

GPSense: Passive Sensing with Pervasive GPS Signals



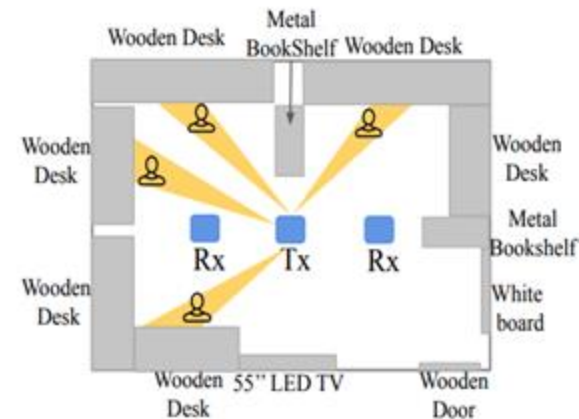
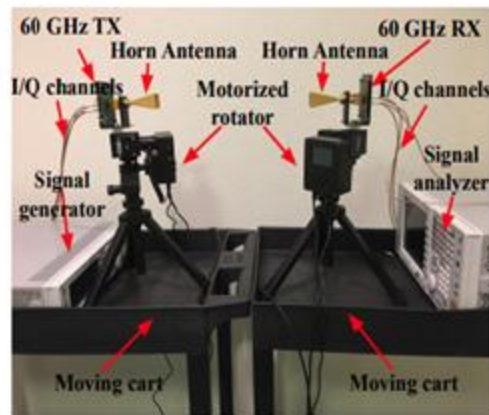
Presenter: Yunxiang Chi
11/13/2025

Background

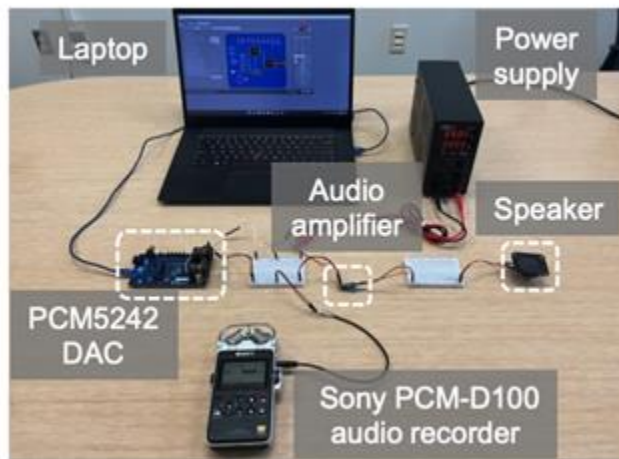
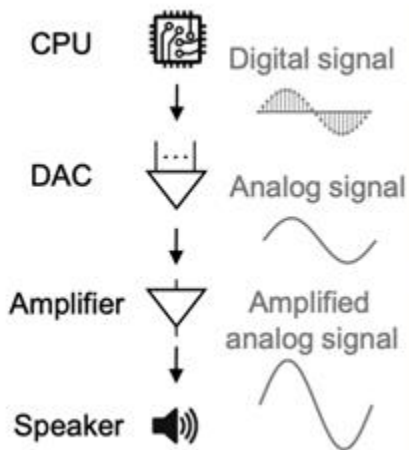
UWB(3-10.6GHz)



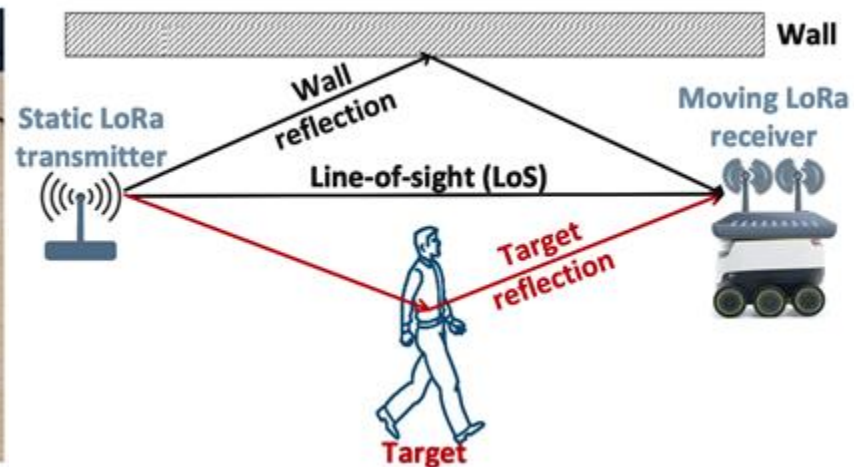
mmWave(24-100GHz)



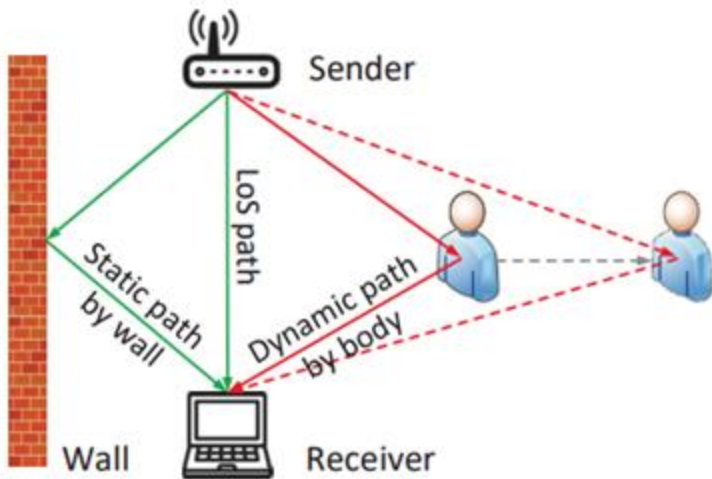
Acoustic



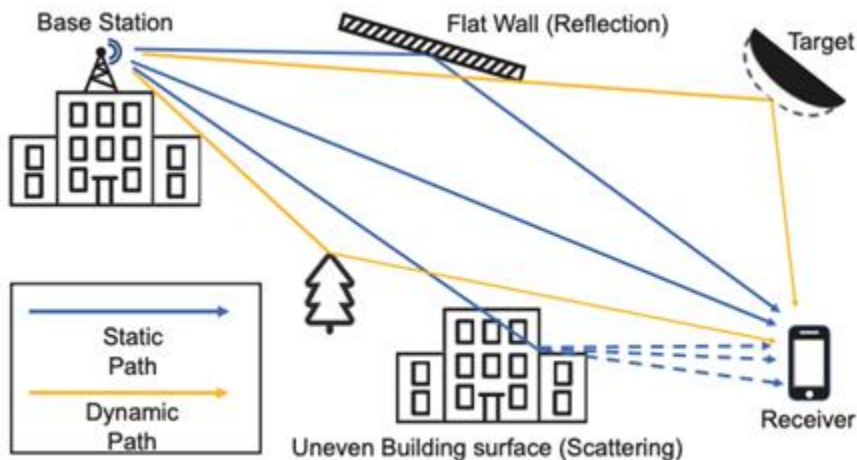
LoRa(915MHz)



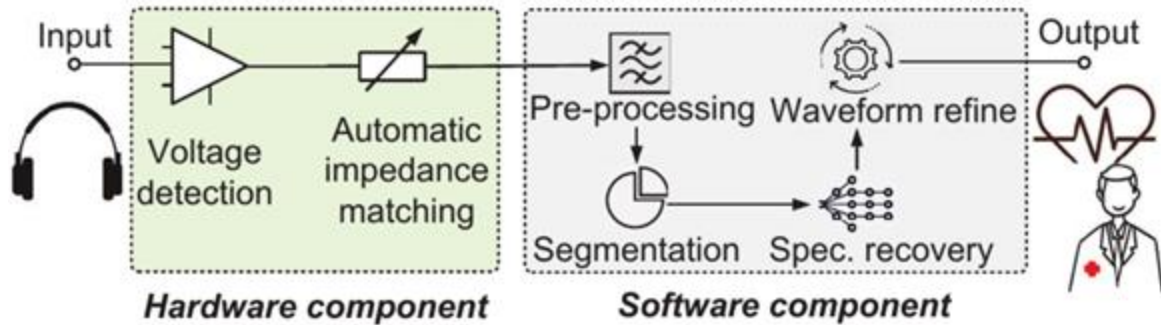
WiFi(2.4, 5GHz)



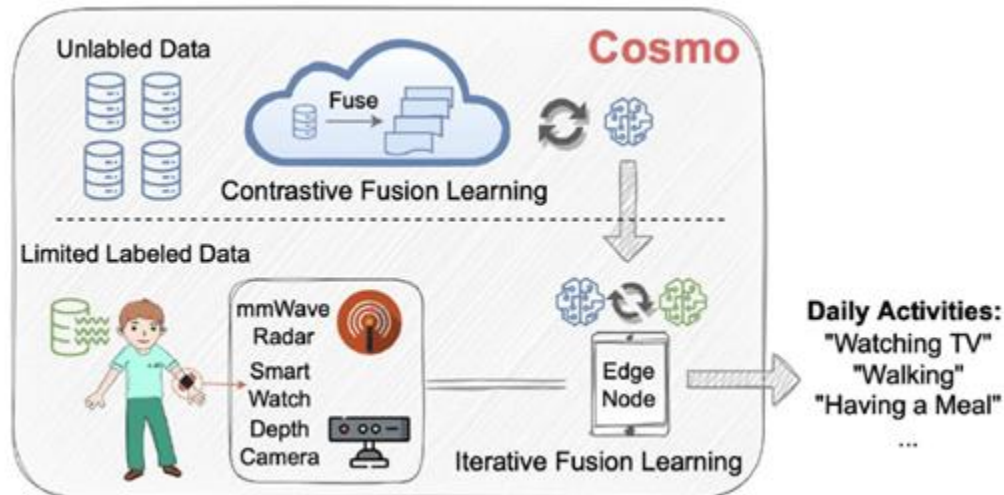
LTE(Sub 6GHz)



Subtle Motion(Vital Signs)



Large motion(Human Activity)



Limitations

1. Sensing coverage

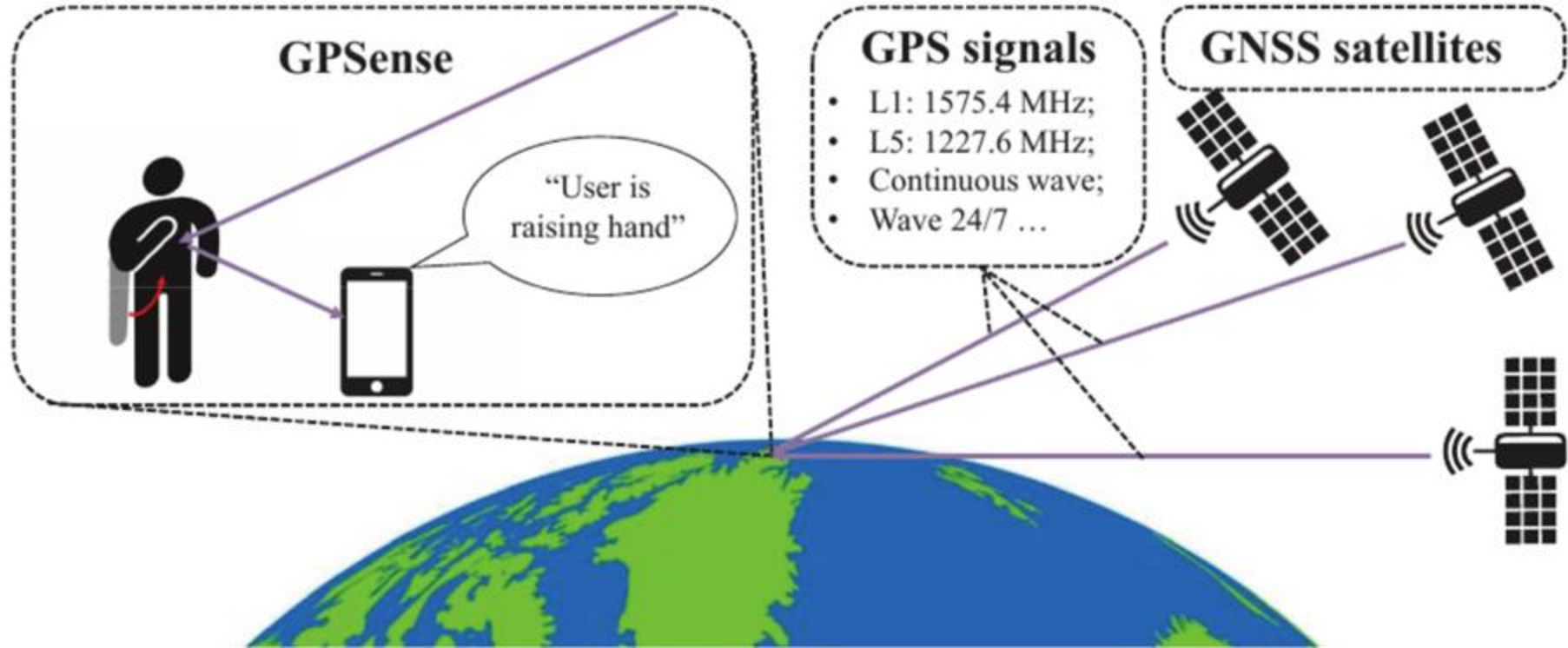
- a. WiFi, UWB, mmWave, etc. -> sensing in meters
- b. LoRa -> sensing in hundreds of meters or km
- c. LTE -> sensing in km
- d. But LoRa and LTE require wide deployment and still ~30% of the US is not covered

