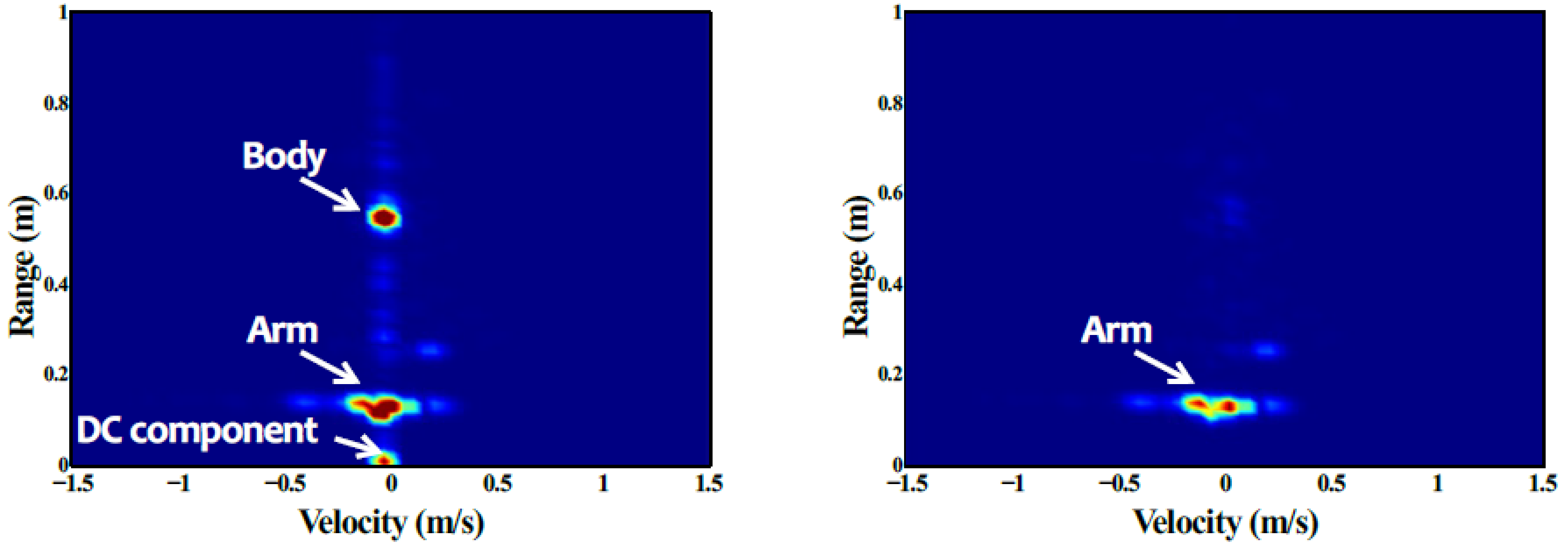


iRadar workflow

System design

❑ mmWave heatmap generation

- ❖ Subtract the average of all IF signals (static noise vector) to obtain the denoised data

