XGait: Cross-Modal Translation via Deep Generative Sensing for RF-based Gait Recognition

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Background

❑ Gait-based person recognition

- ❖ A gait is a manner of limb movements made during locomotion (walking).
- ❖ Different individuals have different gait patterns.
- ❖ Gait recognition does not require a person to perform any specific active task.

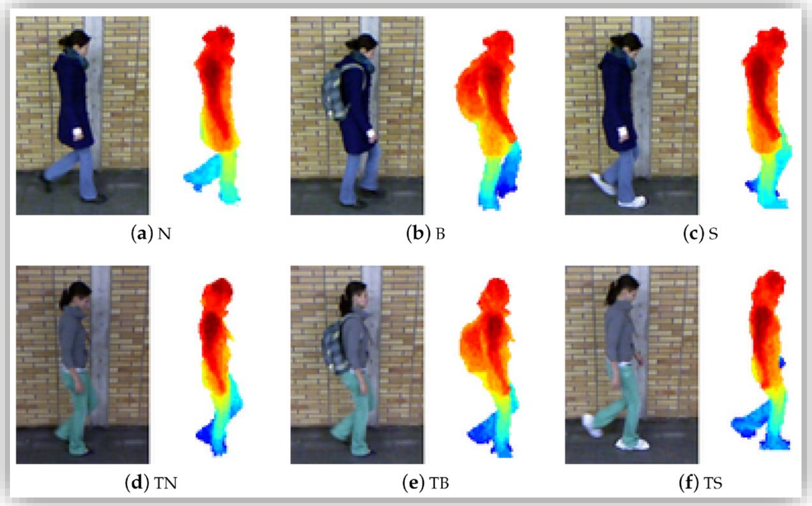
Person gaits

Gaits for different individuals

Background

❑ Gait recognition solutions

- ❖ Video-based solutions require an unobstructed view of the person in good lighting.
- ❖ Wearable-based solutions need user to pick up or wear the device on the body.



Camera-based solutions

Wearable-based solutions

Background

❑ Existing Radio Frequency (RF)-based gait recognition

- ❖ Versatile and penetrates obstacles, and not affected by lighting conditions.
- ❖ **Limitation 1 :** Deployment of RF devices in the data collection area.
- ❖ **Limitation 2 :** Users visiting the target area to pre-collect a few instances.

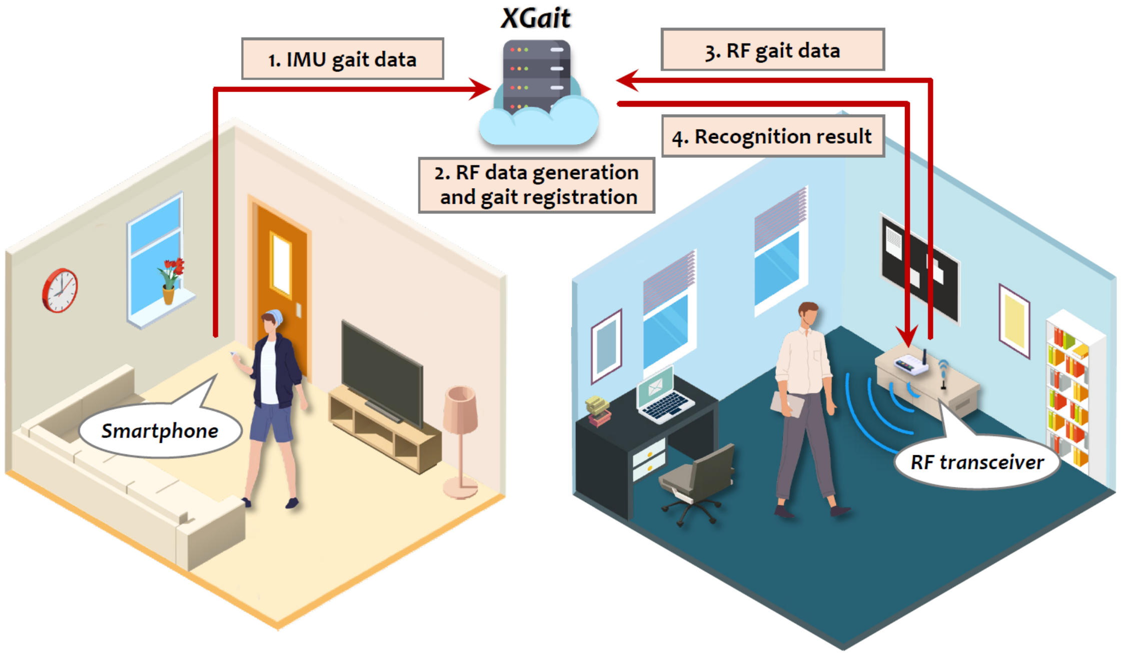
RF sensing-based gait recognition system