2. Affect communication functionality

- a. Interference (e.g. LoRa in the LSencom paper)
- b. Degradation of data rate (e.g. 100-1000 packets/sec need to be transmitted for sensing)

[1] <https://www.historytools.org/products/starlink-vs-lte-how-do-they-compare>

[2] Wilmg: Pushing the Limit of WiFi Sensing with Low Transmission Rates, Yang et al.



Passive Sensing by GPS satellites

- 95% of the earth are covered by at least 4 GPS satellites
- Continuously emit signals 24/7
- No requirement for wear/hold the GPS receiver stationary

Challenge 1 - Data Granularity

Most commercial GPS receiver modules only reports navigation-level quantities that are useful for positioning:

- **Carrier-to-noise-density ratio:** The average signal-to-noise ratio that measures how “strong and clean” the satellite signal is, used for receiver quality and satellite selection—not for waveform analysis.
- **Pseudorange:** The apparent distance between Tx and Rx, derived from delay.
- **Accumulated Carrier Phase**

But what crucial for wireless sensing are not here:

- **Amplitude**
- **Phase**

Thus, require **signal reconstruction** from the coarse navigation-level quantities

$$C/N_0 = 10\log_{10}\left(\frac{P_c}{P_n/B}\right), \quad (1)$$

where P_c is the power of the GPS carrier, P_n is the power of the noise and B is the bandwidth.

$$\rho = r + ct_b + \varepsilon_\rho, \quad (2)$$

where r is the geometric range between the receiver and the satellite, ε_ρ is the measurement error, c is the light speed, and t_b is the clock bias of the receiver.

$$\Phi = \frac{r_0}{\lambda} + \int_0^t f_D t dt + \varepsilon_\Phi, \quad (3)$$

where f_D is the frequency shift caused by Doppler effect, r_0 is the initial geometric range between the receiver and the satellite, and ε_Φ is the measurements errors. Note that phase

Challenge 2 - Lack of Model

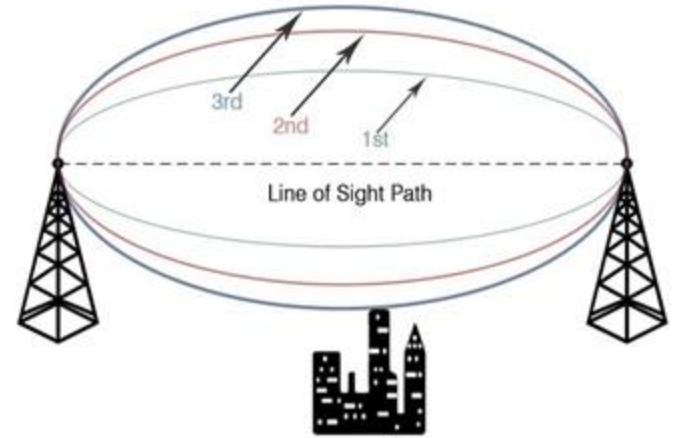
Fresnel Zone Model are mostly used in WiFi, mmWave, LTE, UWB, etc. for wireless sensing
For GPS geometry:

- Satellite altitude $\approx 20\text{-}200\text{km}$ (MEO, or GEO even more)
- Wavelength $\lambda \approx 0.19\text{m}$ (L1 band)
- Target–receiver separation $d \approx 1\text{--}10\text{m}$

$$r_1 = \sqrt{\frac{\lambda d_1 d_2}{d_1 + d_2}} \approx \sqrt{\frac{0.19 \times (2 \times 10^7 \text{m} \times 10 \text{m})}{2 \times 10^7 \text{m}}} \approx 0.43 \text{m}$$

Plus, MEO/GEO moving 4km/s , phase is wildly spinning due to satellite motion

Channel is also non-static, time-varying

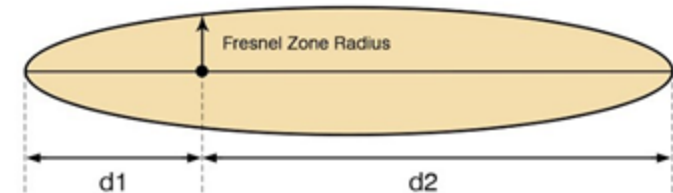


$$\text{Fresnel Zone radius, } R = \sqrt{\frac{n d_1 d_2 \lambda}{d_1 + d_2}}$$

Where,

n = Fresnel Zone number (Should be greater than zero)

λ = Wavelength



Challenge 3 - Satellites Variety

GNSS(global navigation satellite system)
satellites in MEO and GEO moving at
different speeds:

- GPS
- Galileo(Europe)
- Beidou(China)

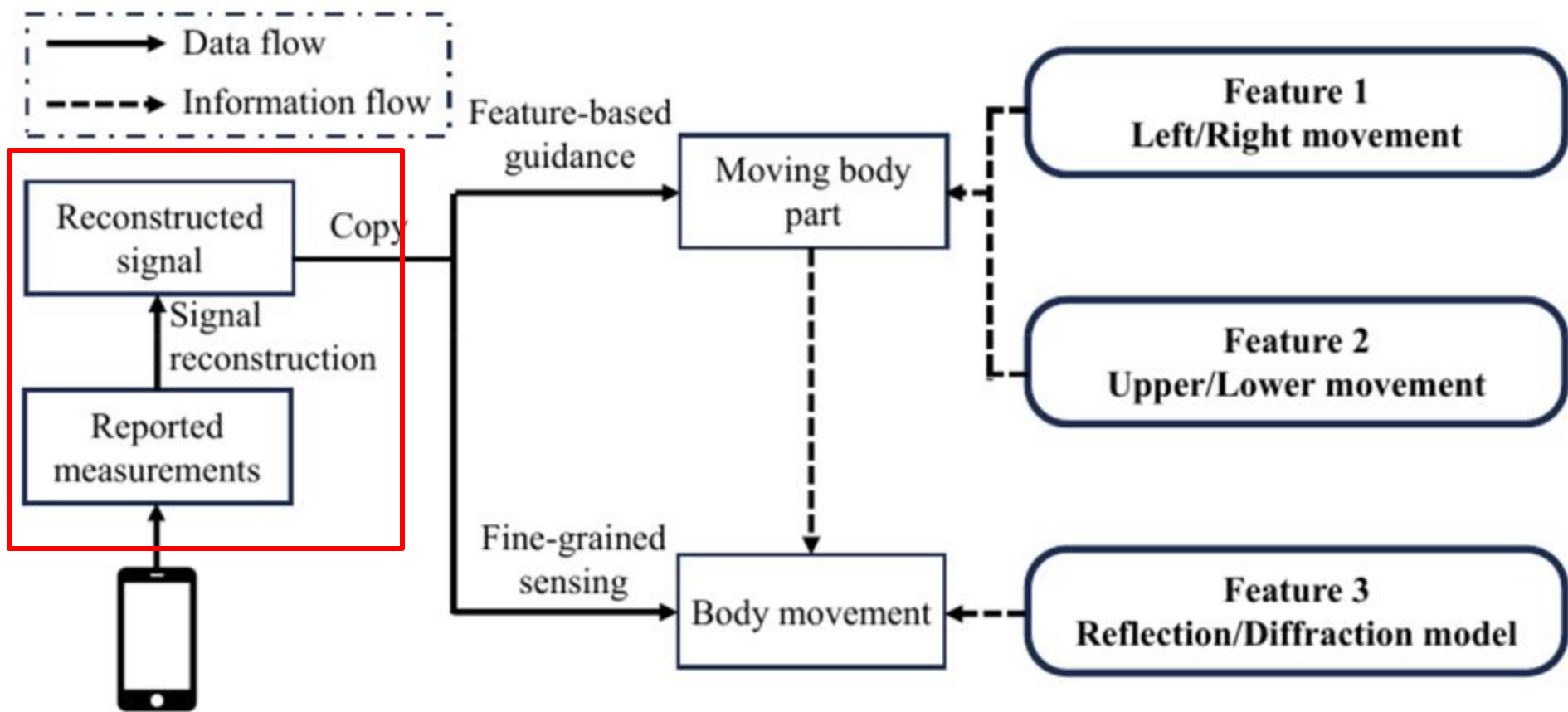
-> a GNSS receiver can get signals from
over 30 satellites above at the same time

GNSS satellites moves faster than earth
rotation

-> the satellites a receiver can capture
signals from vary during a day

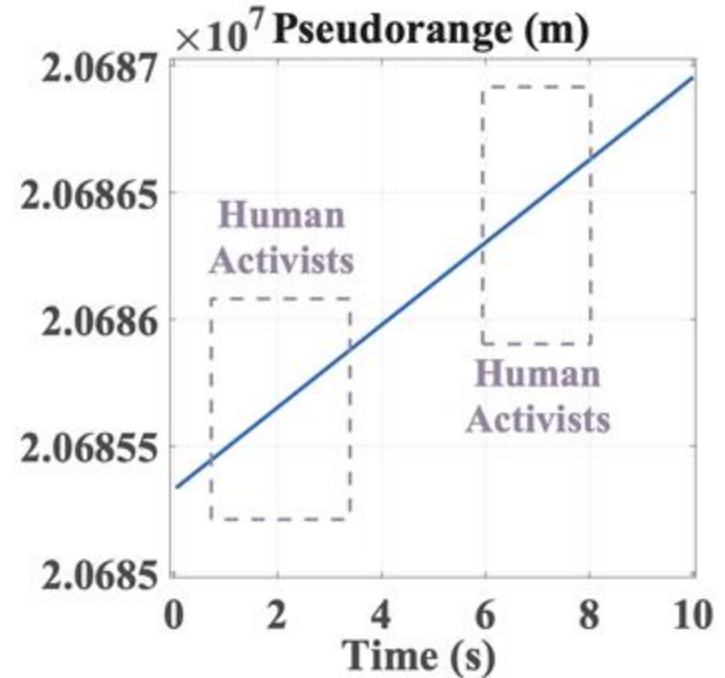


Design



Why measurements can't be used

1. Measurement errors -> sensing signal variation can be buried by the variations from errors
 - a. Weather
 - b. **Clock-drift**
 - c. **Satellite Movements**
2. Too coarse for fine-grained sensing(e.g. respiration)



Pre-processing

- GPS movements

Publicly accessible ephemeris data (sat locations & c)

