CSE610 Special Topics on Mobile Network & Mobile Sensing

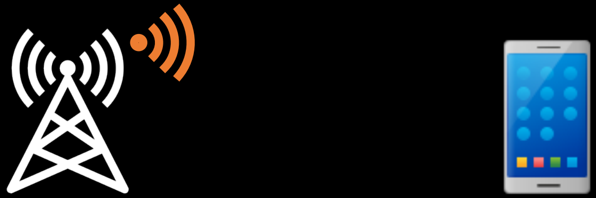
Yaxiong Xie

Lec04 Wireless Sensing

Mobile Sensing

Leveraging the mobile devices to sense the physical world

Wi-Fi signal



5G signal

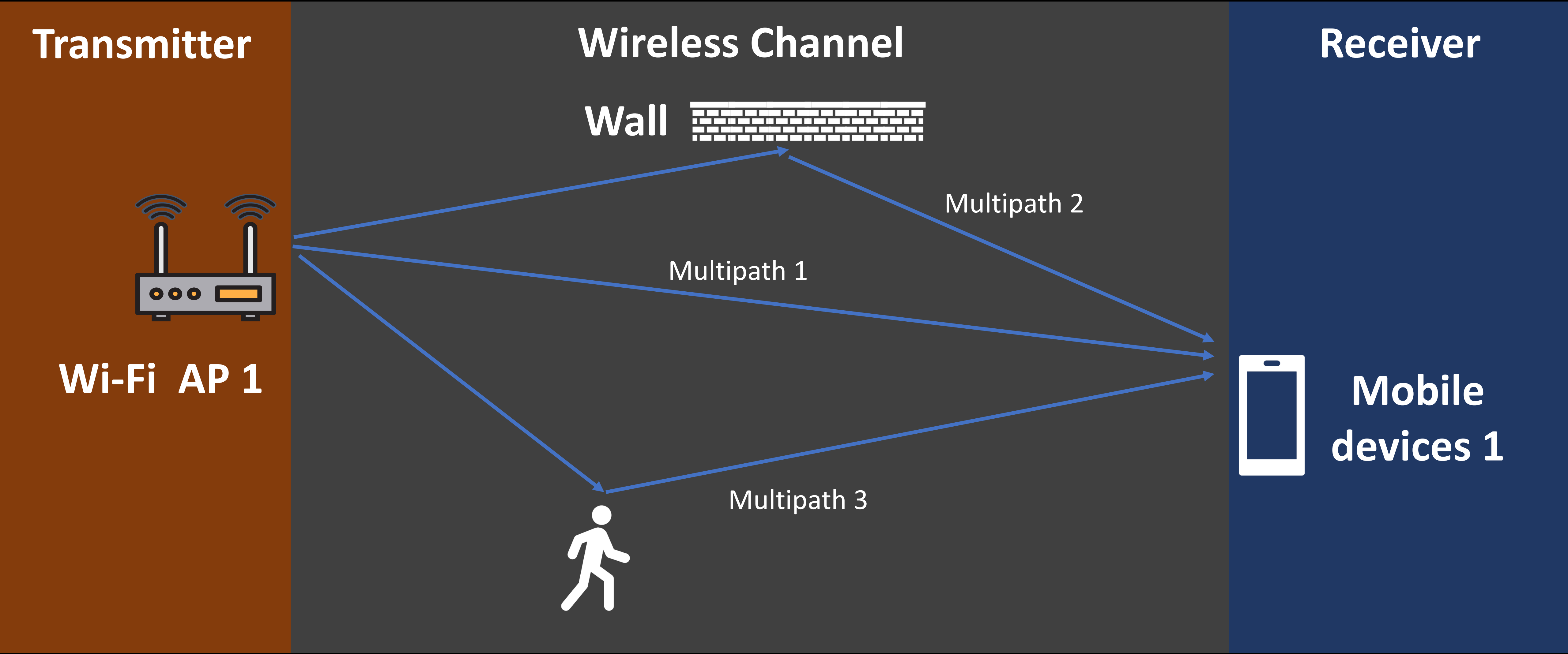
Acoustic signal

Localization

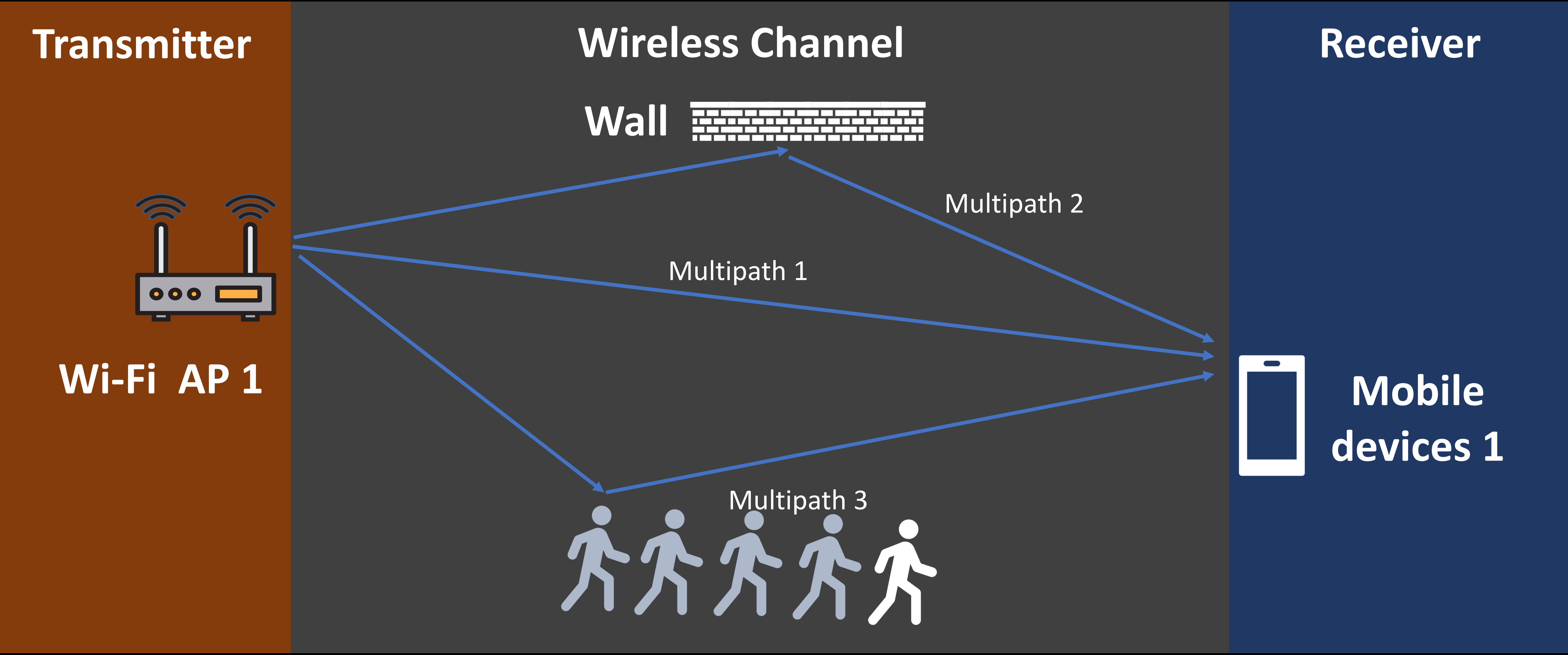
Gesture recognition

Vital signal: respiration

Wireless channel



Wireless channel



Sensing Human Respiration

Sensing Human Respiration

Respiration rate is one vital sign that can provide the insight of one's **general state of health** and can be a **valuable indicator** of one's underlying medical conditions.