Redundant user registration (data collection) process.

Our solution

❑ XGait: Cross-Modal Translation via Deep Generative Sensing for RF gait recognition

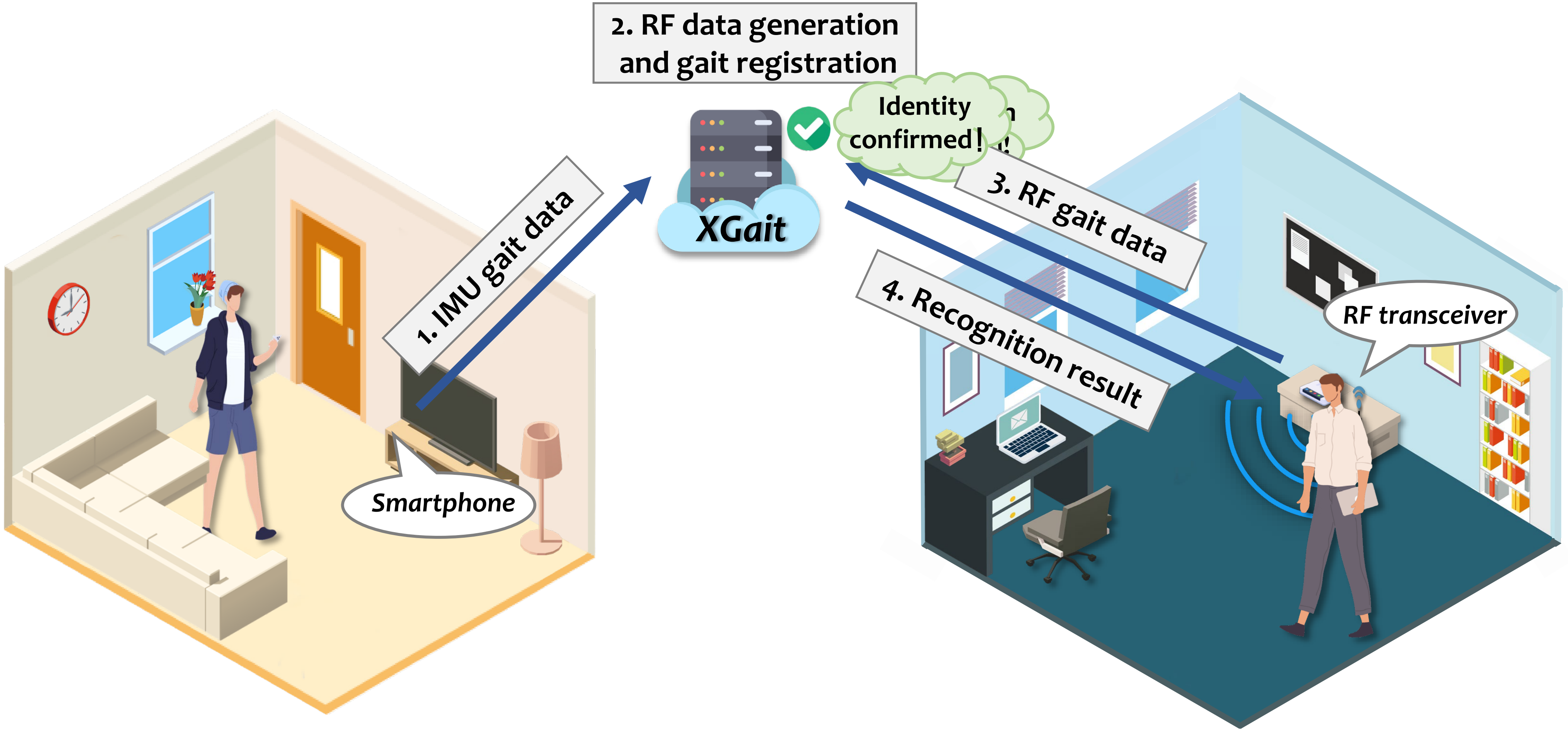
- ❖ Leverage the Inertial Measurement Unit (IMU) signal in modern mobile devices to simulate the RF signals that would be generated if the same person walked near RF devices.
- ❖ Eliminate the need for prior RF data collection.