-> estimation of movement status

-> calculate the effect of the Doppler frequency

-> compensate the phase error from f_D in accu

- Pseudorange: $\rho_i = r_i + ct_b + \varepsilon_i$

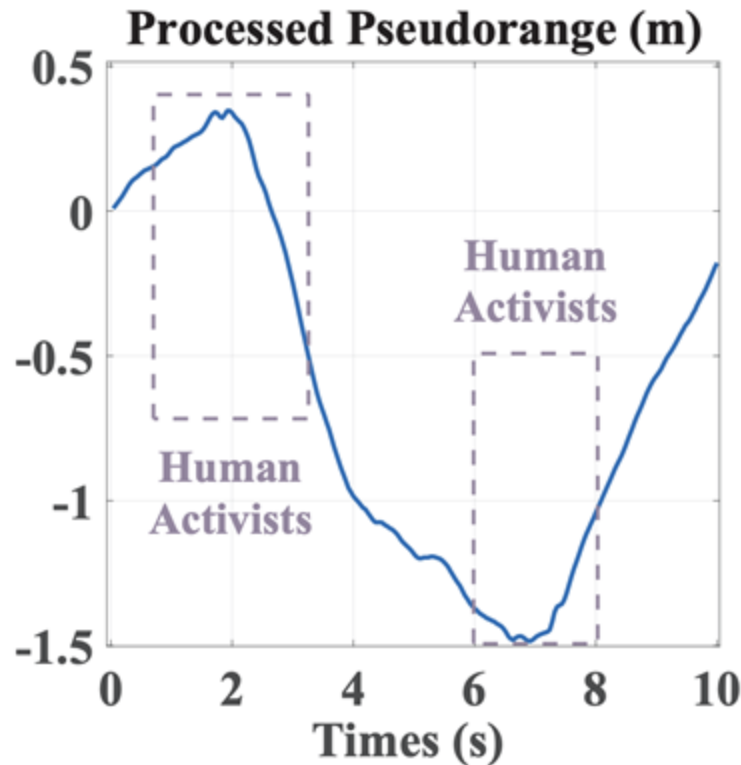
$$\rho = Hx + v, \quad x = [x, y, z, ct_b]^T$$

$$\hat{x} = (H^T W H)^{-1} H^T W \rho$$

$$\hat{x} = \begin{bmatrix} \hat{x} \\ \hat{y} \\ \hat{z} \\ \hat{ct}_b \end{bmatrix}$$

$$\begin{bmatrix} \rho_1 \\ \rho_2 \\ \vdots \\ \rho_N \end{bmatrix} = \begin{bmatrix} \hat{r}_1 \\ \hat{r}_2 \\ \vdots \\ \hat{r}_N \end{bmatrix} +$$

$$\rho_i^{\text{corrected}} = \rho_i - \hat{ct}_b$$



Reconstruct signal

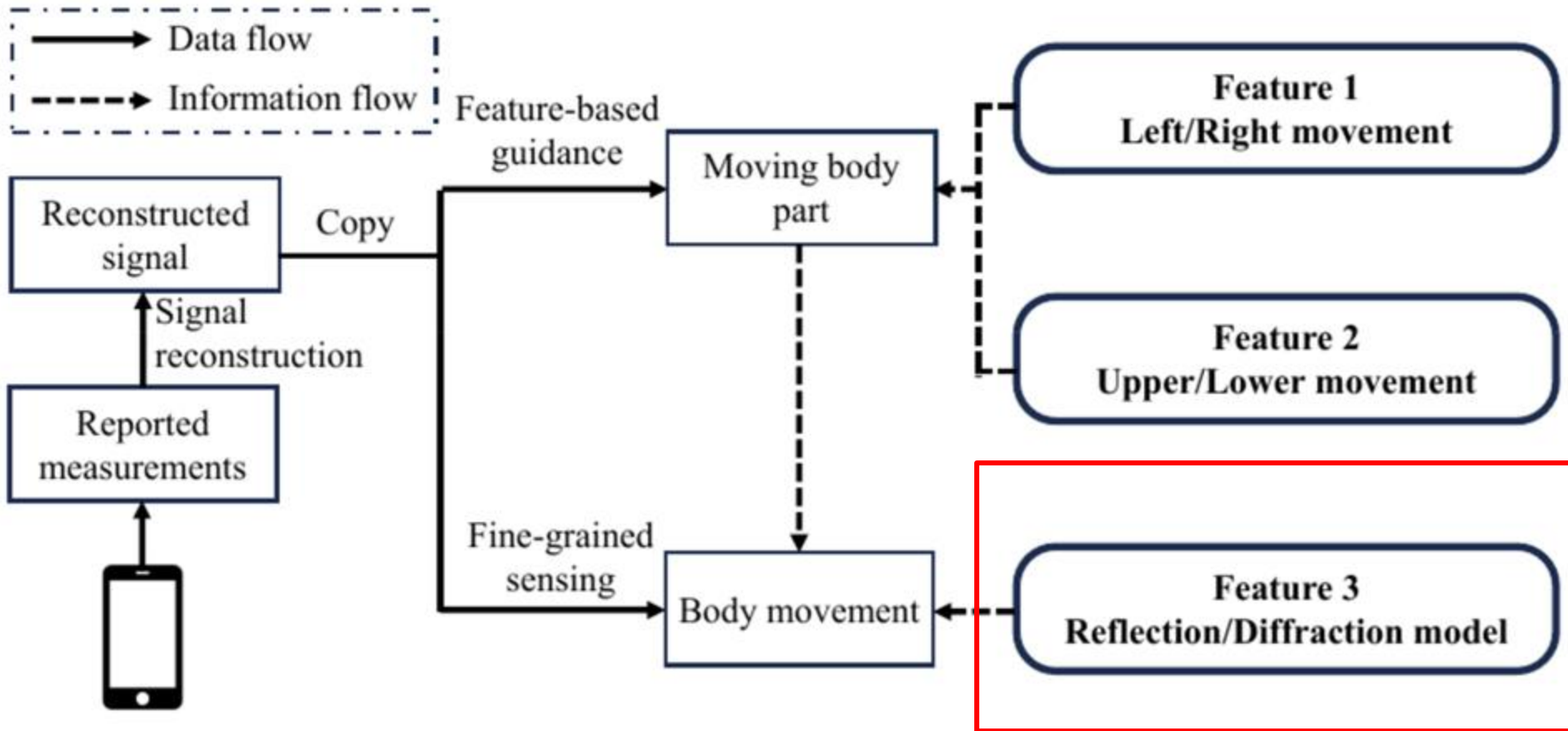
$$Amp(t) = \sqrt{P_n 10^{(C/N_0)/10}}, \quad (4)$$

where $P_n = kT$ is the noise power in a 1-Hz bandwidth [22], k is the Boltzmann constant in Joules per Kelvin, T is the temperature in Kelvin, and C/N_0 is the reported Carrier-to-noise-density ratio. The carrier phase ϕ of the GPS signal

$$\phi(t) = 2\pi\left(\frac{d\Phi}{dt} - f_D t + \frac{\rho - ct_b}{\lambda}\right), \quad (5)$$

where Φ is the reported accumulated carrier phase, ρ is the reported pseudorange, f_D is Doppler frequency shift caused by the satellite movement, t_b is the clock bias of the receiver.

$$S(t) = Amp(t)e^{j\phi(t)}. \quad (6)$$



Challenge 2 - Lack of Model

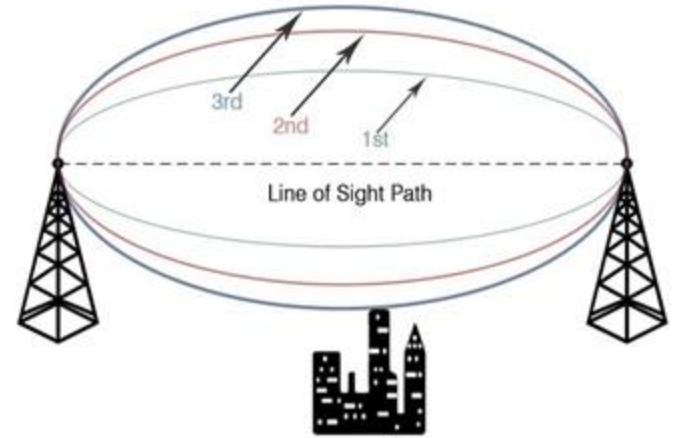
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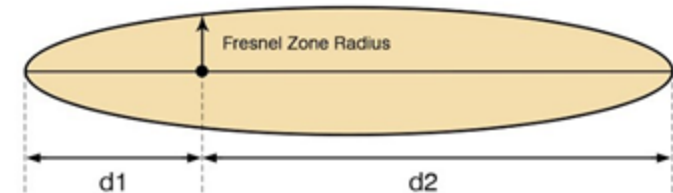


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Where,

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Reflection Model

Target moves -> receiver captures signal from LoS and reflection path d_r from the target

-> horizontal distance from Rx to target: $d = d_r \cos \theta$

-> phase difference: $\phi_{Reflect} - \phi_{LoS} = \frac{4\pi d \cos \theta}{\lambda} + \pi$

Assumed elevation angle is constant in short time

-> Everytime $\Delta\phi$ increases by 2π

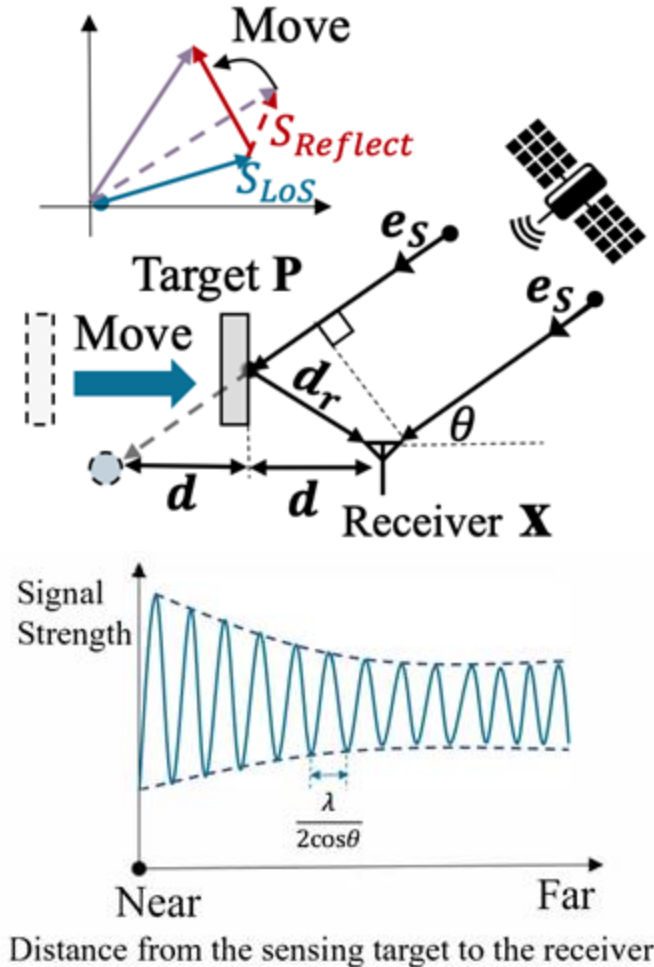
-> one constructive -> destructive -> constructive cycle

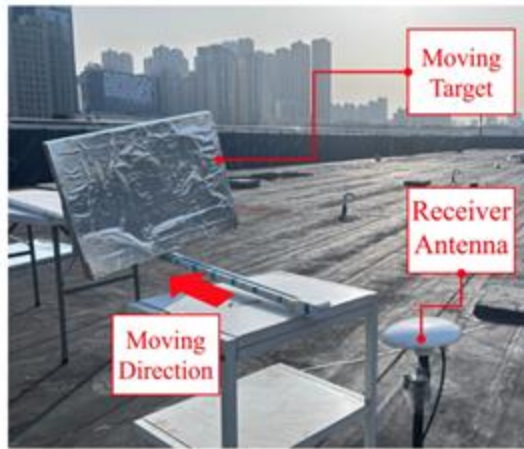
-> d between consecutive peaks: $\Delta d = \frac{\lambda}{2 \cos \theta}$