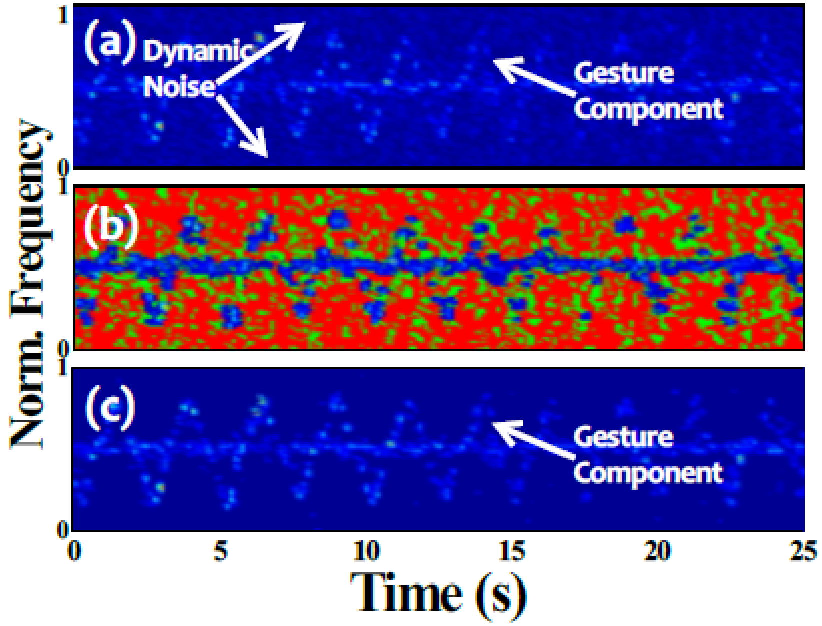


RDM denoising

System design

❑ mmWave Heatmap Generation

- ❖ Morphological Clustering for mmWave Heatmap Enhancement (**MC-MHWE**)
- ❖ 1) K-means clustering: segregate the pixels into two discrete categories, discard **red** part
- ❖ 2) Morphological closure operations: bridge the discontinuities, shown in **green**

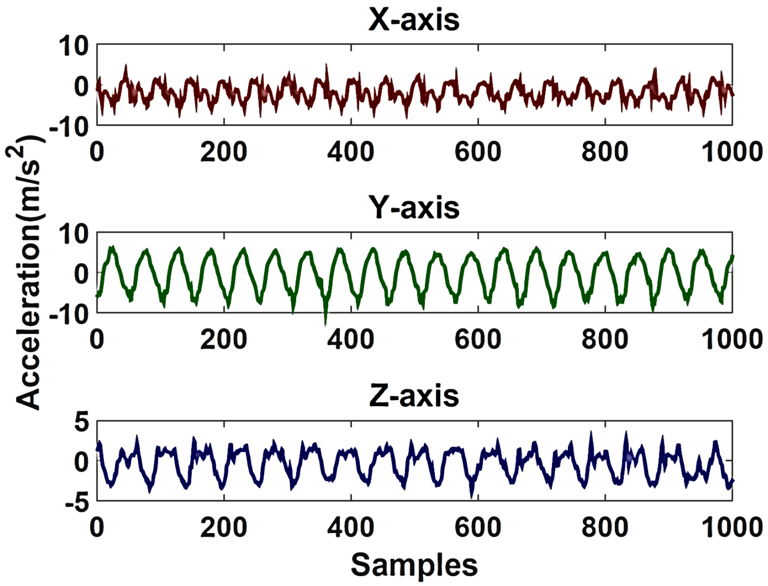


MC-MHWE process

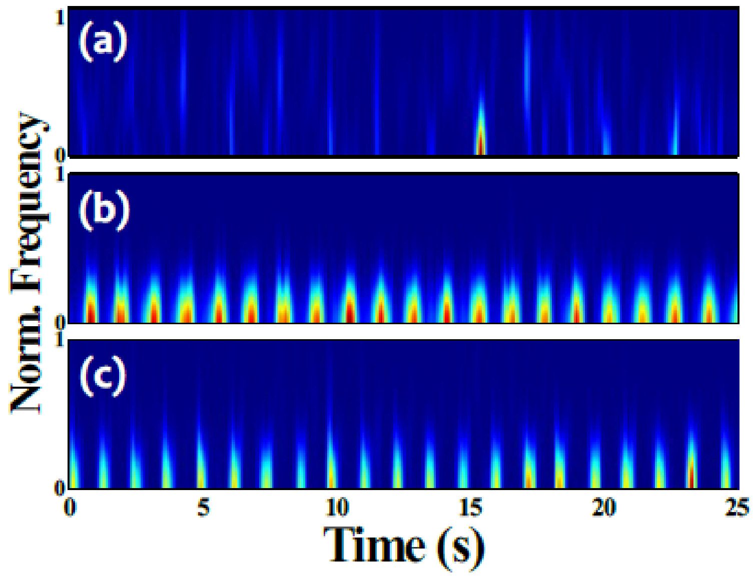
System design

❑ IMU Spectrogram Generation

- ❖ Maximal Overlap Discrete Wavelet Transform (MODWT) for denoising.
- ❖ Short-Time Fourier Transform (STFT) for spectrogram generation.