(a) Home: Gait registration using IMU (b) Office: Gait recognition using RF signal

An application scenario of XGait

Our solution



Register at anywhere

RF sensing-based identification

Challenges

❑ Diversity of RF devices

- ❖ Various RF signals operate at different frequencies and use different modulation methods.
- ❖ Consistently extracting and representing essential gait features across different RF signals remains a challenge.

❑ Intrinsic difference between IMU and RF signals

- ❖ Due to the complex nature of human walking patterns, it is difficult to derive corresponding RF data from IMU data using mathematical calculations.

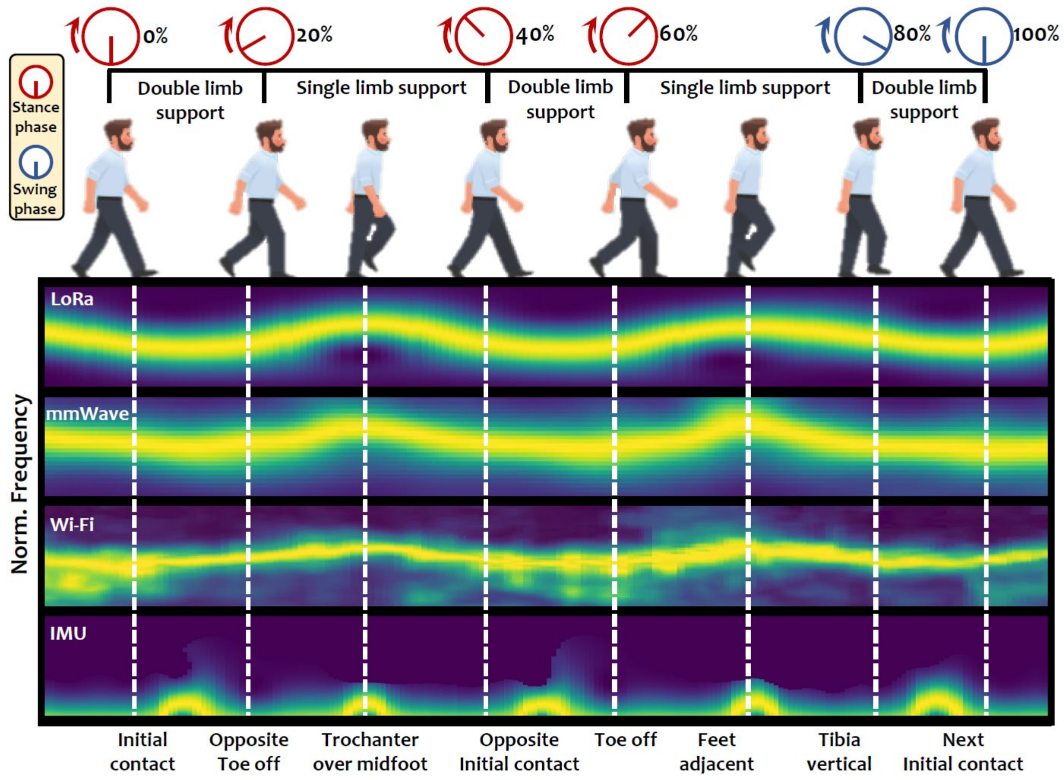
❑ Complexity of gait

- ❖ Gait is the coordinated movement involves 2 phases, 8 events, and 24 body parts.
- ❖ Similarity of gait signals among different people further hampers the recognition accuracy.