+ signal strength decreases as target moves from RX

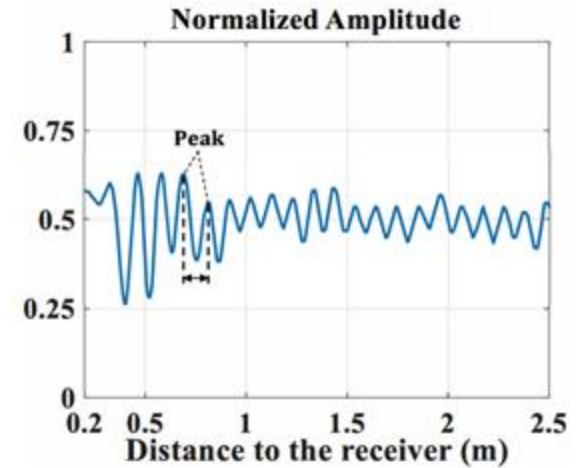
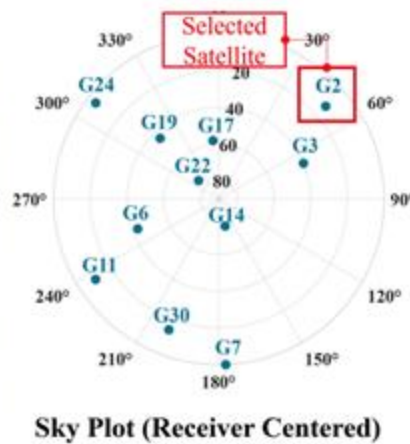
-> target's movement

Weak signal (-120dBm) -> only reflection from large body part, e.g. torso -> use diffraction later to sense arms & legs





(a) Experiment Setup.



(b) Amplitude changes.

Figure 4: Reflection Verification Experiment: a metal box moves away from the GPS Receiver.

- The average of measured moving distances between two peaks is 0.105 m, which matches the theoretical distance (0.101 m)
- For this model, only the reported signal incident angle is required for sensing

Diffraction Model

Diffraction effect dominates when the human target is very close to or on the LoS path of the GPS signal

When a GPS signal wave impinges on the edge of an object, the outgoing rays are in the shape of a cone[1]

A target goes across LoS path between GPS TX and RX

-> signals diffracted at the edge of the moving target

When the target moves further

-> the object's Keller Cone due to diffraction appears

-> RX receives a combination of the diffracted signals

the LoS signals

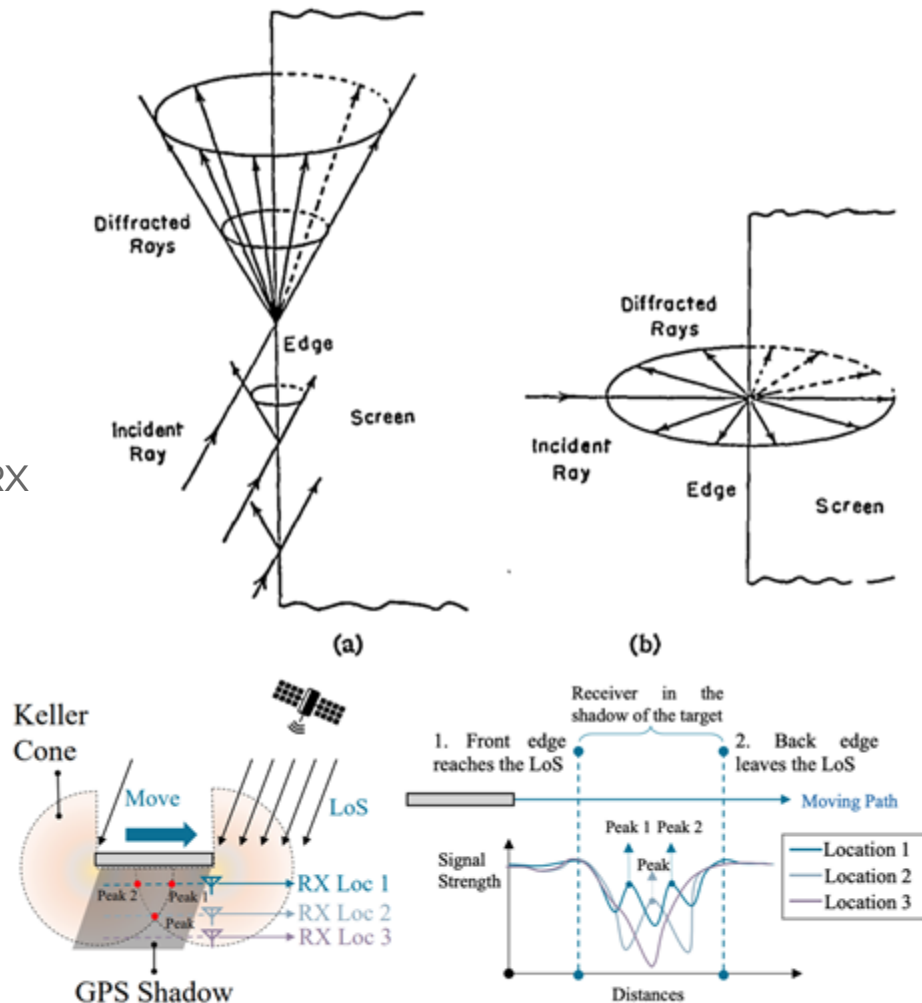
-> a small variation of the combined signal strength

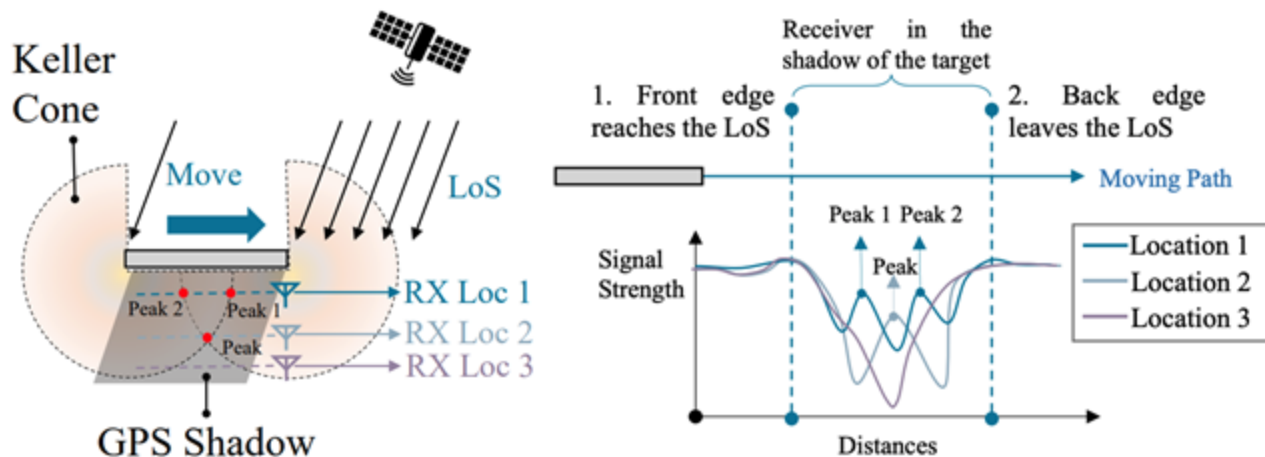
as the LoS path signal still dominates

When the target moves further

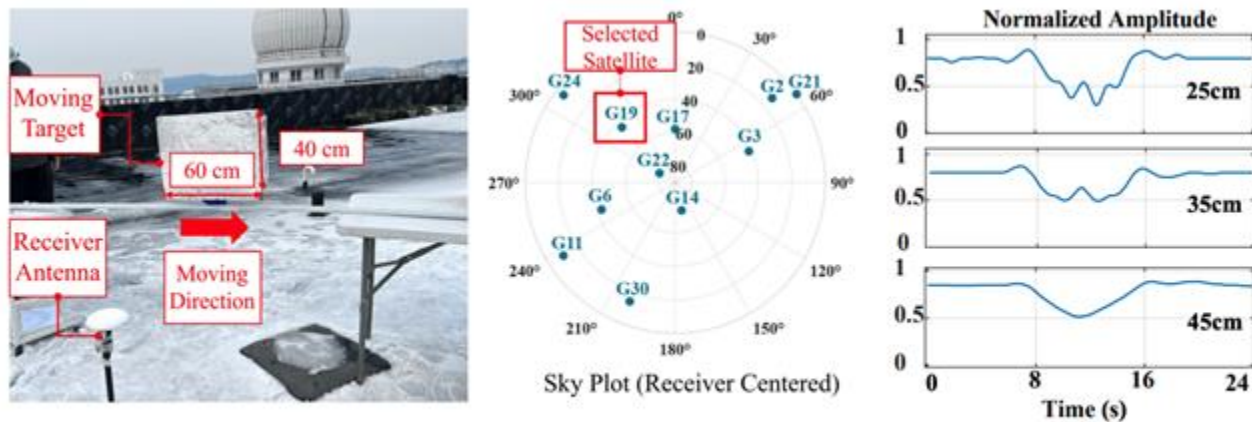
-> LoS path is obstructed, strength of received signal decreases rapidly

[1] Geometrical theory of diffraction, Keller et al.





(a) Diffraction of GPS signals. (b) Theoretical signal strength changes.



(a) Experiment Setup.

(b) Features.

Challenge 3 - Satellites Variety

GNSS(global navigation satellite system)
satellites in MEO and GEO moving at
different speeds:

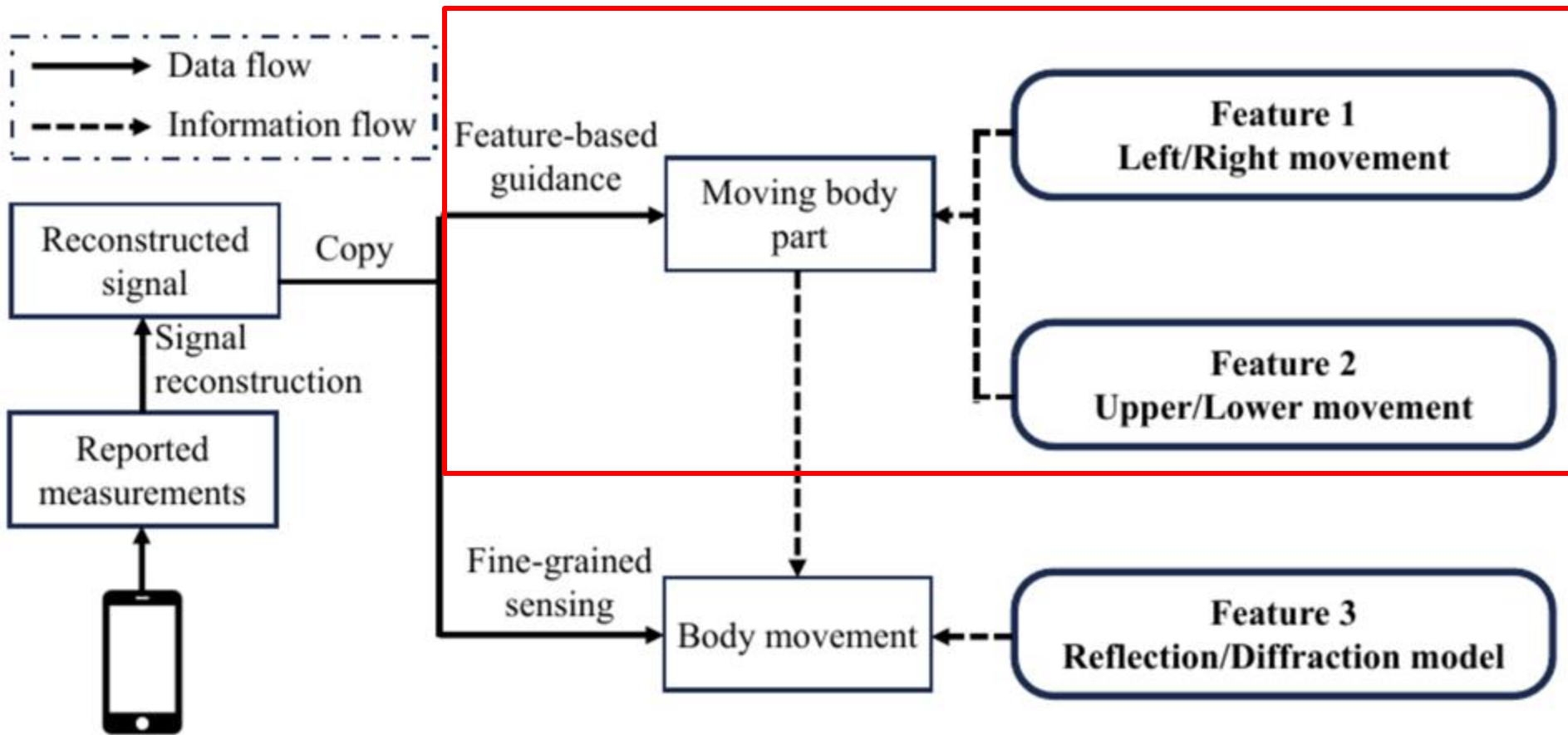
- GPS
- Galileo(Europe)
- Beidou(China)