Sensing Human Respiration

Sensing Human Respiration

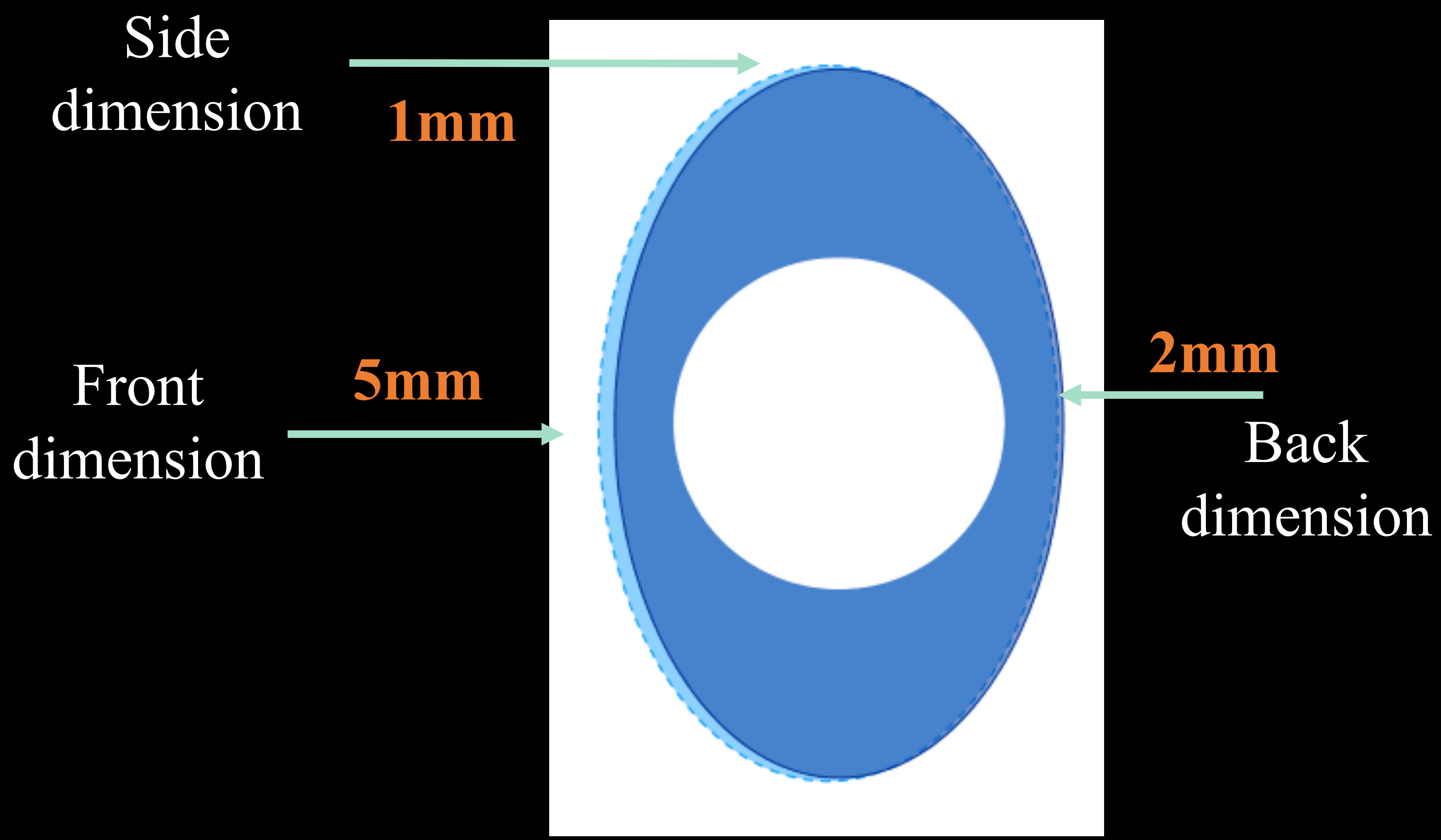
- **Pros:** Very accurate
- **Cons:** Expensive

  Intrusive

  Not convenient for long-term monitoring

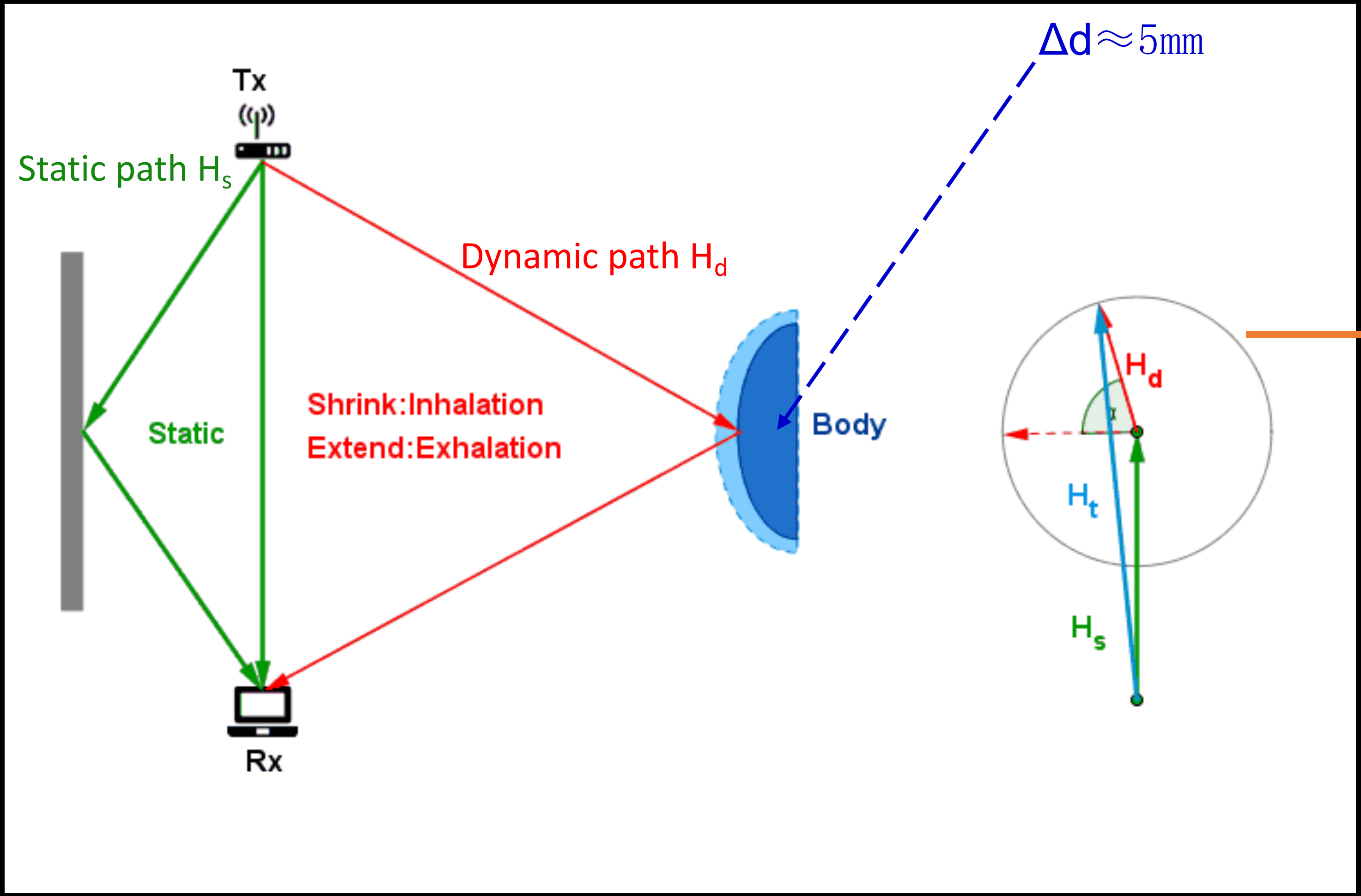
Sensing Human Respiration

Human body is modeled as a cylinder with varying sizes

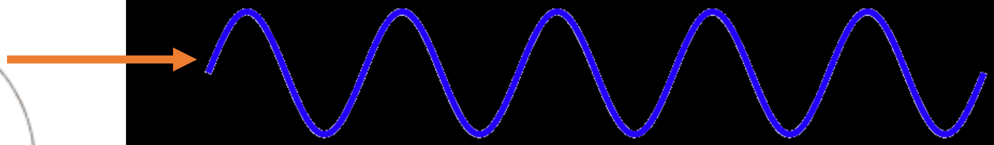


Sensing Human Respiration

Path length change ≈ 1cm < 5.7cm (wavelength)