Feasibility study

❑ Correlation model

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

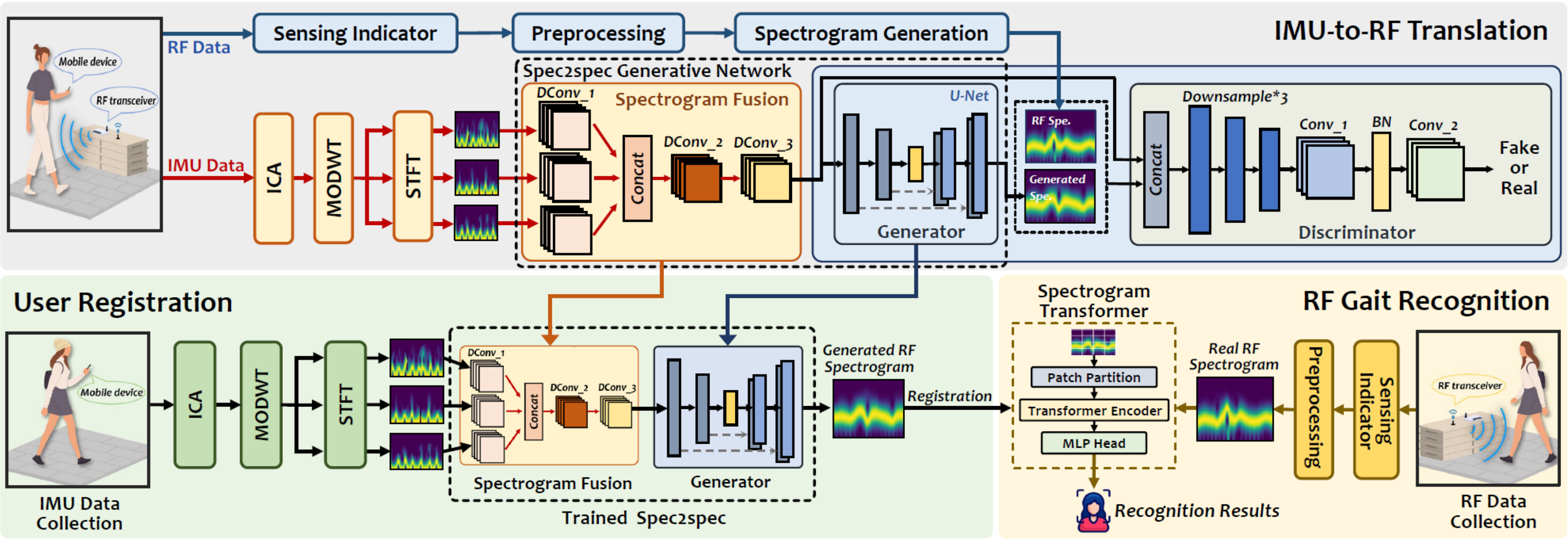


Gait cycle and the corresponding spectrograms

System overview

❑ XGait workflow

- ❖ 1) User Registration, 2) IMU-to-RF Translation, 3) Gait Recognition.