-> a GNSS receiver can get signals from
over 30 satellites above at the same time

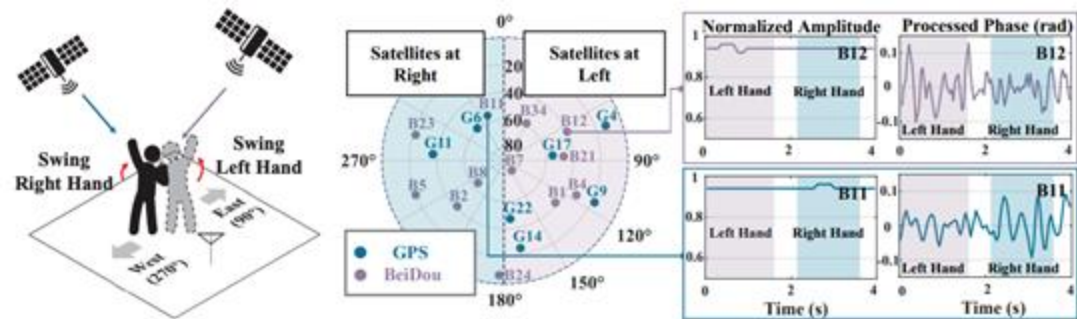
GNSS satellites moves faster than earth
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-> the satellites a receiver can capture
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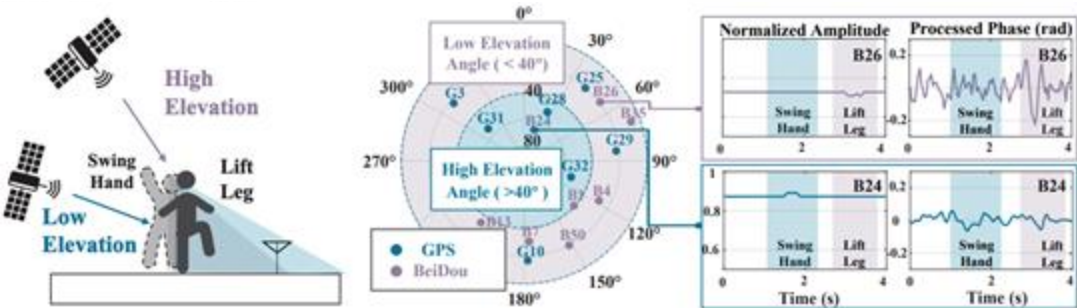




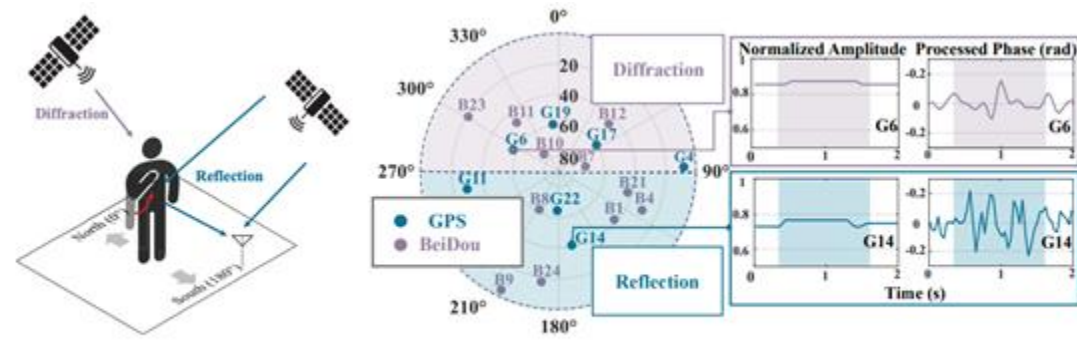
Feature 1: Satellite on the right/left of the target show superior sensing capability for movements on corresponding side of the body



Feature 2: Satellite at high/low elevation angle show superior sensing capability for movements on the corresponding part of body



Feature 3: Satellite at same/opposite side of the target show superior sensing capability for diffraction/reflection model influence

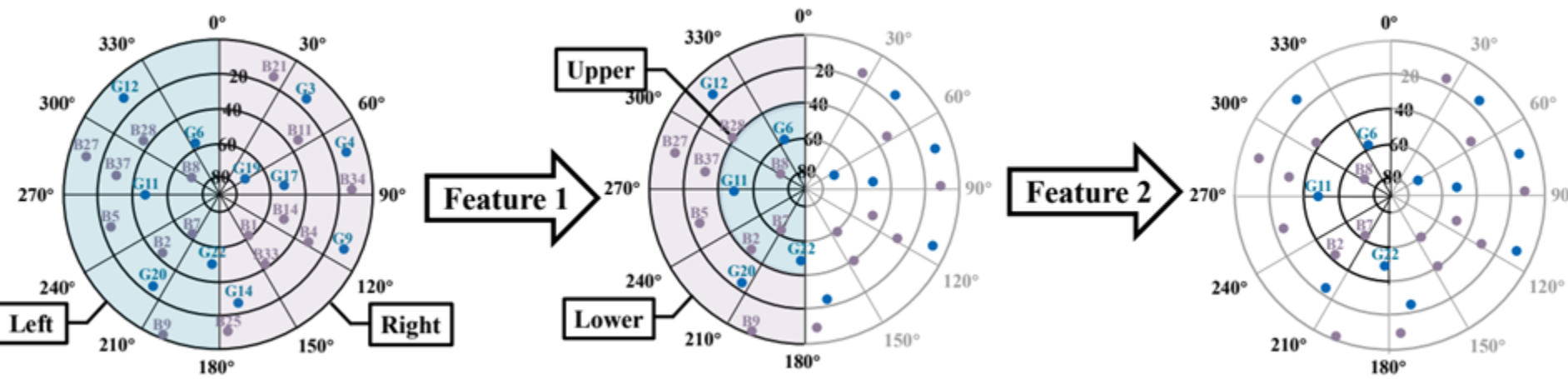


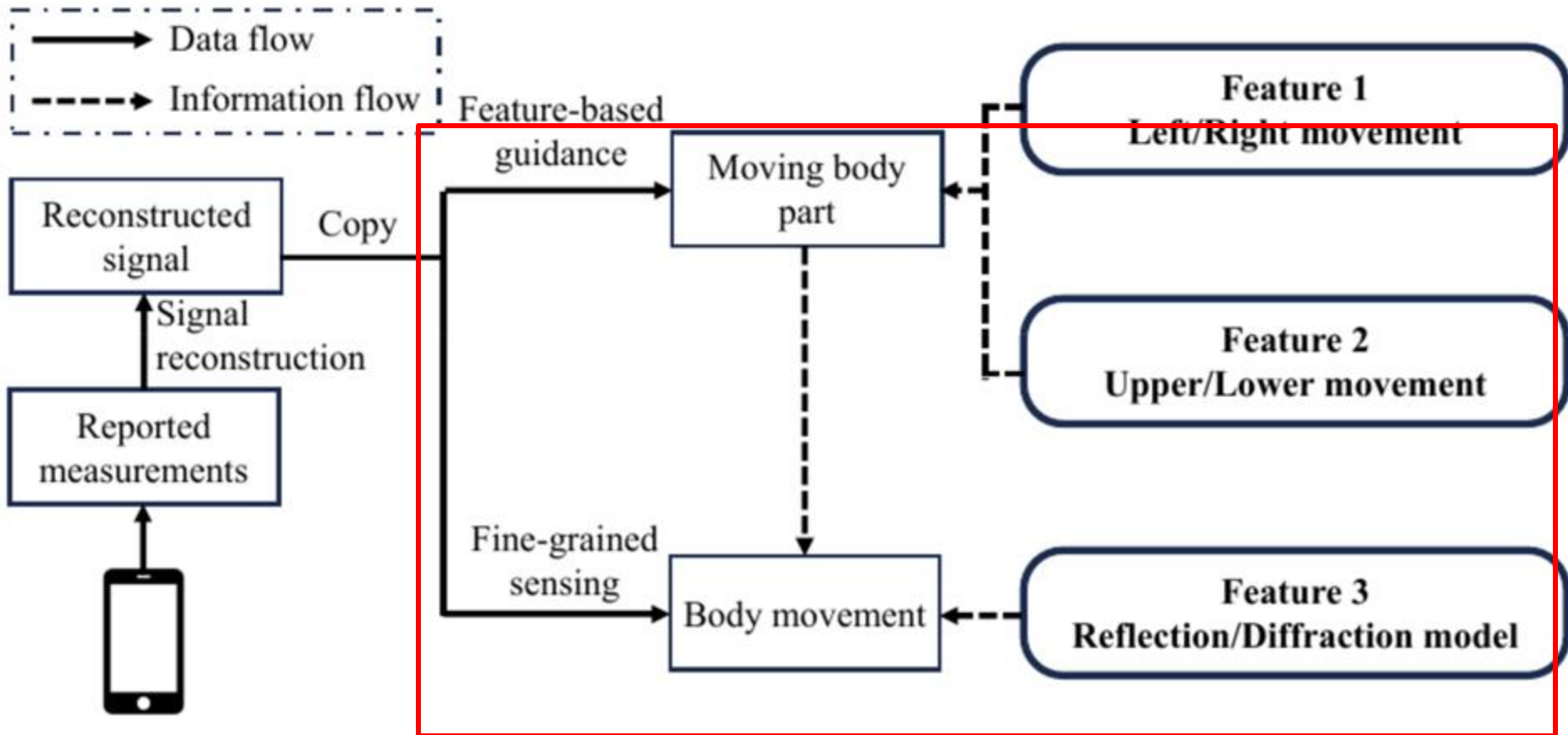
(a) Conceptual setup.

(b) Signal features.