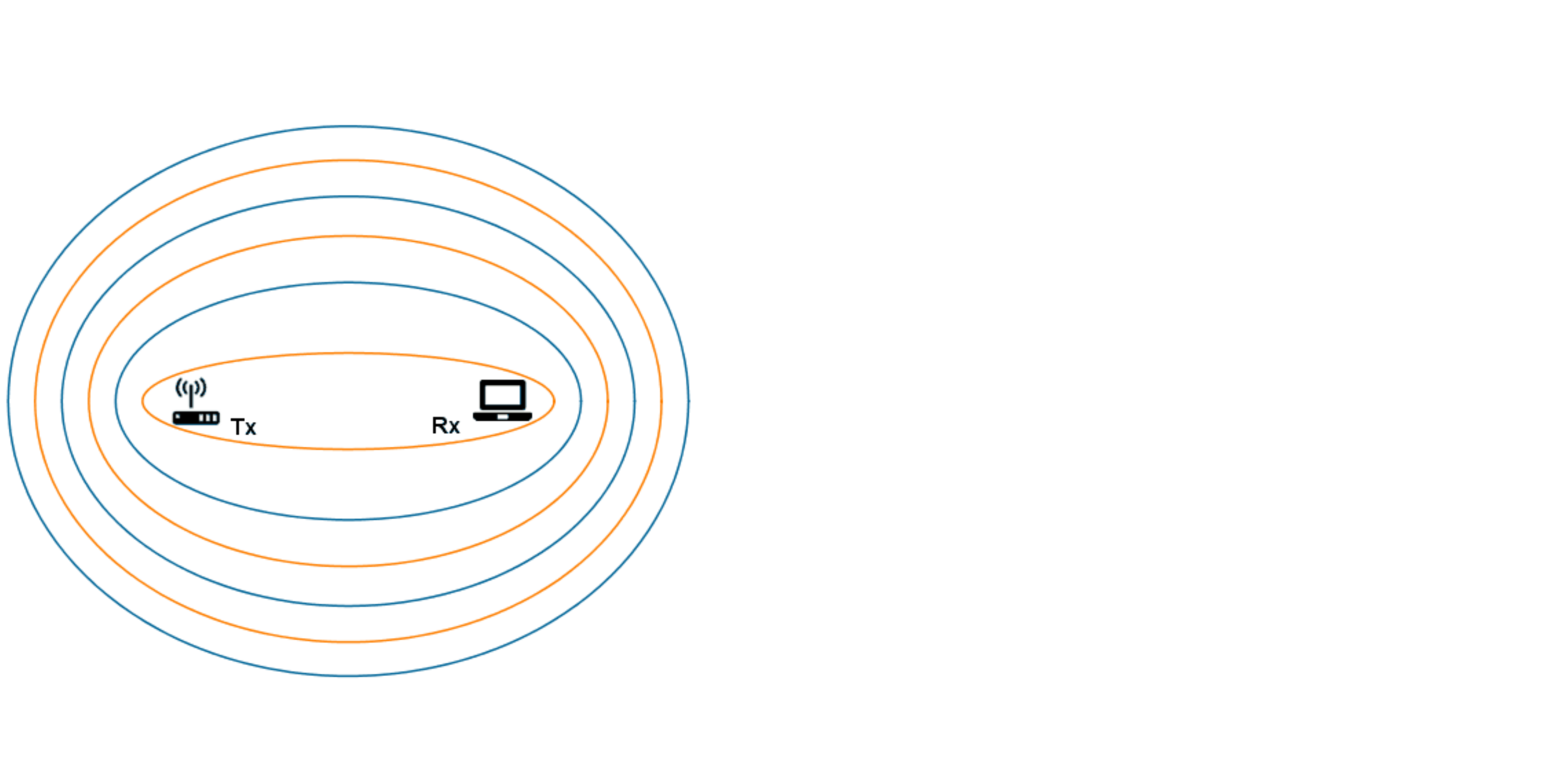


Phase or amplitude variations!



Sensing Human Respiration

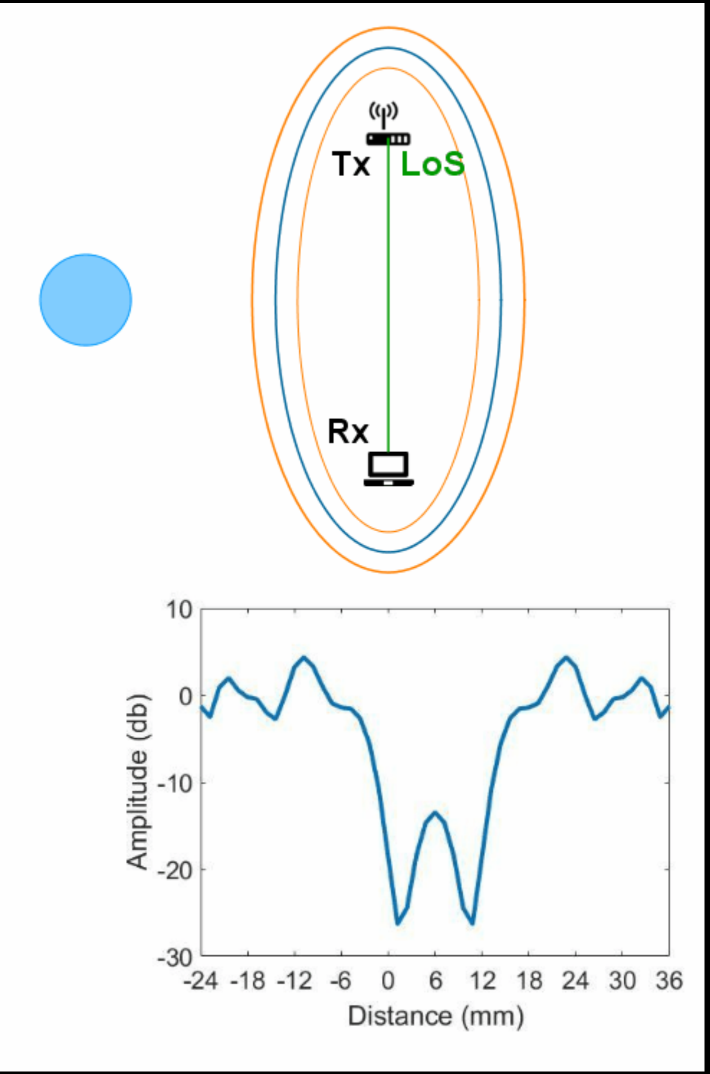
Fresnel zones



Sensing Human Respiration

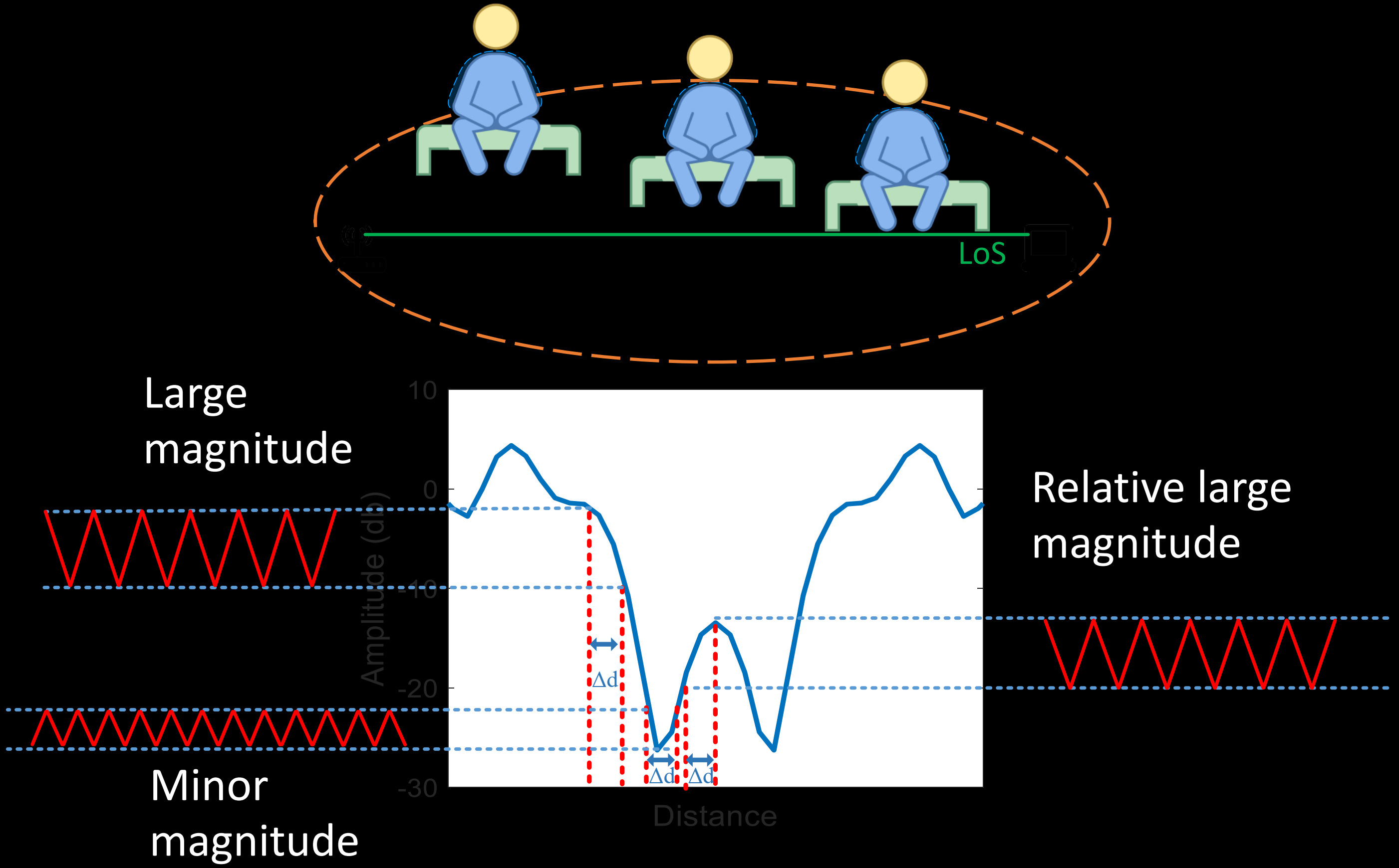
A circular cylinder moves across the first Fresnel zone

The signal strength varies with the location of the reflector

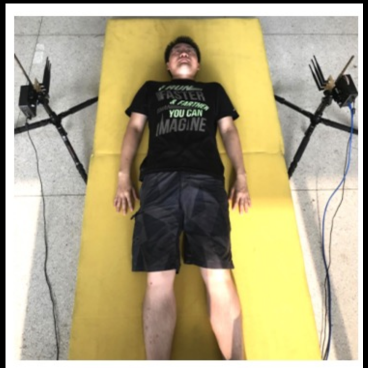


Sensing Human Respiration

The location of the reflector (the human) determines the performance of the sensing system!