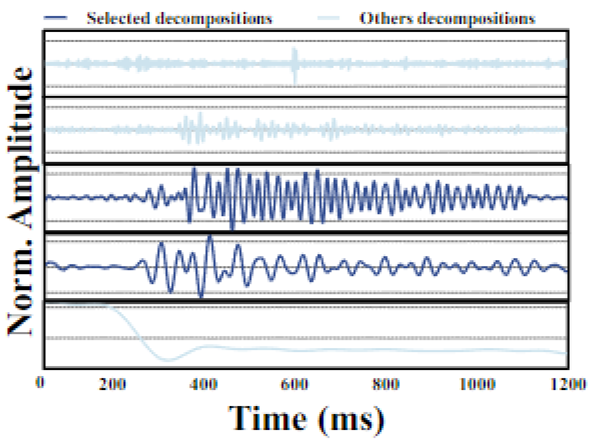


System overview

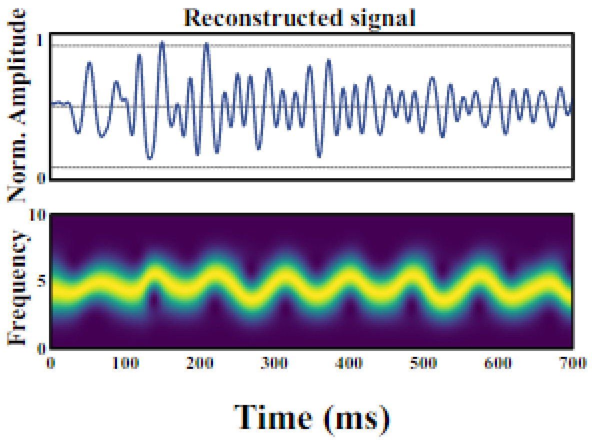
System design

❑ RF/IMU signal processing and spectrogram generation

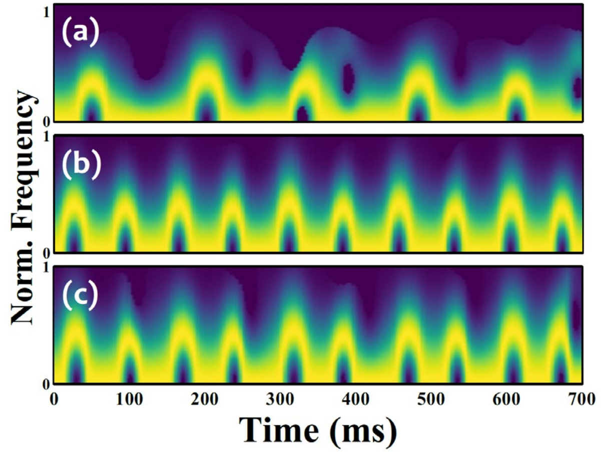
- ❖ Maximal Overlap Discrete Wavelet Transform (MODWT) for denoising.
- ❖ Short-Time Fourier Transform (STFT) for spectrogram generation.



MODWT decomposition



Reconstructed results

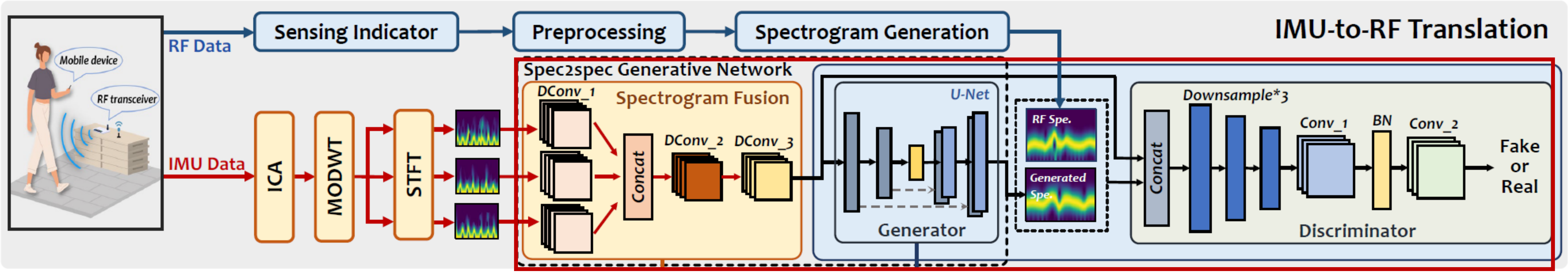


Extracted IMU feature

System design

❑ Spec2Spec generative network for IMU-to-RF translation

- ❖ Deformable Convolutional Network (DCN)-based spectrogram fusion.
- ❖ Conditional Generative Adversarial Network (cGAN) architecture for translation.