Compare the average signal variation from satellites on the left side with that from the right side
-> If value from left is higher, then concludes that the movement is from the left side of the target
-> only consider GPS signals from the left side, vice versa

Compare the average signal variation at high-elevation angles with that at low-elevation angles
-> Elevation angle threshold is set as 40 degrees
-> If value from high-elevation angles is higher, then concludes that the movement pertains to upper body part of the target
-> only consider GPS signals from the upper part, vice versa





Challenges for fine-grained sensing

The next step is to **identify** which human activity (e.g., arm swing, walk) from the corresponding patterns

- The same activity never looks identical in time: different users or repetitions might be slightly faster/slower
- Different satellites see the same motion at different angles and thus with different timing or phase lag
- So you can't just compare two signals sample-by-sample (that would misalign them)

the satellite positions during the collection of the current template differ from those during the collection of the reference template

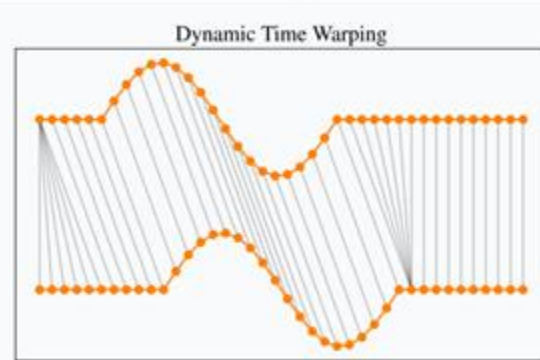
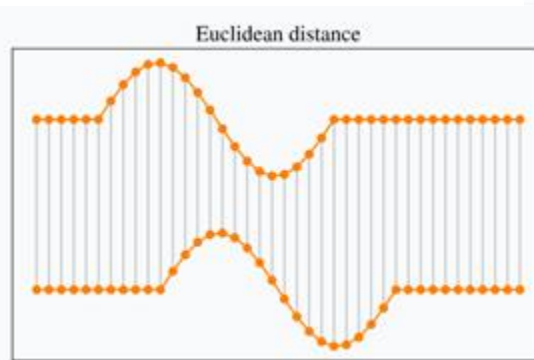
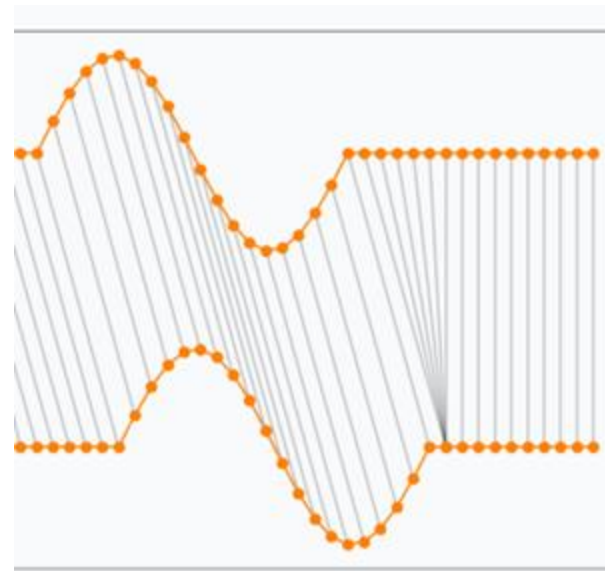
Dynamic Time Warping (DTW)

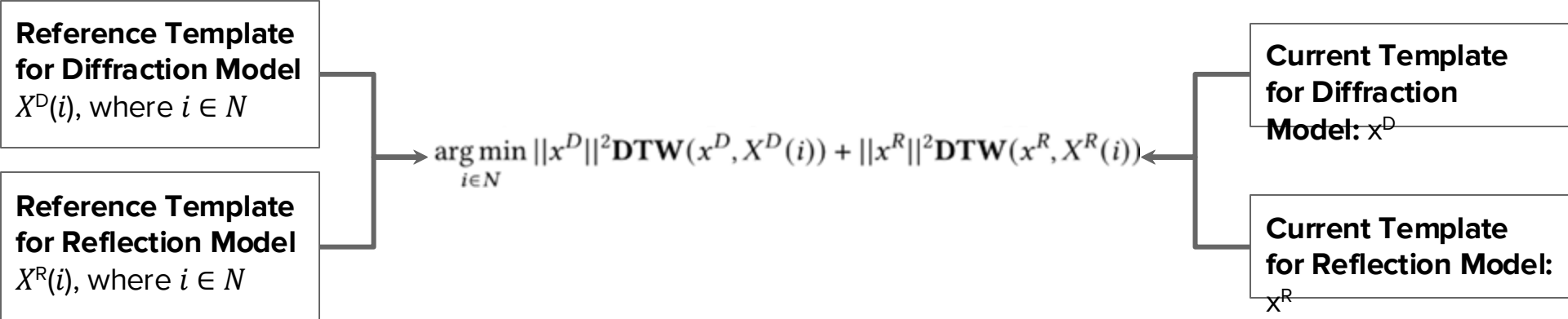
DTW finds the best nonlinear alignment between two sequences may be stretched or compressed in time.

- **Reference template:** signal pattern for a known activity (e.g., one arm swing)
- **Observed signal:** real-time measured signal for an unknown movement

They might have the same shape but one is performed faster or slower.

DTW helps align them.





Challenges for fine-grained sensing

The satellite positions during the collection of the current template differ from those during the collection of the reference template

DTW assumes that two sequences differ only in **time** scaling

However, the satellite's geometry changes over time ($\approx 3-4$ km/s in MEO)

-> different positions and different incident angles

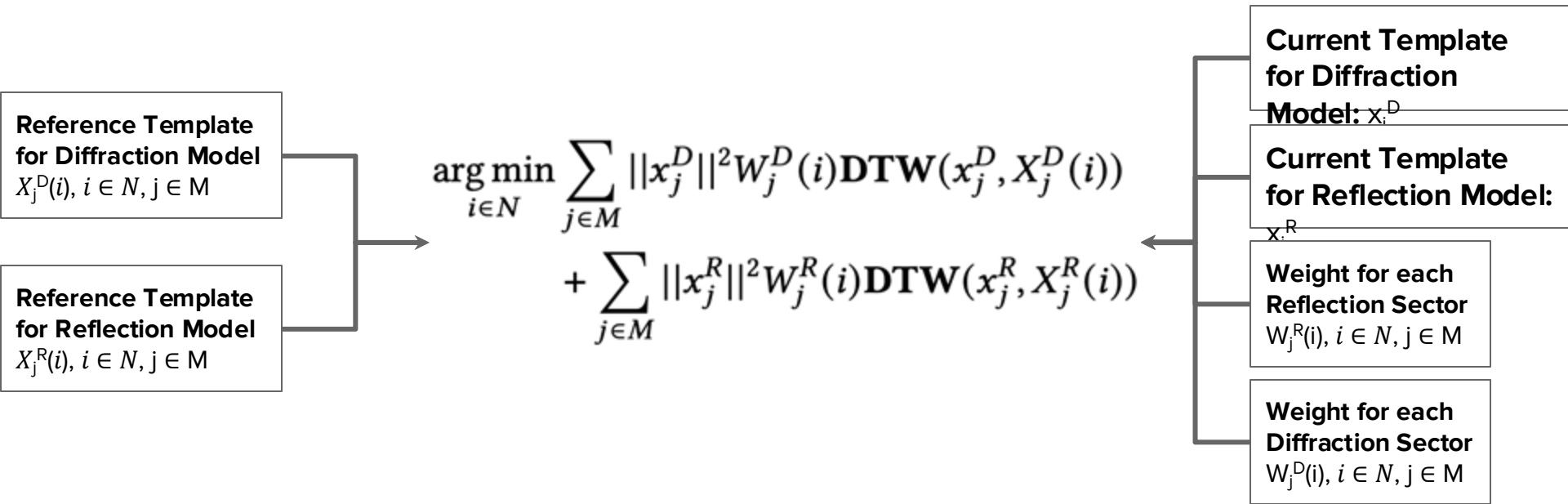
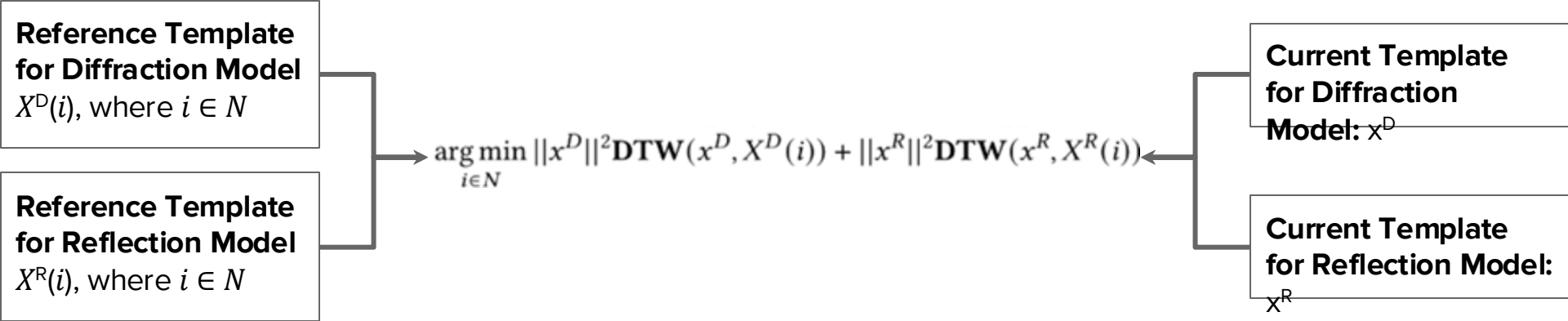
-> path lengths, reflection geometry, and diffraction edges all shift.

-> the received signal variation changes also in shape and scale

From experiments:

Satellites whose azimuth and elevation angles are close to each other (within 30° azimuth, 20° elevation) produce very similar signal variation patterns for the same movement.

Same angular sectors -> similar signal variation



Evaluations

Setup

GPS Receiver: Ublox F9P GNSS module
with update rate: 25Hz

Different GPS RX module for testing:
Ublox M10, Ublox M9N, Ublox M8N

Update rate: 10, 25, 15Hz

Google Pixel 4, update rate: 1Hz

Processing unit: Intel i7 CPU, 16GB RAM



Figure 13: GNSS Module.

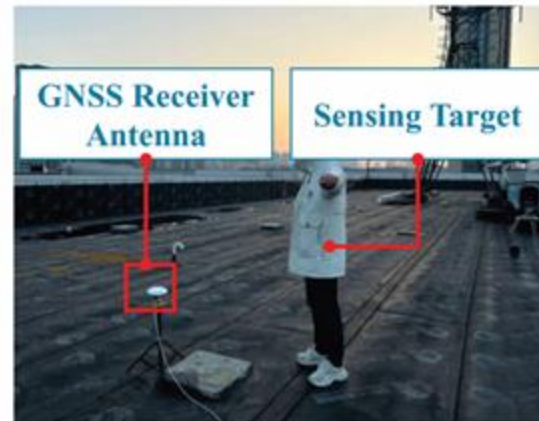
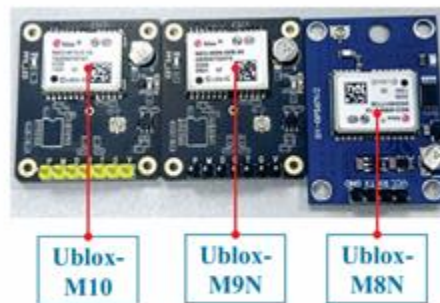


Figure 14: Default setup.



(a) Sensors.

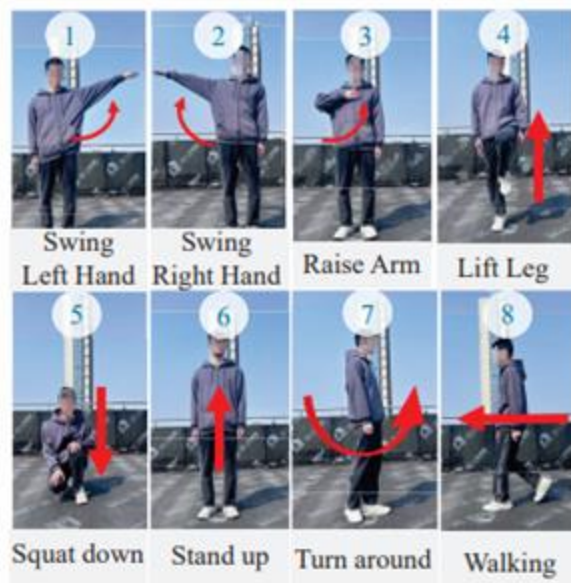


(a) Experiment Setup.