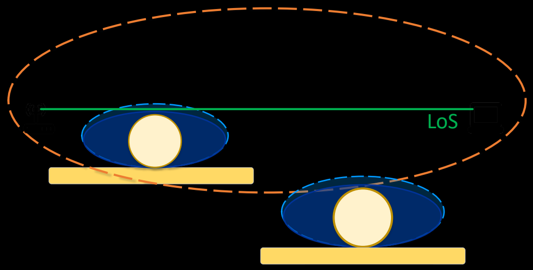


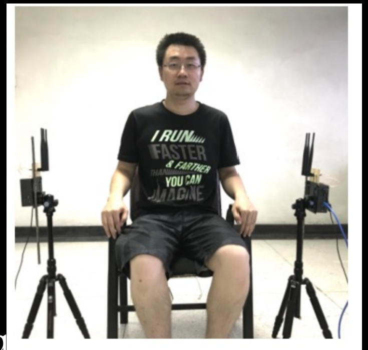
Sensing Human Respiration



(a) lying

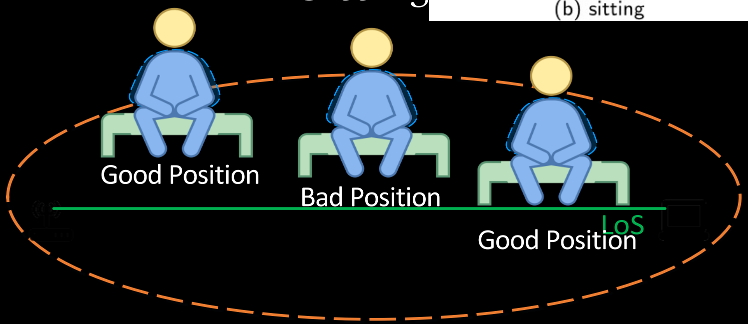
Lying

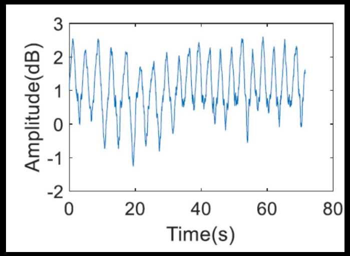




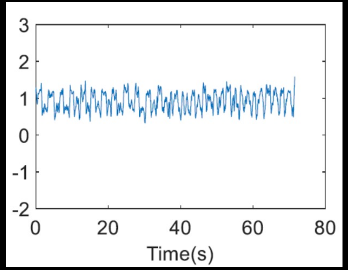
(b) sitting

Sitting

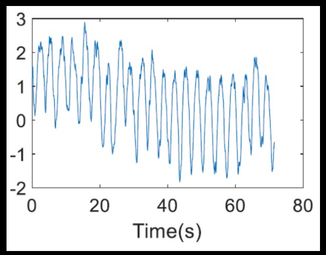




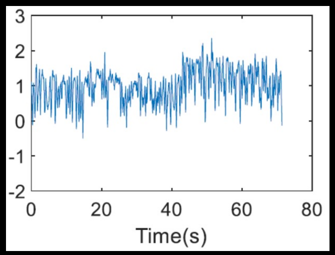
Good Position



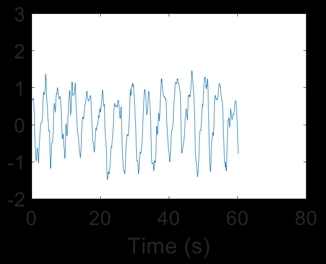
Bad position



Good Position



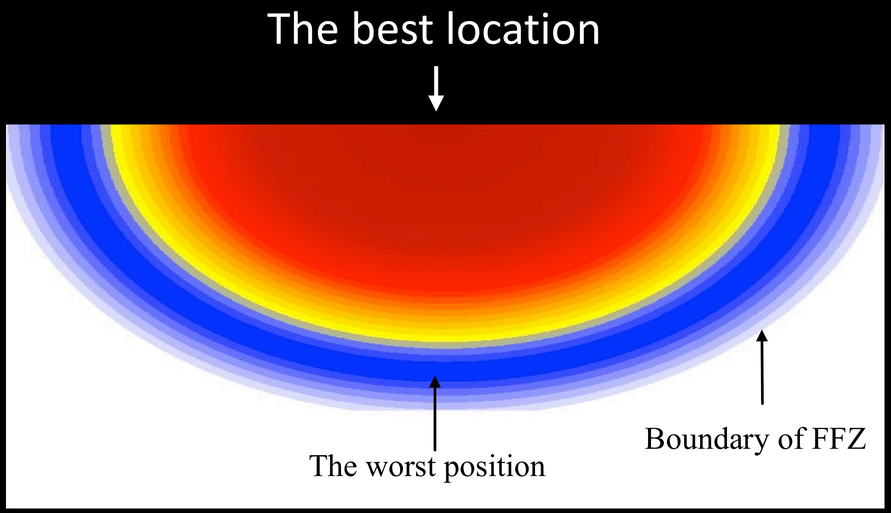
Bad Position



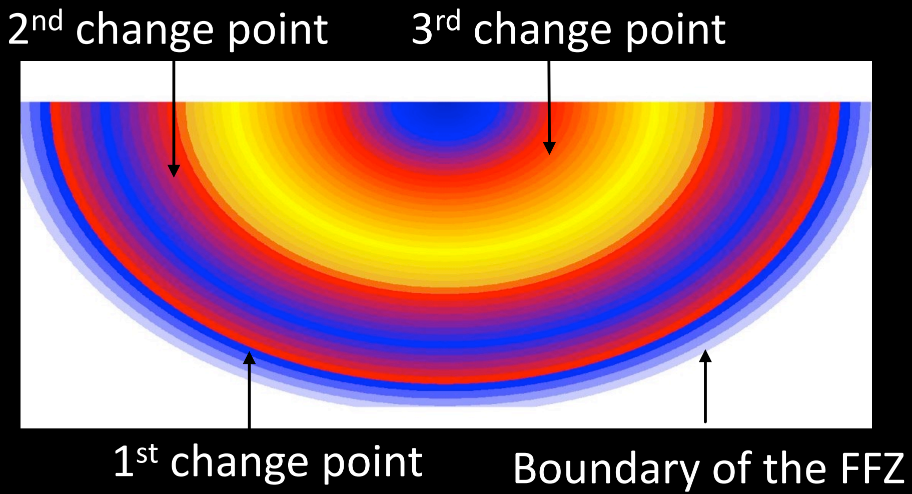
Good Position

Sensing Human Respiration

- Lying： the positions on the boundary of FFZ are bad positions, whereas most inner positions are good positions
- Sitting： alternating good and bad positions in FFZ