Spec2Spec generative network

System design

❑ **Spec2Spec neural network for IMU-to-RF translation**

- DCN-based spectrogram fusion.
- Spectrogram translation using cGAN architecture.

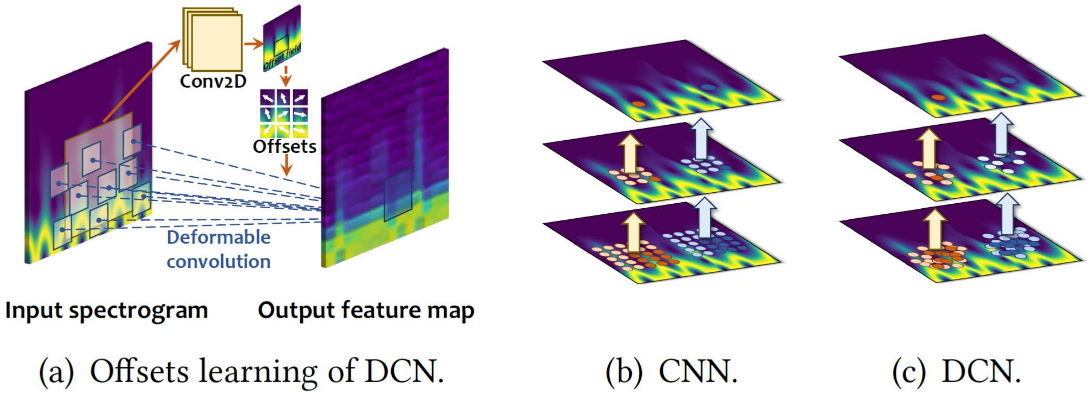
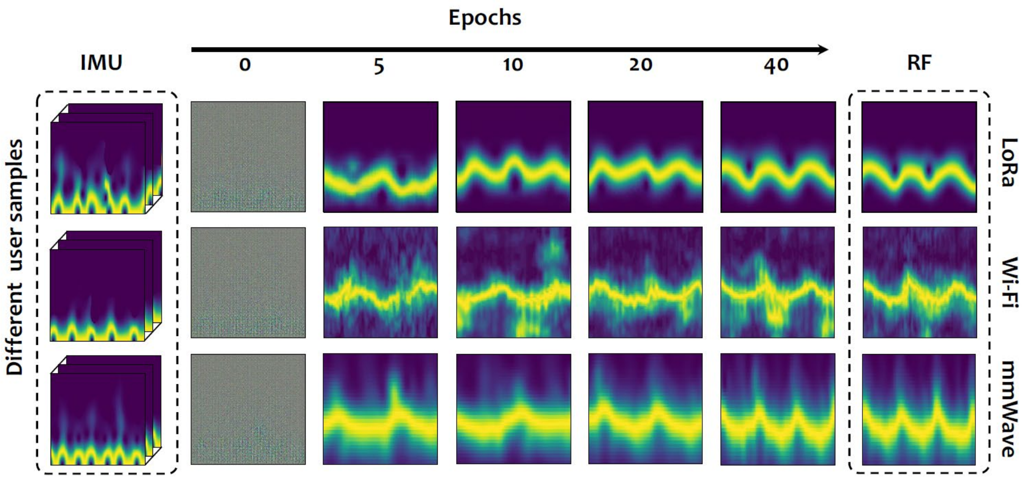