Raw IMU data

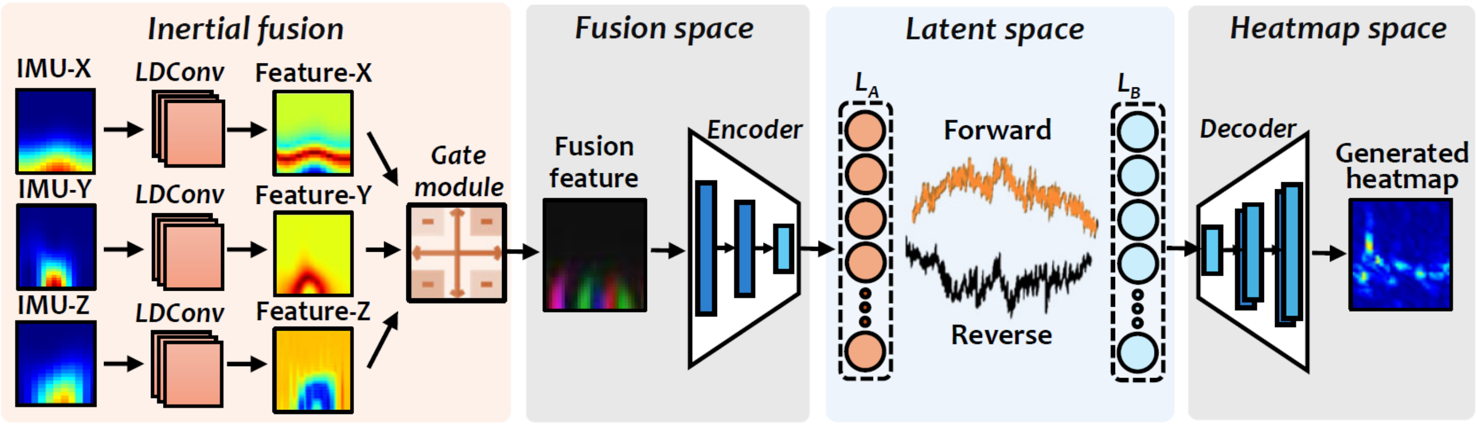


Extracted IMU spectrogram

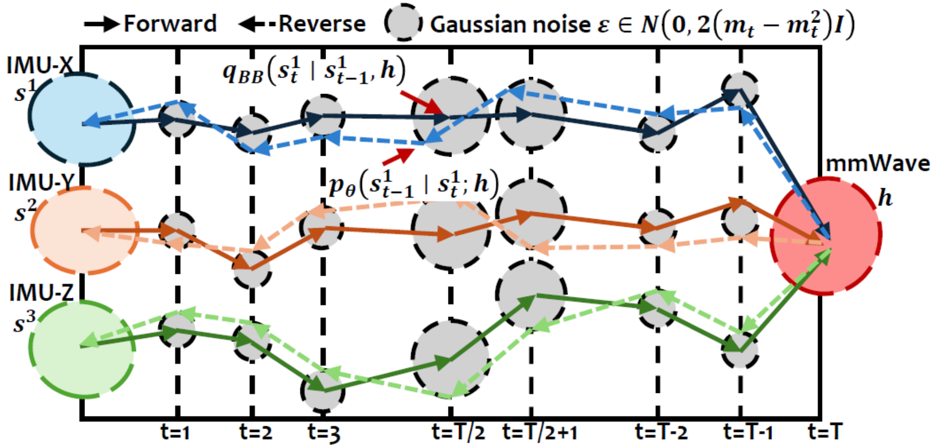
System design

❑ IMU-to-Radar (I2R) diffusion model

- ❖ Bridge diffusion-based translation (Brownian bridge diffusion)
- ❖ It offers direct mapping and bidirectional transformation capabilities, enabling efficient and stable conversions



(a) Structure of IMU-to-Radar diffusion model



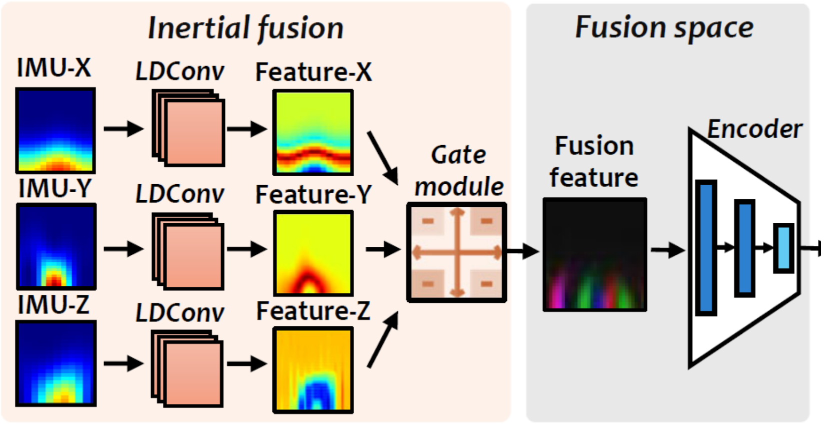
(b) Forward and reverse process

I2R diffusion model.