Lying

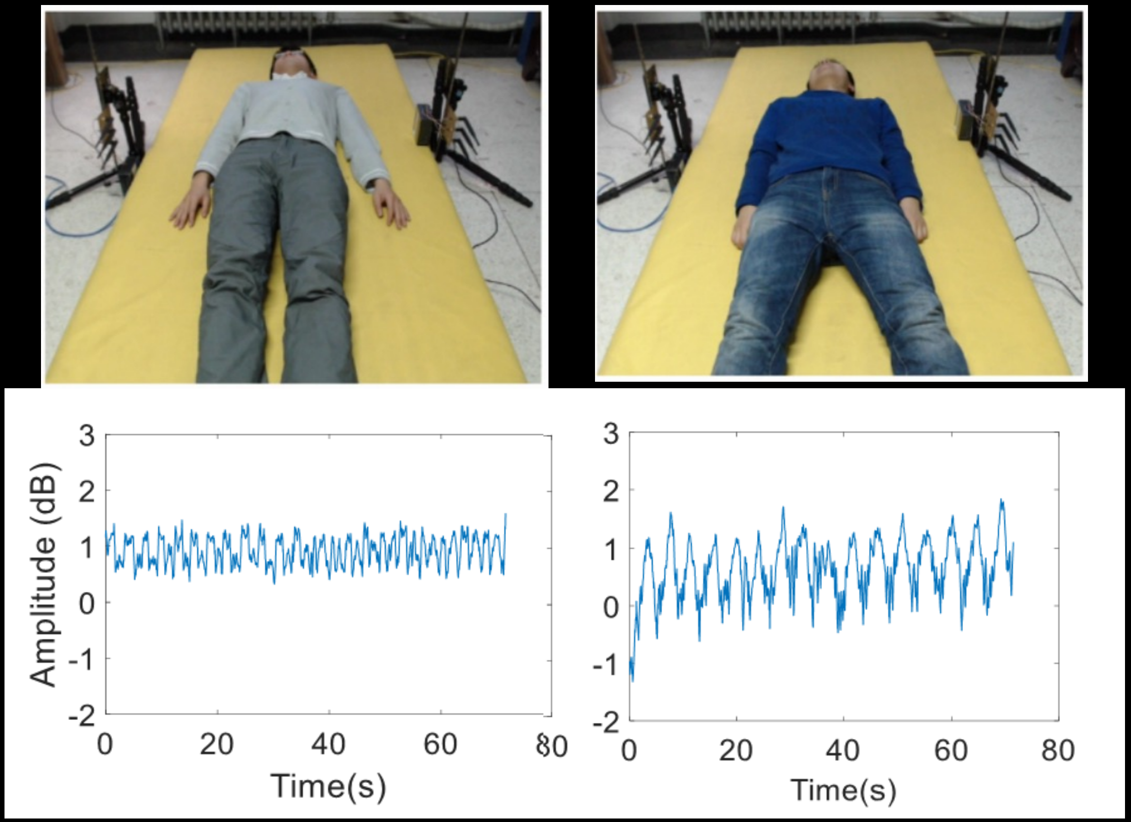


Sitting

Sensing Human Respiration

A same location can be bad for person A but good for person B.

Body thickness person B=20cm

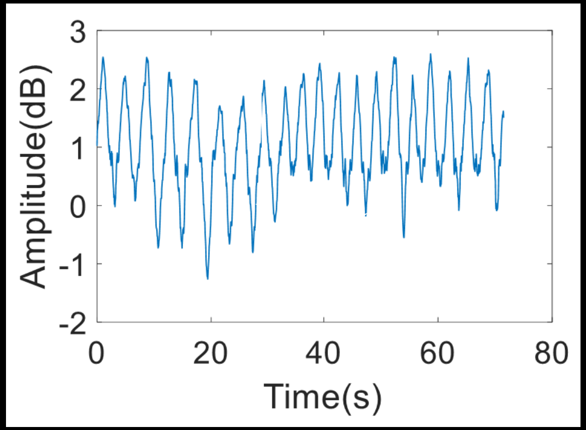


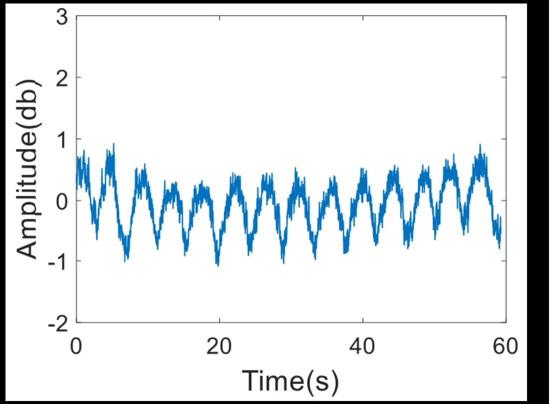
Body thickness person B=25cm

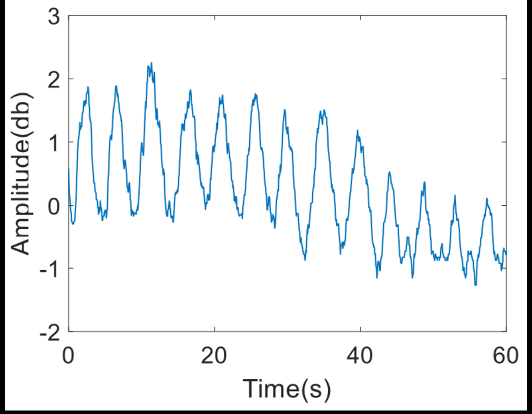
Sensing Human Respiration

At a good position, different lying postures also affect the performance.

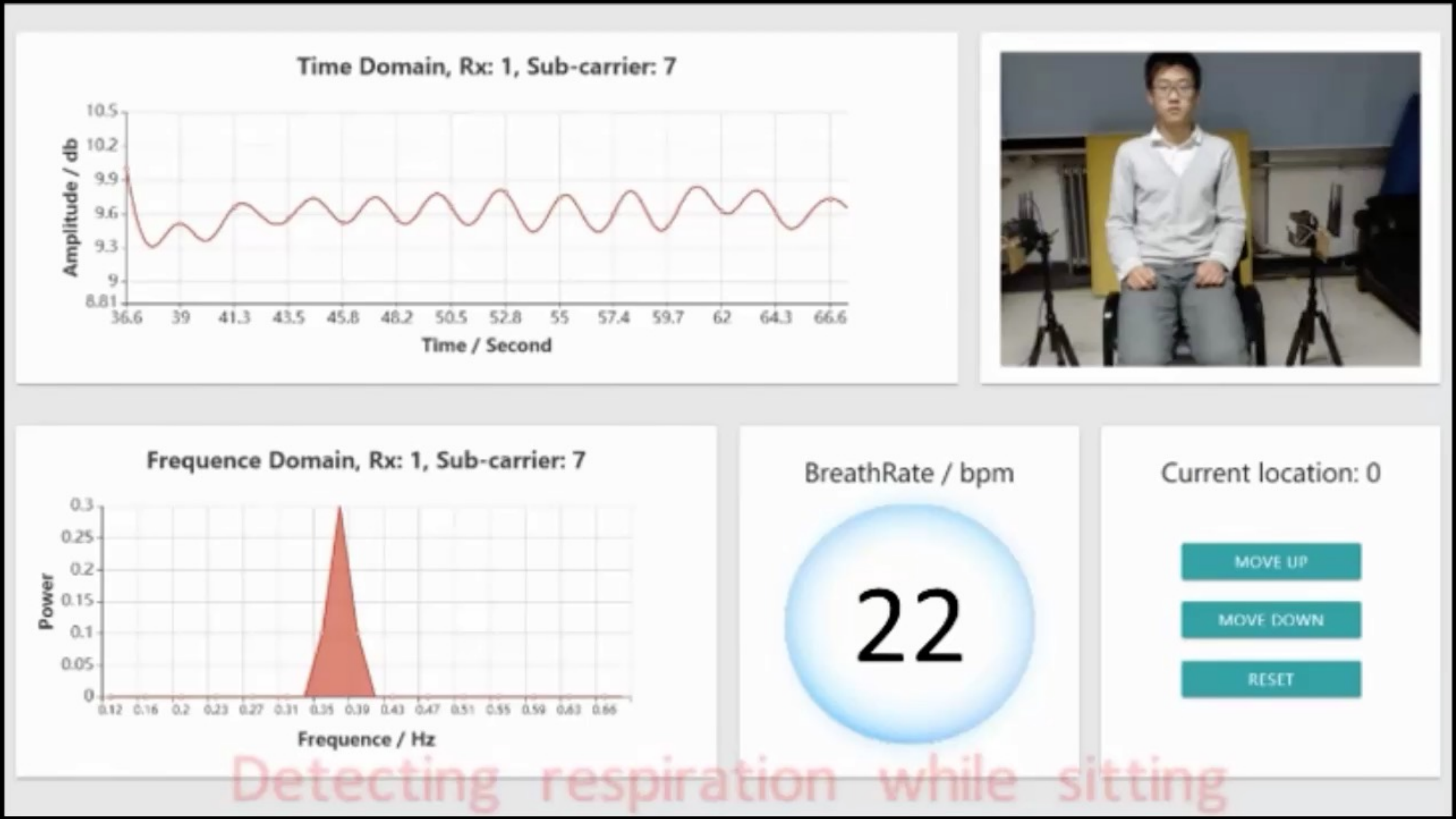








Demo- the first-generation Wi-Fi base respiration sensing system

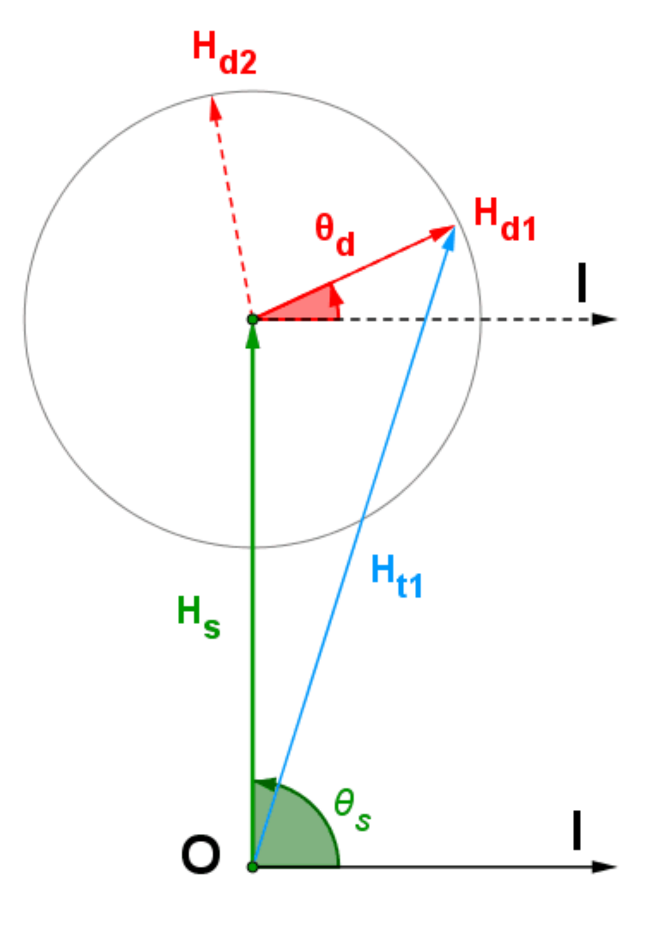


Demo- the second-generation Wi-Fi base respiration sensing system

FarSense: Extending the Range of WiFi-based Respiration Sensing with CSI Quotient

Can we improve the sensing performance?
We still have bad locations!