Illustration of the deformable convolution

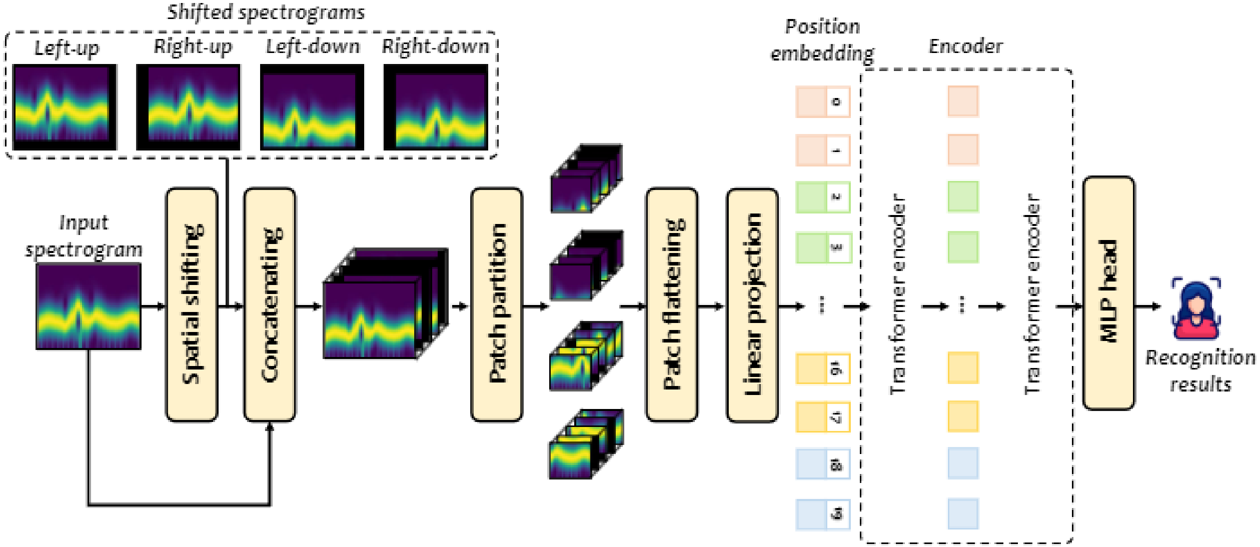


Training progress

System design

❑ Spectrogram transformer for gait recognition

- ❖ Shifted spectrogram patches, patch embedding layer, locality self-attention mechanism.
- ❖ Address the data-hungry nature and complex training requirements of conventional transformer models.



Spectrogram transformer

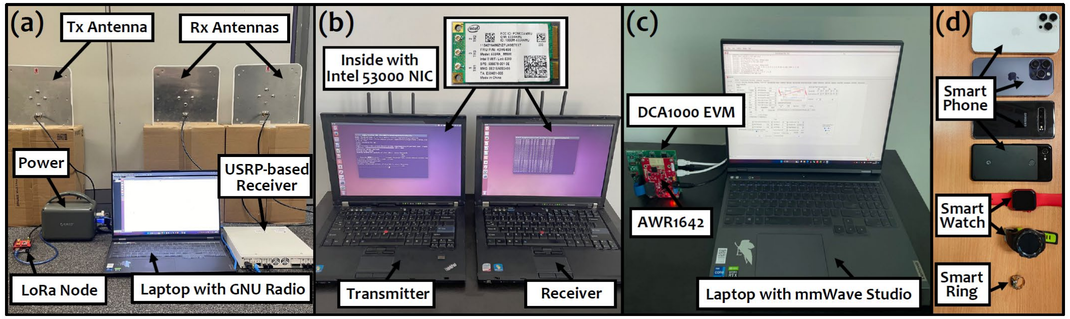
Experimental settings

❑ Data collection

- ❖ Wi-Fi, LoRa, mmWave RF devices and different mobile devices.
- ❖ Indoor, outdoor, and through-wall experiments.

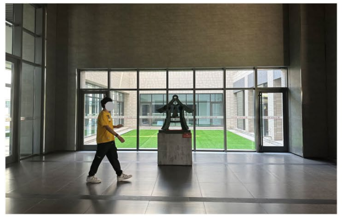
❑ Metrics

- ❖ Top-N accuracy: this measures how frequently the correct user appears within the top N predictions.