Human Activity Sensing

Eight body movements

Repeats each movements for 100 times while taking one of them as reference template



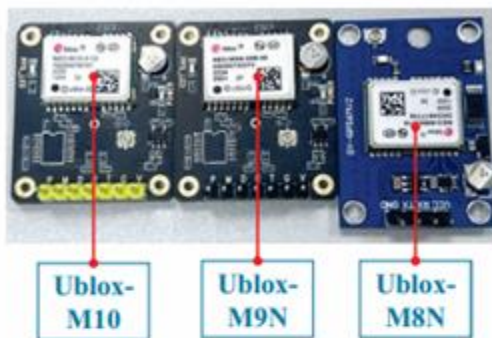
(a) Activities.

True Class	1	2	3	4	5	6	7	8
	94.1%	5.9%						
	2.8%	97.2%						
			100%					
				100%				
					98.3%		1.7%	
						96.6%	3.4%	
					3.4%		96.6%	
Classified Class					1.6%			98.4%

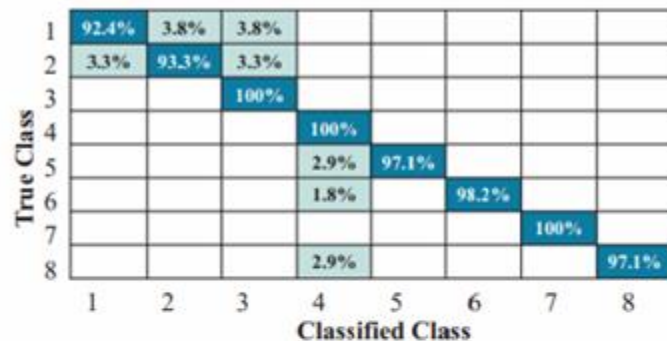
(b) Accuracy.

Figure 15: Overall human activities sensing accuracy.

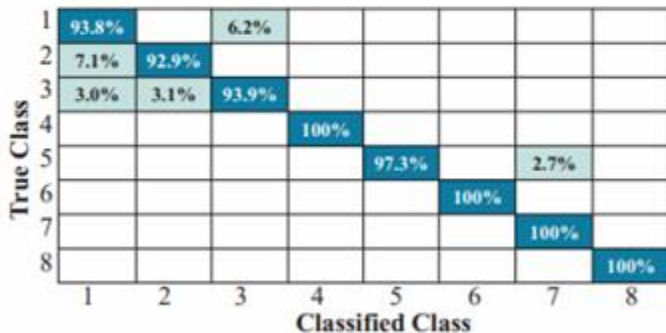
Sensing with different GNSS receiver modules



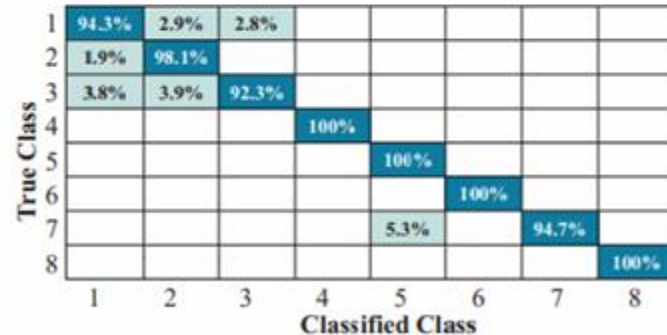
(a) Sensors.



(b) U-blox M10.



(c) U-blox M9N.



(d) U-blox M8N.

Sensing with commodity smartphones



(a) Experiment Setup.

True Class	1	96%	0%	4%	0%	0%	0%	0%	0%
	2	4%	96%	0%	0%	0%	0%	0%	0%
	3	6%	0%	94%	0%	0%	0%	0%	0%
	4	0%	0%	0%	86%	0%	12%	2%	0%
	5	0%	0%	0%	0%	90%	0%	0%	10%
	6	0%	0%	0%	0%	0%	100%	0%	0%
	7	0%	0%	0%	0%	2%	0%	90%	8%
	8	0%	0%	2%	4%	0%	4%	0%	90%
		Classified Class							

(b) Accuracy.

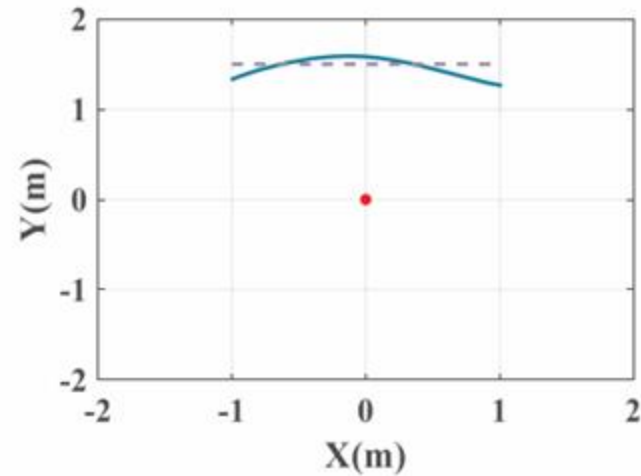
Figure 17: GPS sensing with a smartphone.

Passive tracking

Target doesn't carry a GNSS receiver

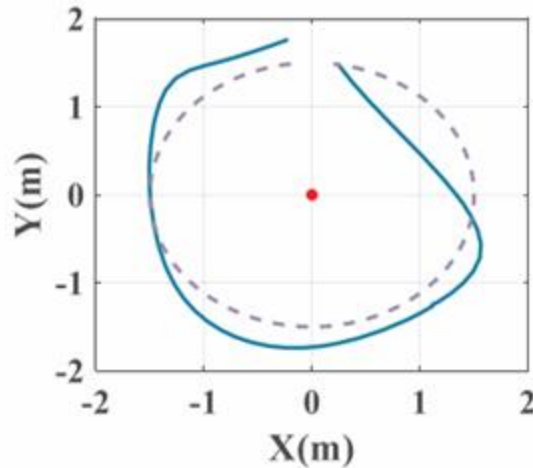
Trajectories: straight line, circle, rectangle

● GNSS Receive Antenna



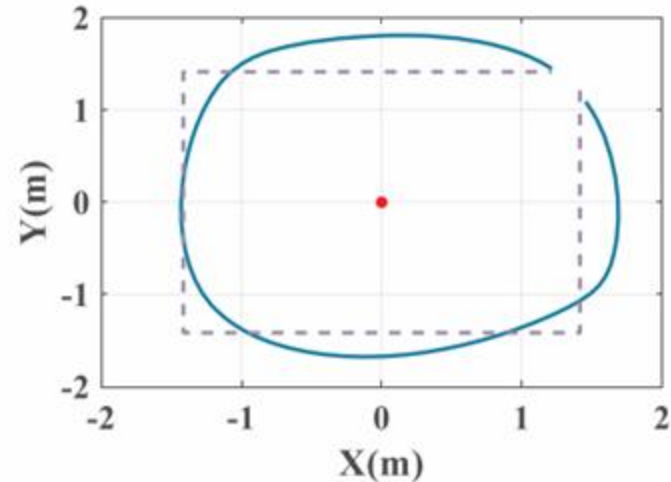
(a) Line.

— Trajectory



(b) Circle.

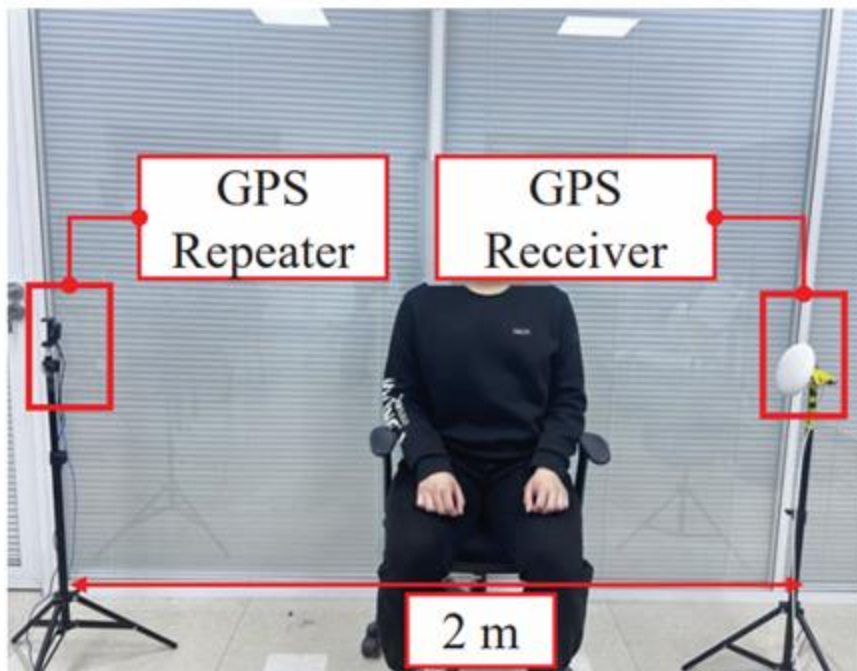
-- Ground Truth



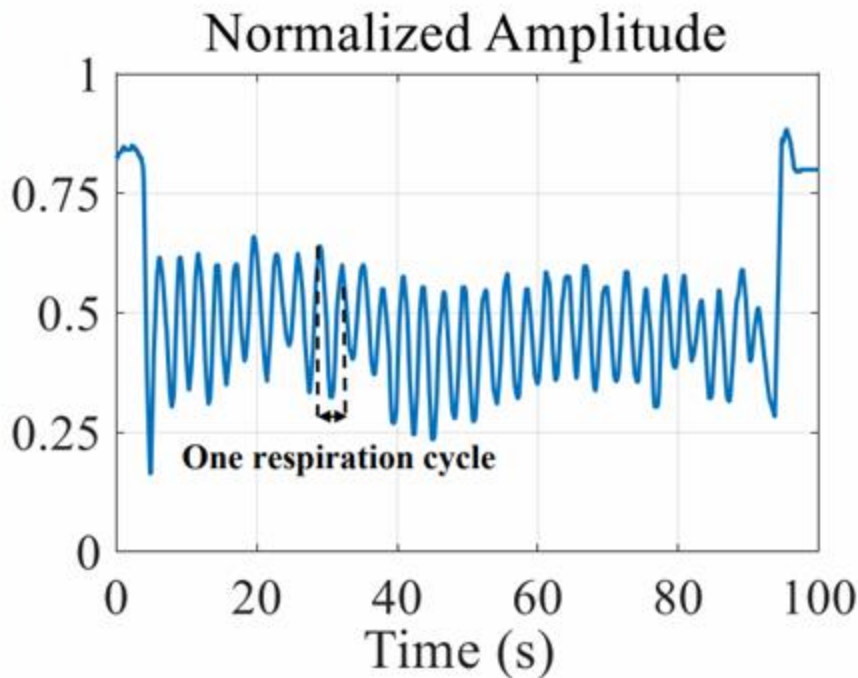
(c) Rectangle.