Quantifying the sensing performance



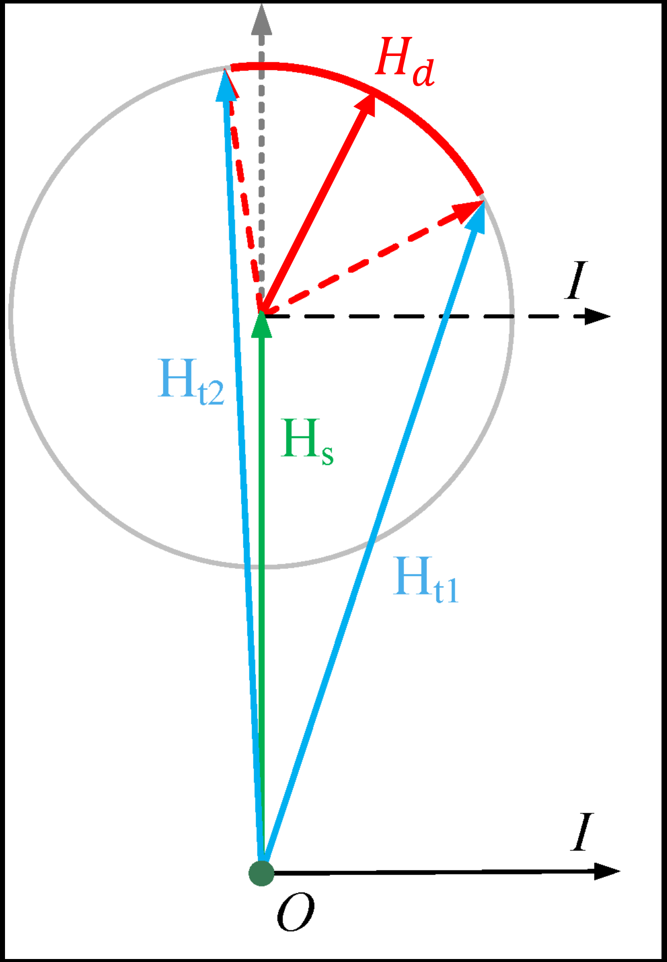
The amplitude difference

$$\Delta|H| = |H_{t2}| - |H_{t1}|$$

The amplitude of H_{t2}

The amplitude of H_{t1}

First Factor: Distance

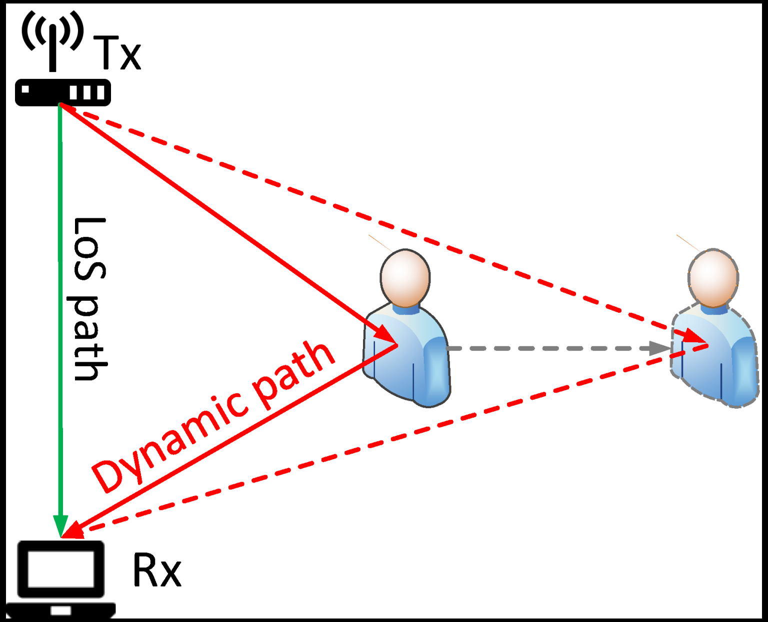


Sensing Performance

$$\Delta|H| \propto |H_d| \sin\frac{\Delta\theta_d}{2} \sin \Delta\theta_{sd}$$