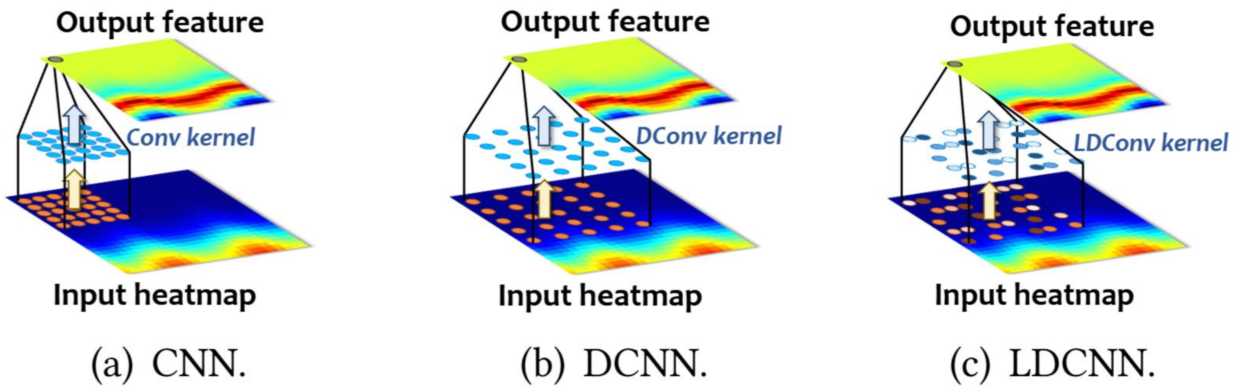
System design

❑ **I2R diffusion model**

- ❖ 1) Learnable Dilated Convolutional Neural Network (LDCNN)-based feature extraction
- ❖ 2) Gate module for feature fusion