Respiration monitoring

Indoor environments with a low-cost GNSS repeater, repeater-Rx distance 2m



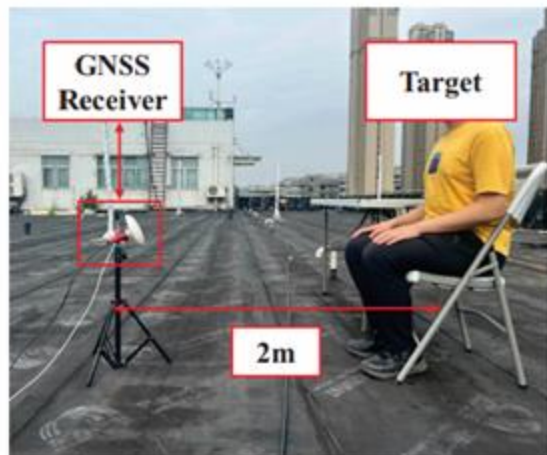
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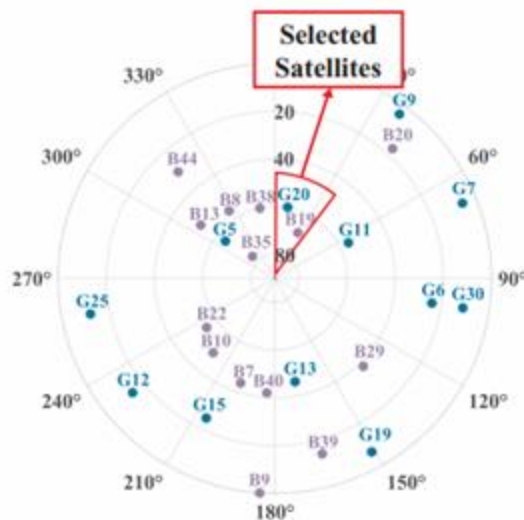
(b) Extracted Amplitude.

Respiration monitoring

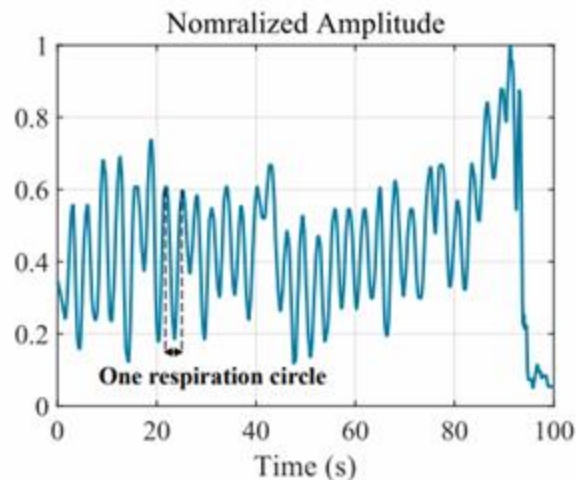
Outdoor environments with target-Rx distance 2m



(a) Setup.

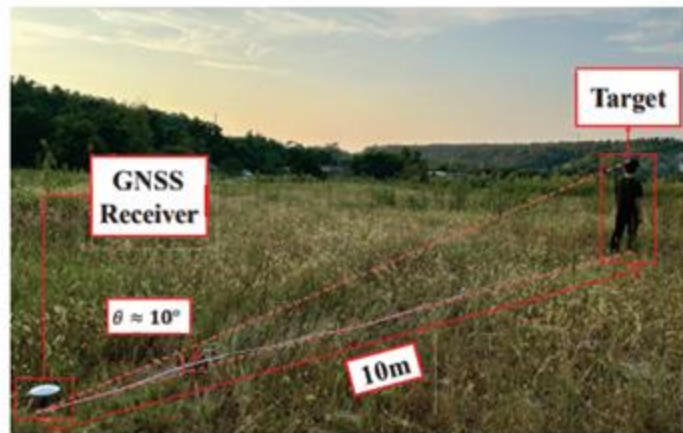


(b) Sky plot.

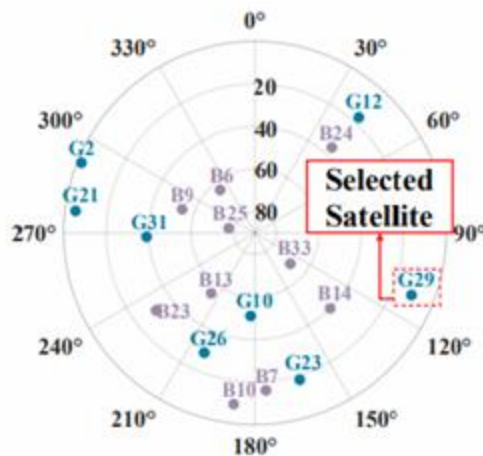


(c) Extracted Amplitude.

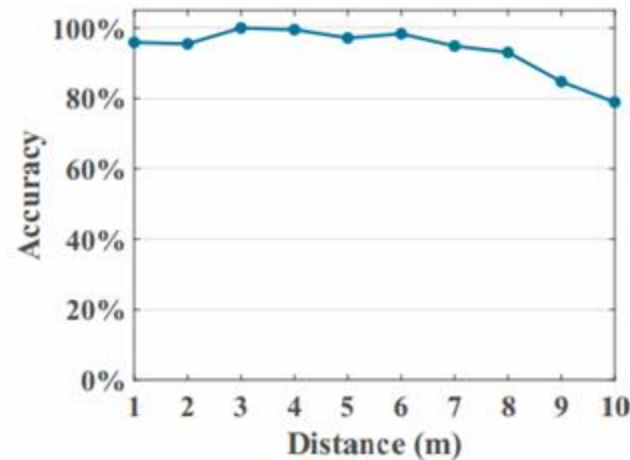
Performance boundary - coverage



(a) Experiment Setup.

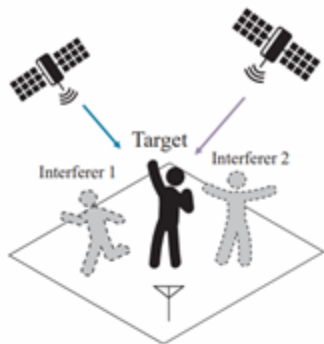


(b) Sky plot.



(c) Recognition accuracy.

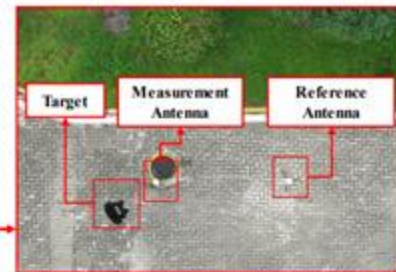
Performance boundary - interference



(a) Setup.

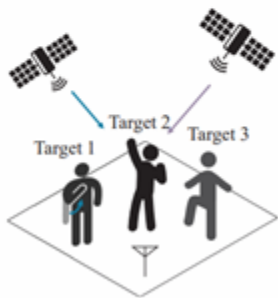
	Sit down	Stand up	Swing Hand	Walking
Sit down	100%			
Stand up		100%		
Swing Hand		3.3%	93.3%	3.3%
Walking				100%

(b) Accuracy.

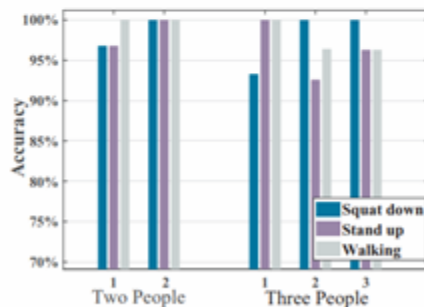


(a) Experiment Setup.

Figure 22: One target and two interferers.



(a) Setup.



(b) Accuracy.

True Class	1	2	3	4	5	6	7	8
1	75%	0%	25%	0%	0%	0%	0%	0%
2	10%	88%	2%	0%	0%	0%	0%	0%
3	0%	50%	50%	0%	0%	0%	0%	0%
4	0%	0%	0%	38%	62%	0%	0%	0%
5	0%	0%	0%	2%	94%	0%	0%	4%
6	0%	0%	0%	14%	0%	86%	0%	0%
7	0%	0%	0%	0%	16%	0%	84%	0%
8	0%	0%	0%	0%	0%	0%	0%	100%
Classified Class	1	2	3	4	5	6	7	8

(b) Accuracy with a single receiver.

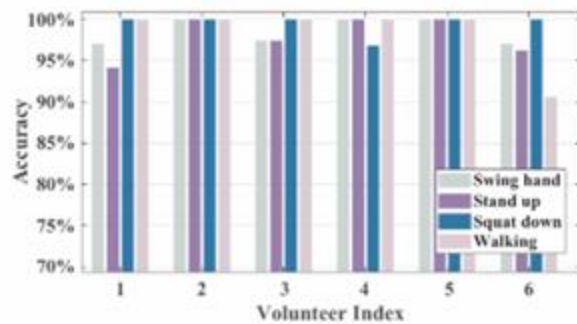
True Class	1	2	3	4	5	6	7	8
1	90%	0%	10%	0%	0%	0%	0%	0%
2	7.5%	90%	2.5%	0%	0%	0%	0%	0%
3	0%	25%	75%	0%	0%	0%	0%	0%
4	0%	0%	0%	80%	20%	0%	0%	0%
5	0%	0%	0%	2%	98%	0%	0%	0%
6	0%	0%	0%	4%	0%	94%	0%	2%
7	0%	0%	0%	0%	16%	0%	84%	0%
8	0%	0%	0%	0%	0%	0%	0%	100%
Classified Class	1	2	3	4	5	6	7	8

(c) Accuracy with two receivers.

Figure 23: Three targets.



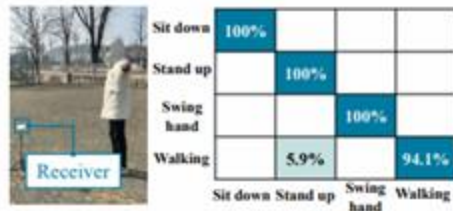
(a) Various targets.



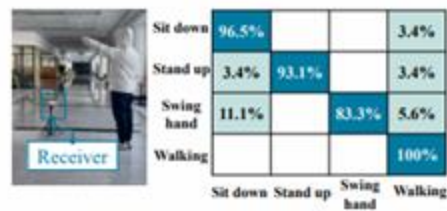
(b) Sensing Accuracy.



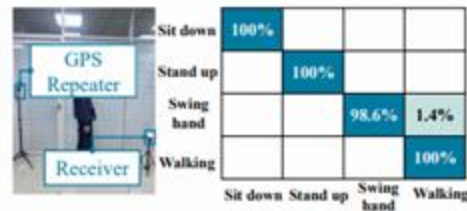
(a) Roof Top.



(b) Outdoor.



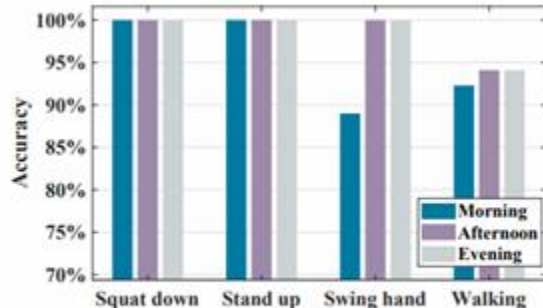
(c) Indoor.



(d) Indoor with repeater.



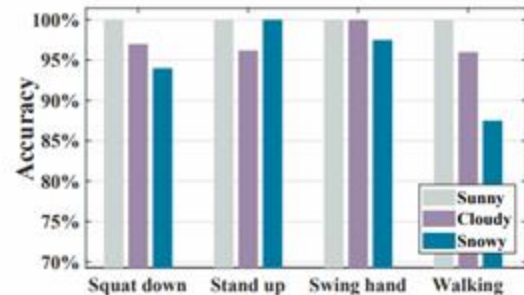
(a) Different time.



(b) Experiment result.



(a) Experiment Weather.



(b) Experiment result.

Future Works & Opinions

Discussion

1. Limited number of activities (machine learning-based classification models could increase the num of activities)
2. Improves sensing performance by utilizing both GPS and other wireless module on the smartphone -> multimodal sensing

Opinions

1. Great paper overall
 - a. Very clear explanations, especially the figures are really good
 - b. Comprehensive experiments
2. More plots to show the baseline plots would be better
3. Experiments **hardcoded** the human's facing angle and elevation angle
-> IDEA: use the sensing results from all of these available satellites to determine the pose(heading, speed, behavior) of the human.
4. Practical issues: Accuracy will be affected heavily by interference, e.g. human, multipath, heights, weather, time-of-the-day, etc.
 - a. Require more experiments
 - b. Require a smarter strategy from reference antenna approach

Perusall