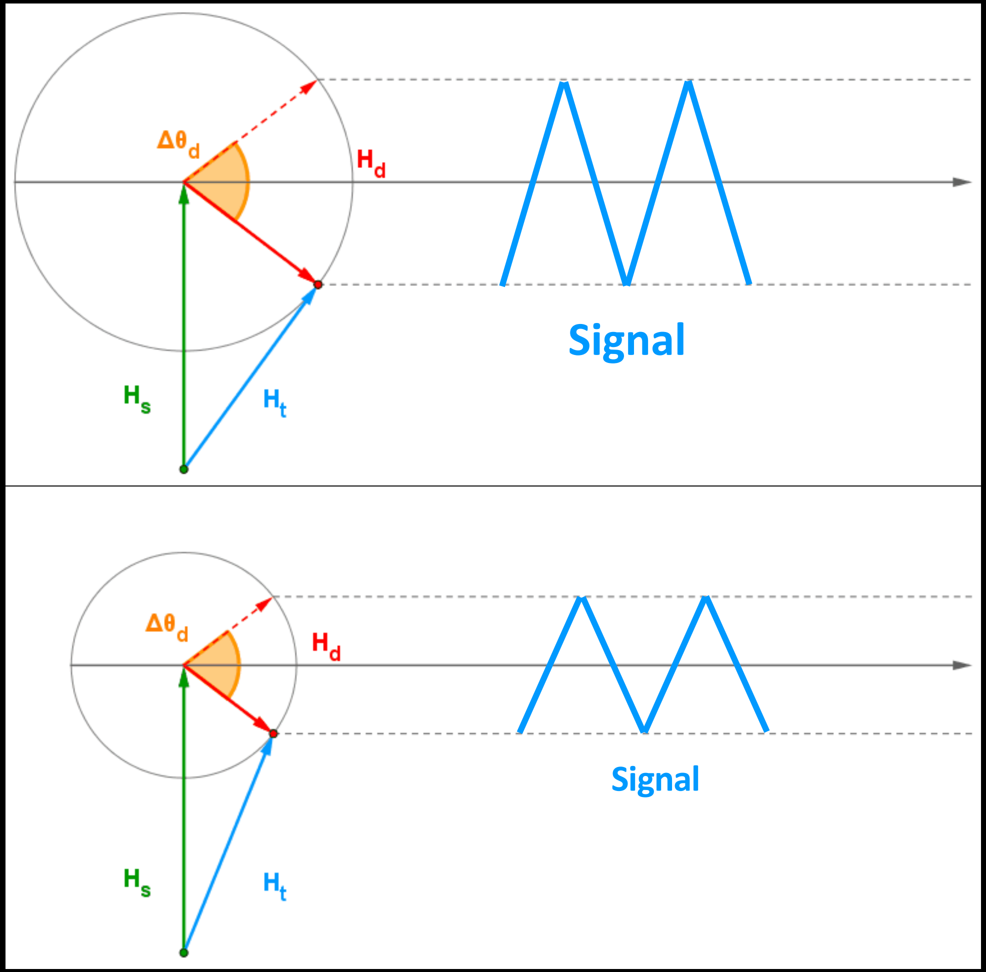
Distance between human and transceivers

First Factor: Distance

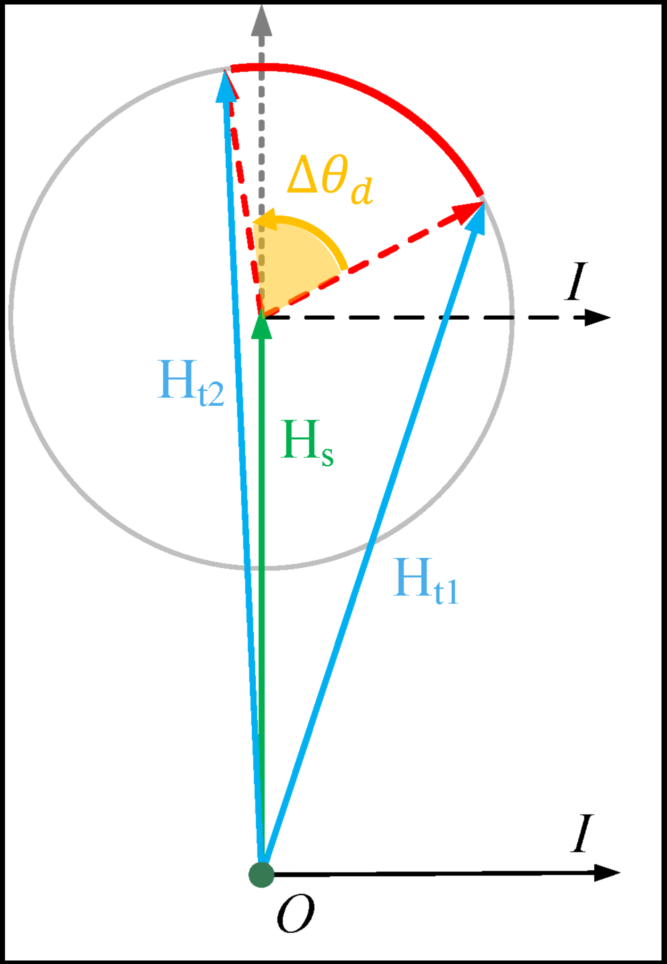


Near

Far



First Factor: Displacement



Sensing Performance

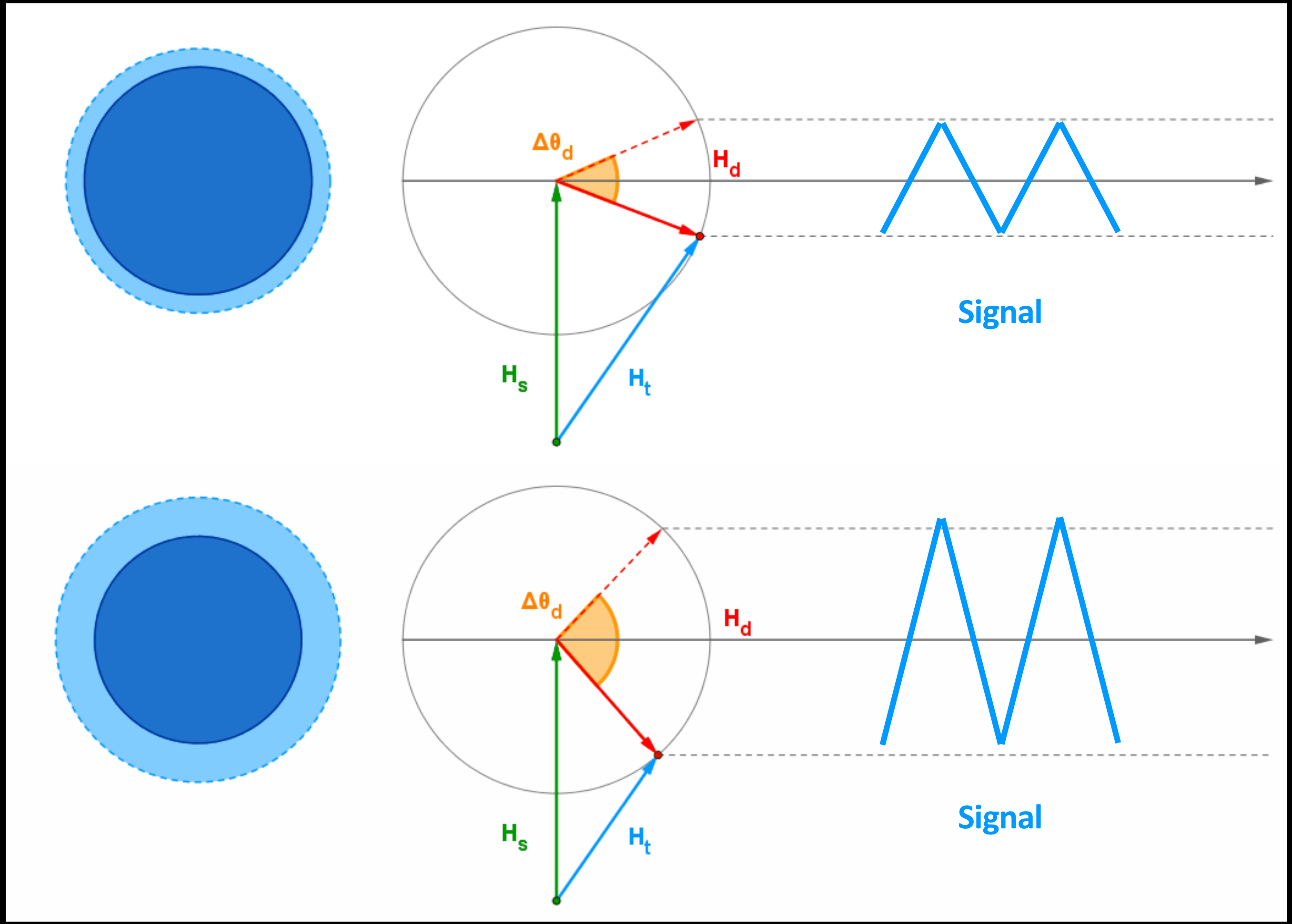
$$\Delta|H| \propto |H_d| \sin\frac{\Delta\theta_d}{2} \sin\Delta\theta_{sd}$$