Inertial fusion

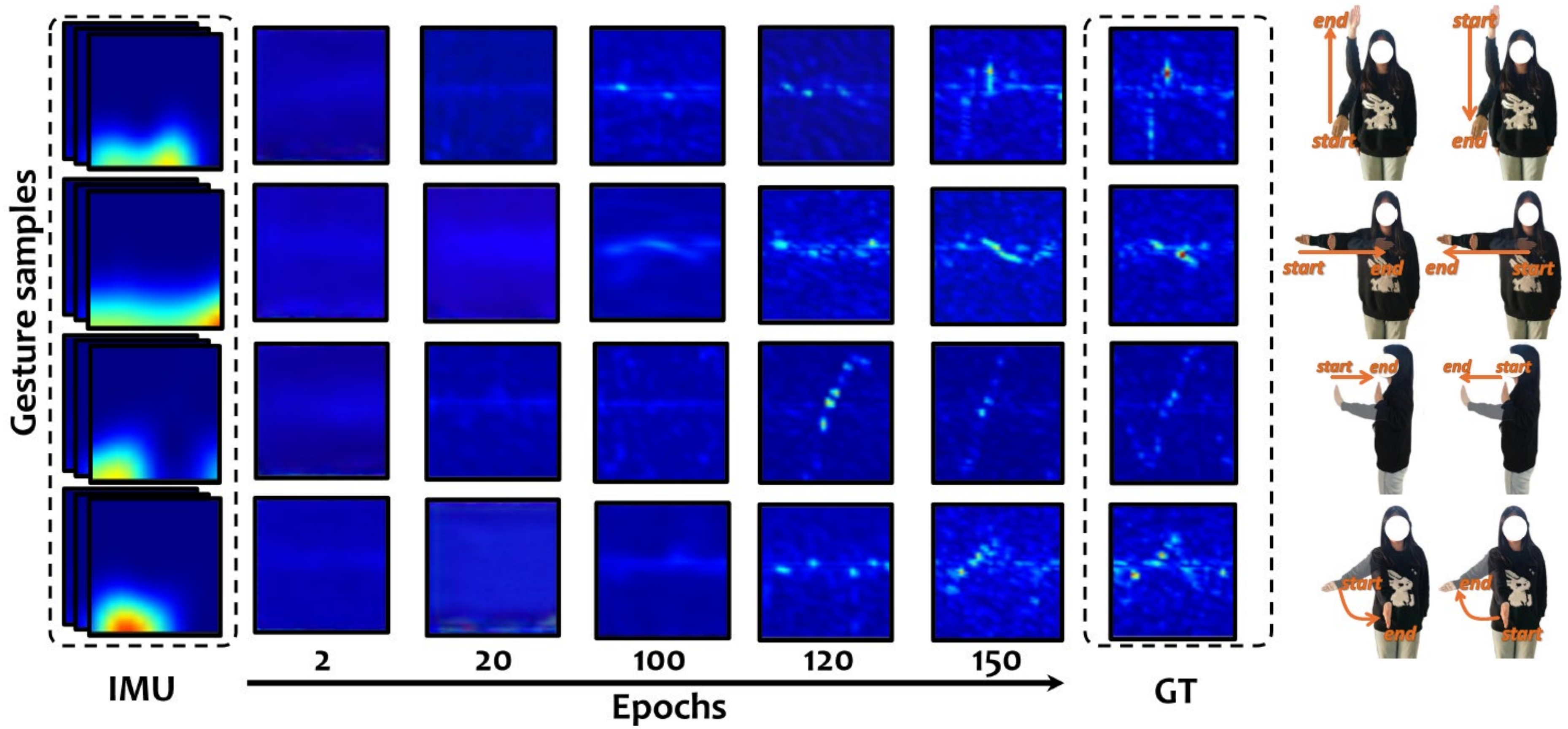


Learnable Dilated Convolution

System design

❑ I2R diffusion model training progress

- ❖ Front raise, lateral-to-front raise, push, and forearm supination

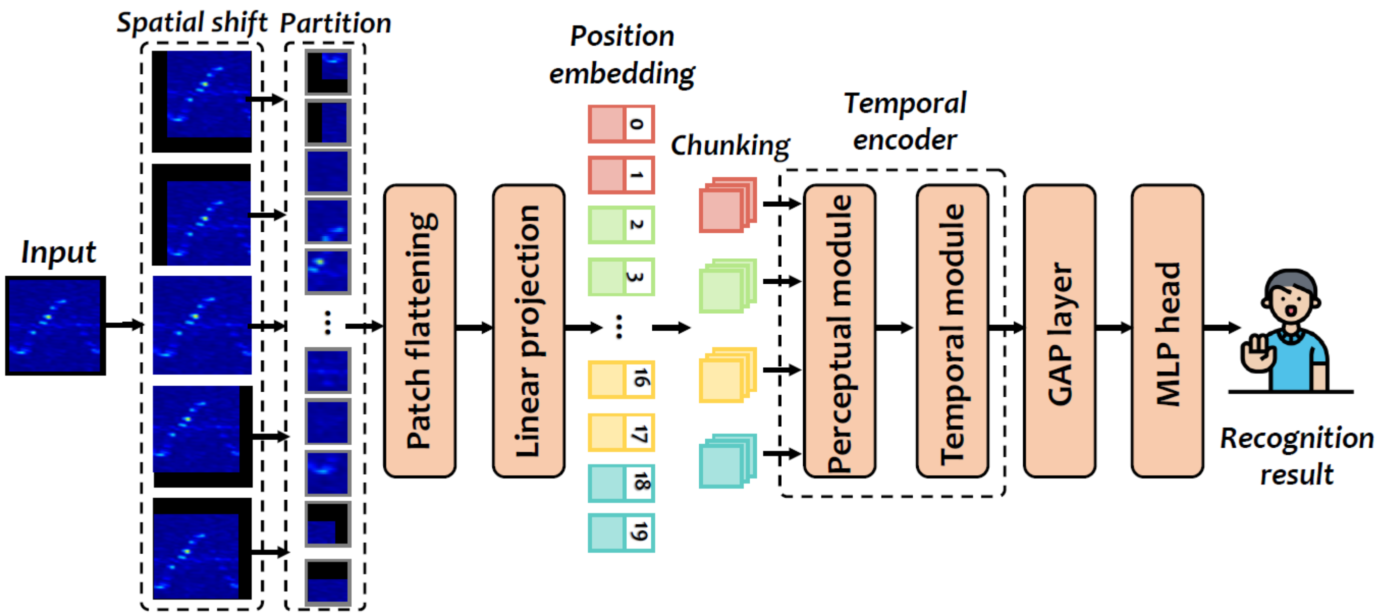


Training progress for various gestures.