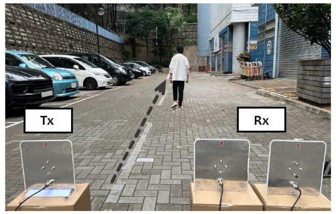


Devices

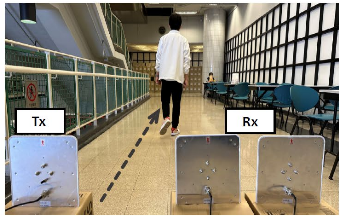
(a) Outdoor registration.



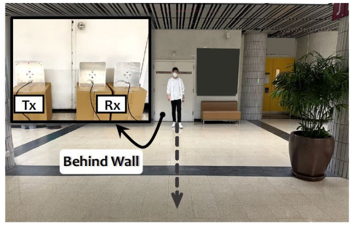
(b) Indoor registration.



(c) Outdoor recognition.



(d) Indoor recognition.



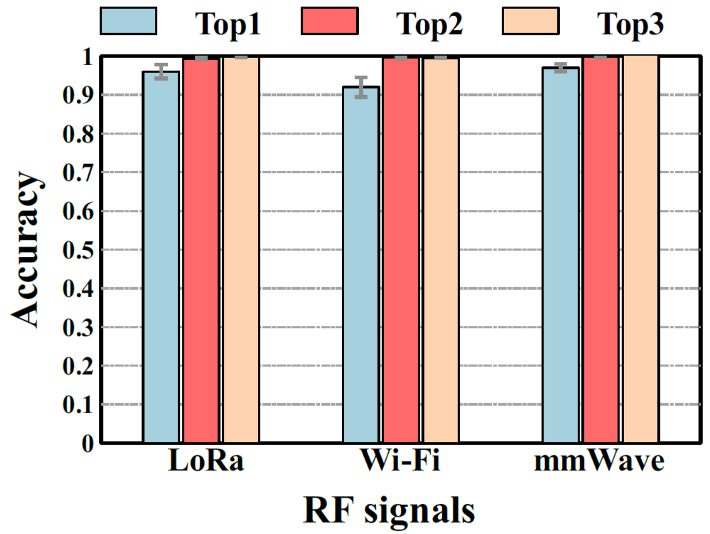
(e) Through-wall recognition.

Scenarios

Experiment results

❑ Overall performance

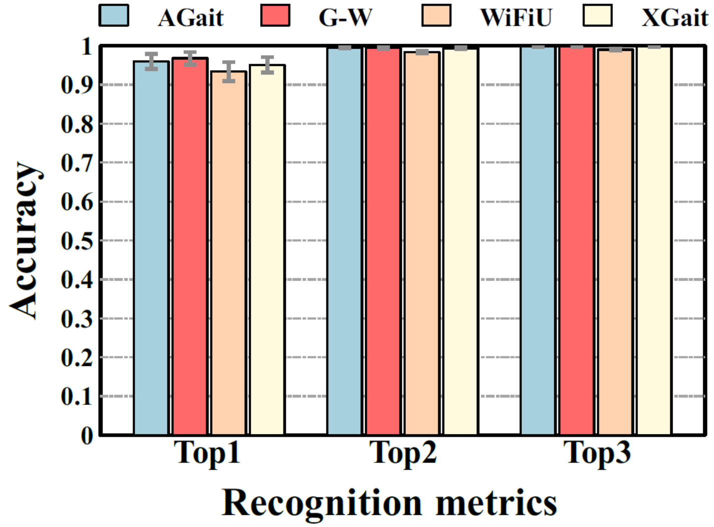
- The Top-1 accuracy for LoRa, Wi-Fi, and mmWave are 96.21%, 92.14%, and 96.97%, respectively.
- Top-3 accuracy values are above 99%.



Overall performance

❑ Comparison with baselines

- *AGait* (RF-based), *Gait-Watch* (IMU-based), and *WiFiU* (RF-based with explicit features).
- XGait demonstrated comparable performance to state-of-the-art systems.



Comparison with baselines

Conclusion&future work

- We introduce XGait, the first RF-based gait recognition system that addresses the key limitations of existing RF devices and explicit data collection methods.

- Our comprehensive evaluation shows XGait'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 gait abnormality analysis.

Thank you!