System design

❑ Doppler transformer for gesture recognition

- ❖ Spatial heatmap shift and patch embedding for enriched representation information
- ❖ Temporal attention layer for comprehensive understanding

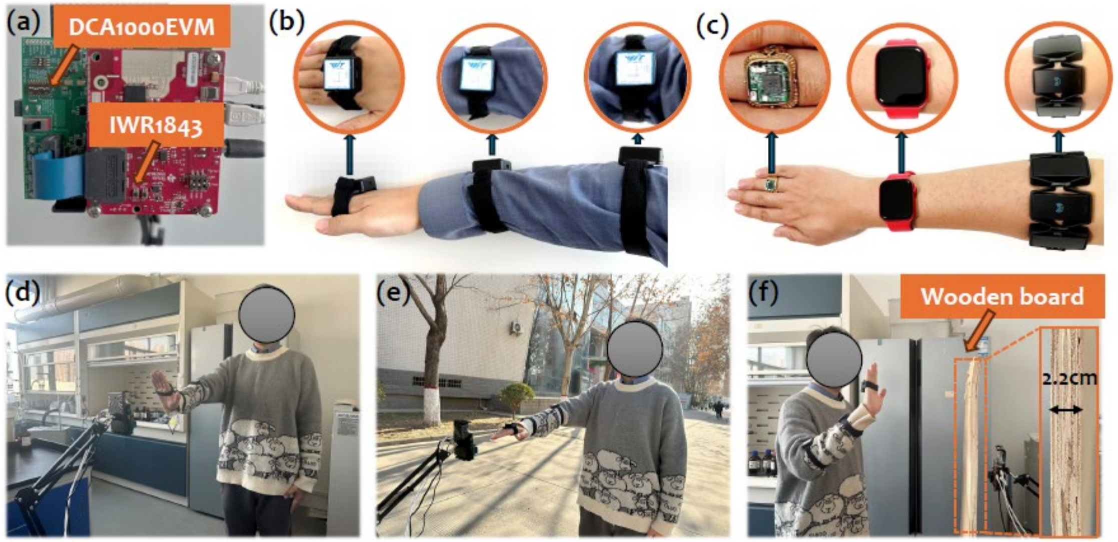


Doppler transformer

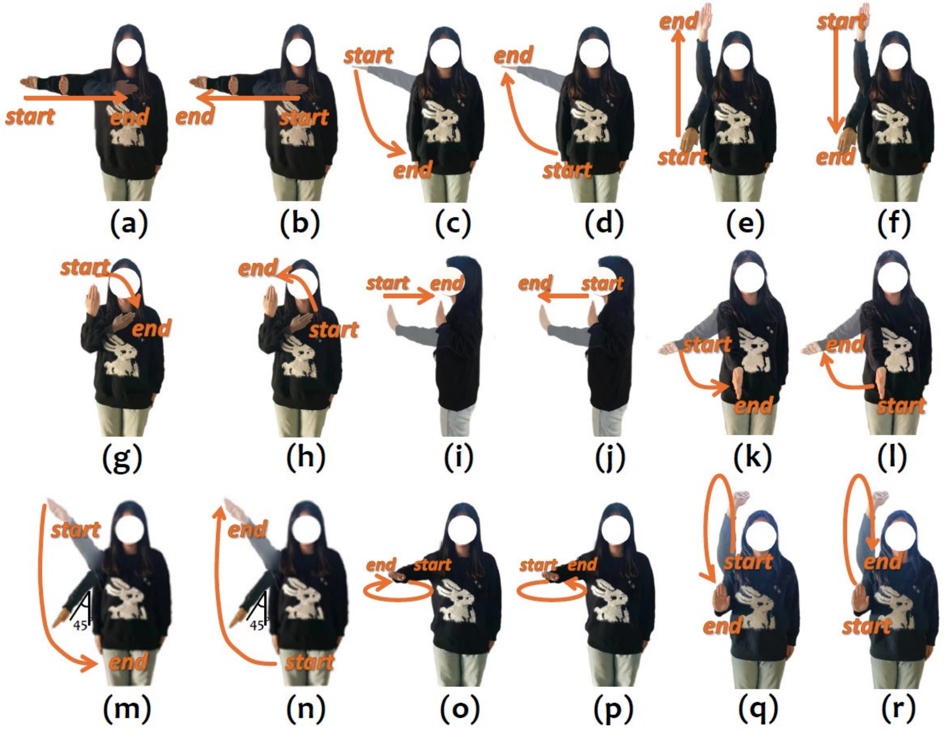
Experimental settings

❑ Data collection

- ❖ IWR1843 mmWave radar and different mobile devices
- ❖ Indoor, outdoor, and through-wall experiments
- ❖ 18 distinct gestures



Devices and scenarios

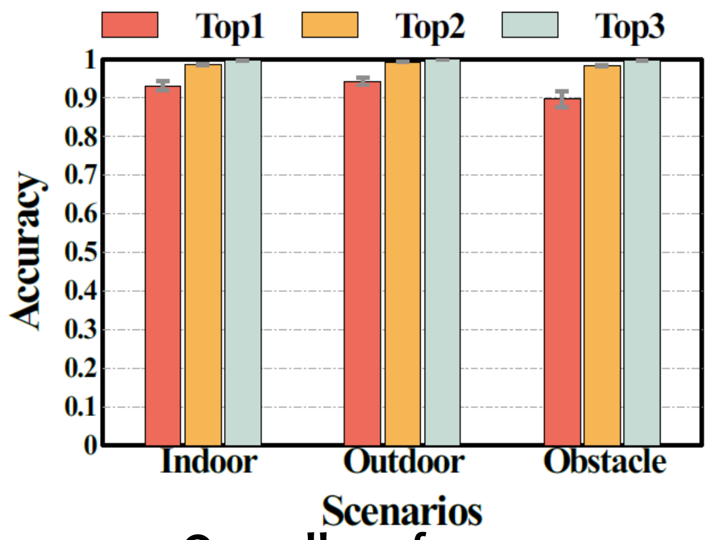


Gestures in the dataset.

Experiment results

❑ Overall performance

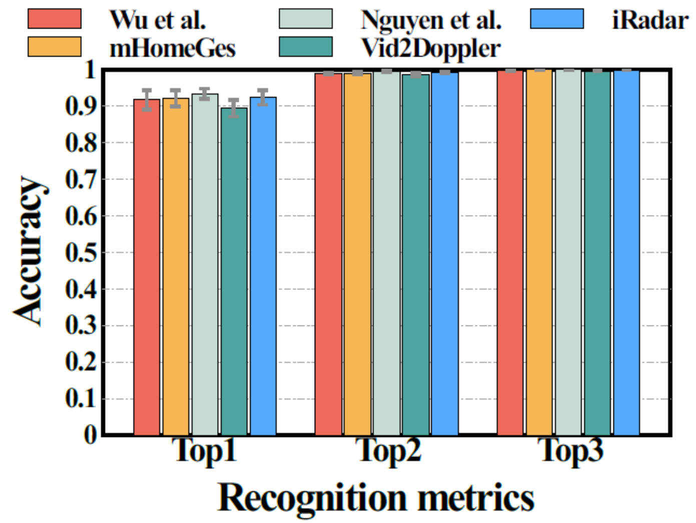
- ❖ The Top-1 accuracy for indoor, outdoor, and through-obstacle are 93.1%, 94.3%, and 89.6%, respectively.
- ❖ Top-3 accuracy values are above 99%.



Overall performance

❑ Comparison with baselines

- ❖ *Wu et al.* (Doppler map-based), *mHomeGes* (point clouds-based), *Nguyen et al.* (IMU-based), and Vid2Doppler (video translated mmWave heatmaps).
- ❖ iRadar demonstrated comparable performance to state-of-the-art systems.



Comparison with baselines

Conclusion & future work

- We introduce iRadar, the first mmWave-based gesture recognition system that addresses the key limitations of explicit data collection.

- Our comprehensive evaluation shows iRadar's exceptional performance, achieving over 99% Top-3 accuracy across diverse scenarios.

- Future work will be directed towards expanding the application of this system to other use-cases such as human activity analysis.

Thank you!