Displacement of fine-grained activity

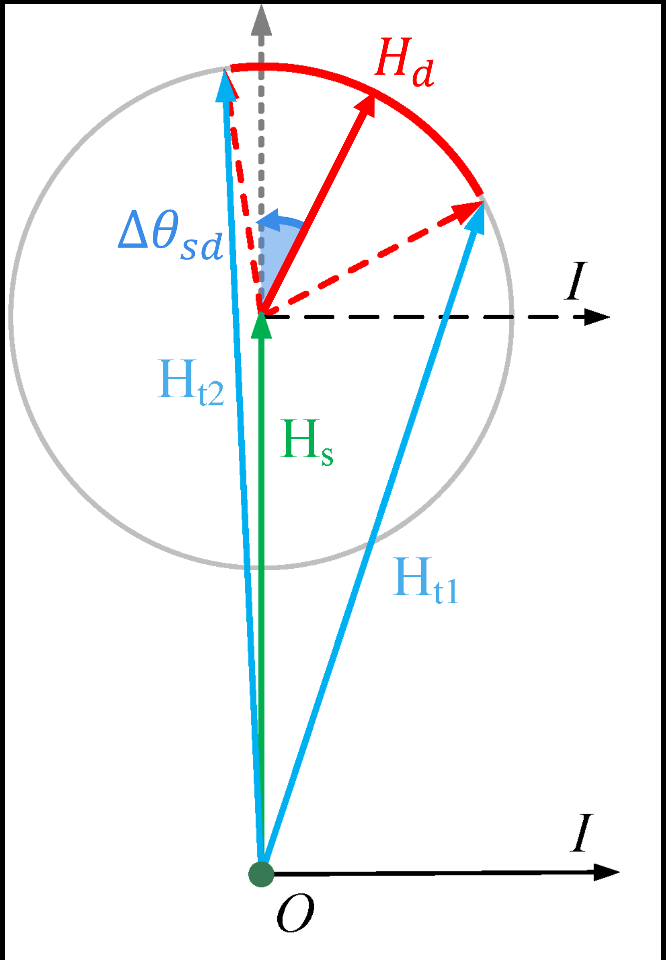
First Factor: Displacement

Small displacement

Large displacement



First Factor: Location

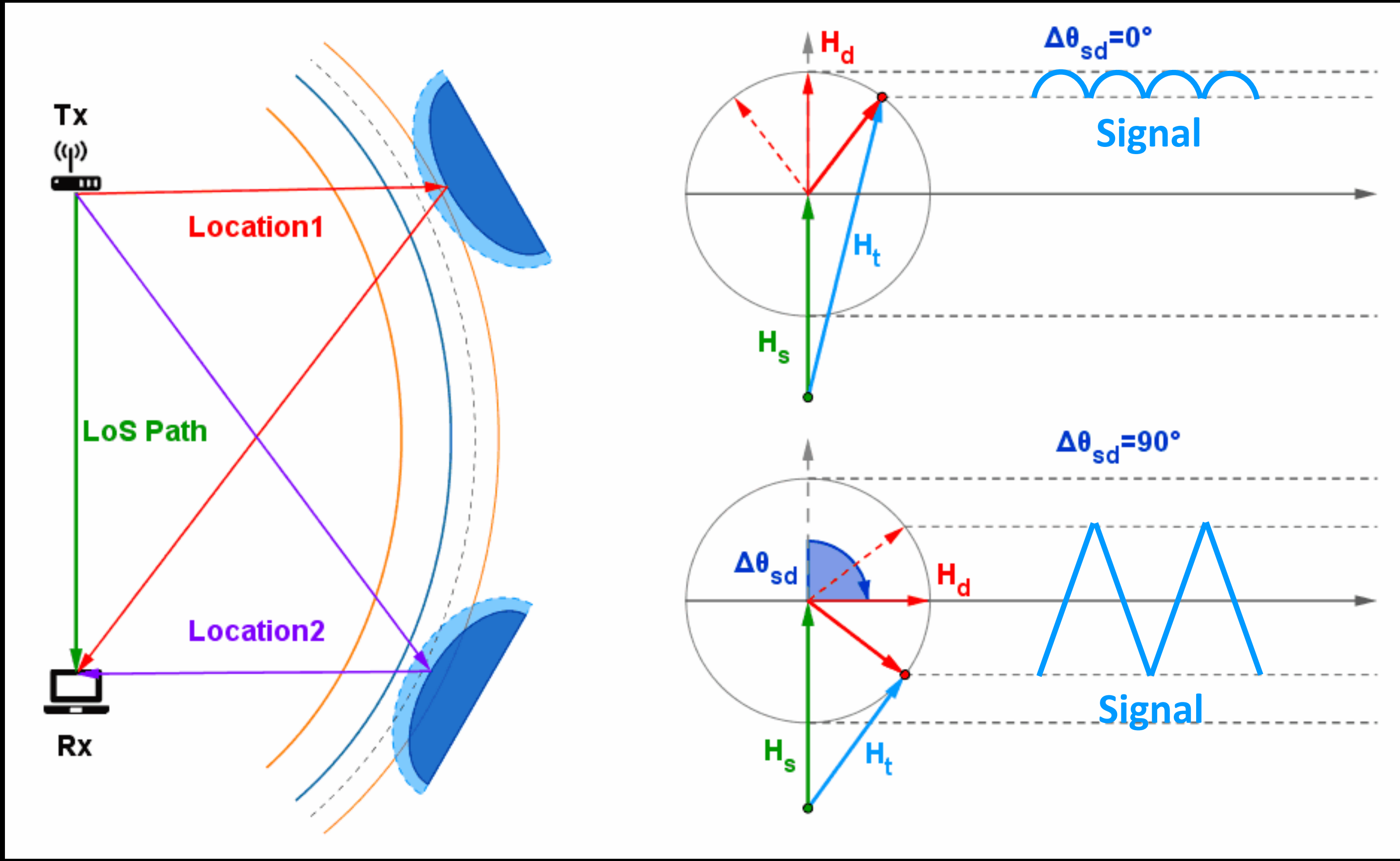


Sensing Performance

$$\Delta|H| \propto |H_d| \sin\frac{\Delta\theta_d}{2} \sin\Delta\theta_{sd}$$

Location in Fresnel Zone

First Factor: Location



The factors that affects the sensing performance

Sensing Performance

$$\Delta|H| \propto |H_d| \sin\frac{\Delta\theta_d}{2} \sin\Delta\theta_{sd}$$

Distance between human and

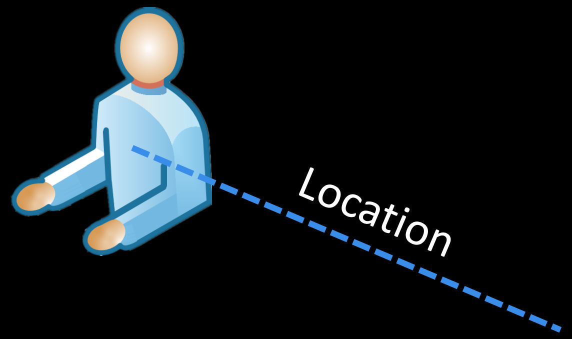
Displacement of

Location in

How can we improve the performance if the user is at a bad location?

How to improve the performance

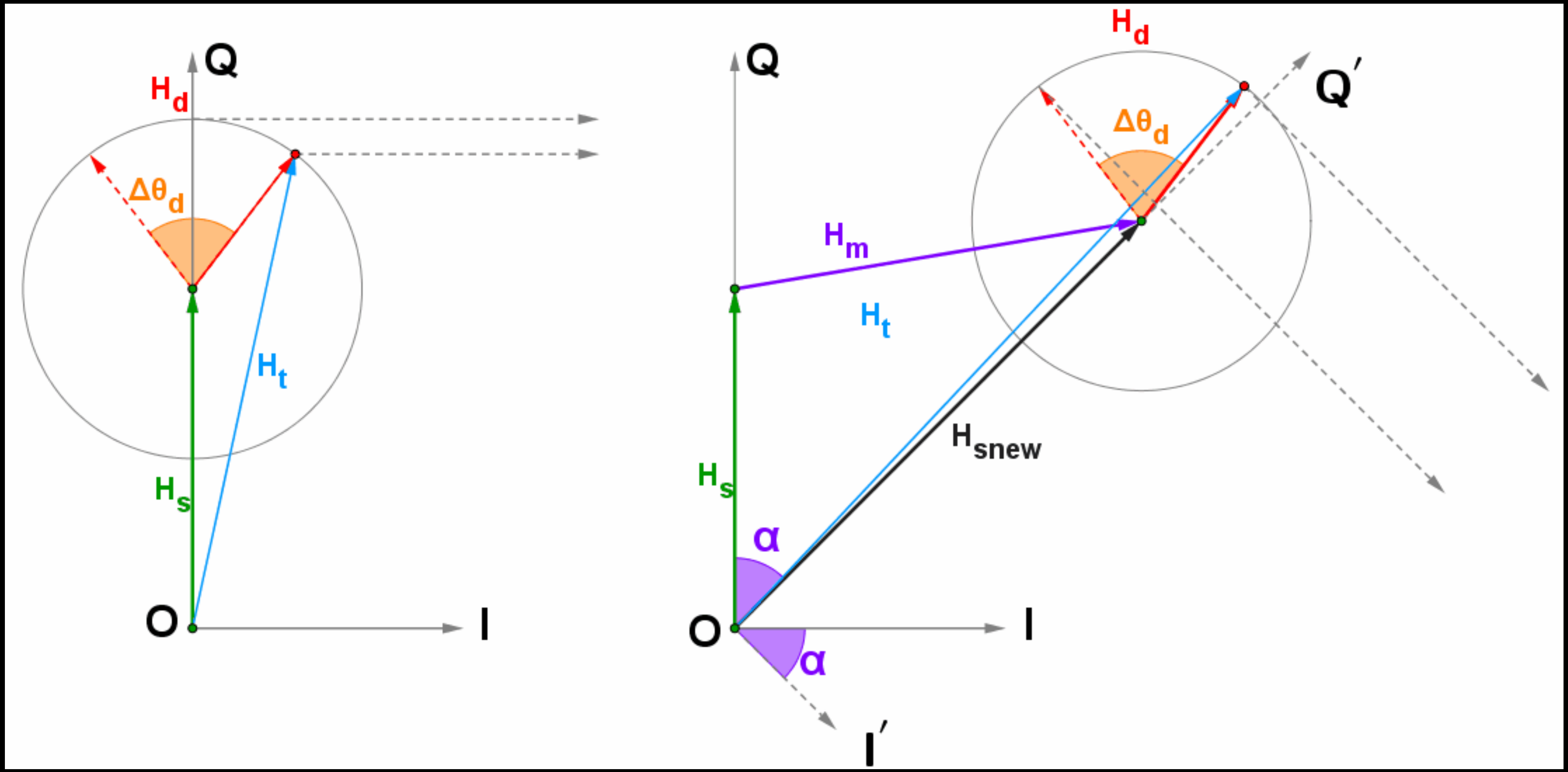
Ask the human to change his location



Disadvantages:

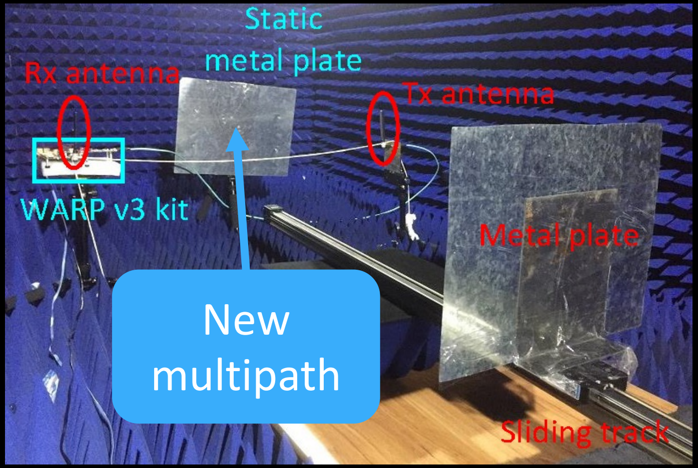
1. Intrusive
2. Difficult to change the location by a precise small amount say 5cm

Improving the performance by adding multipath



How to add a multipath?

Physical Multipath



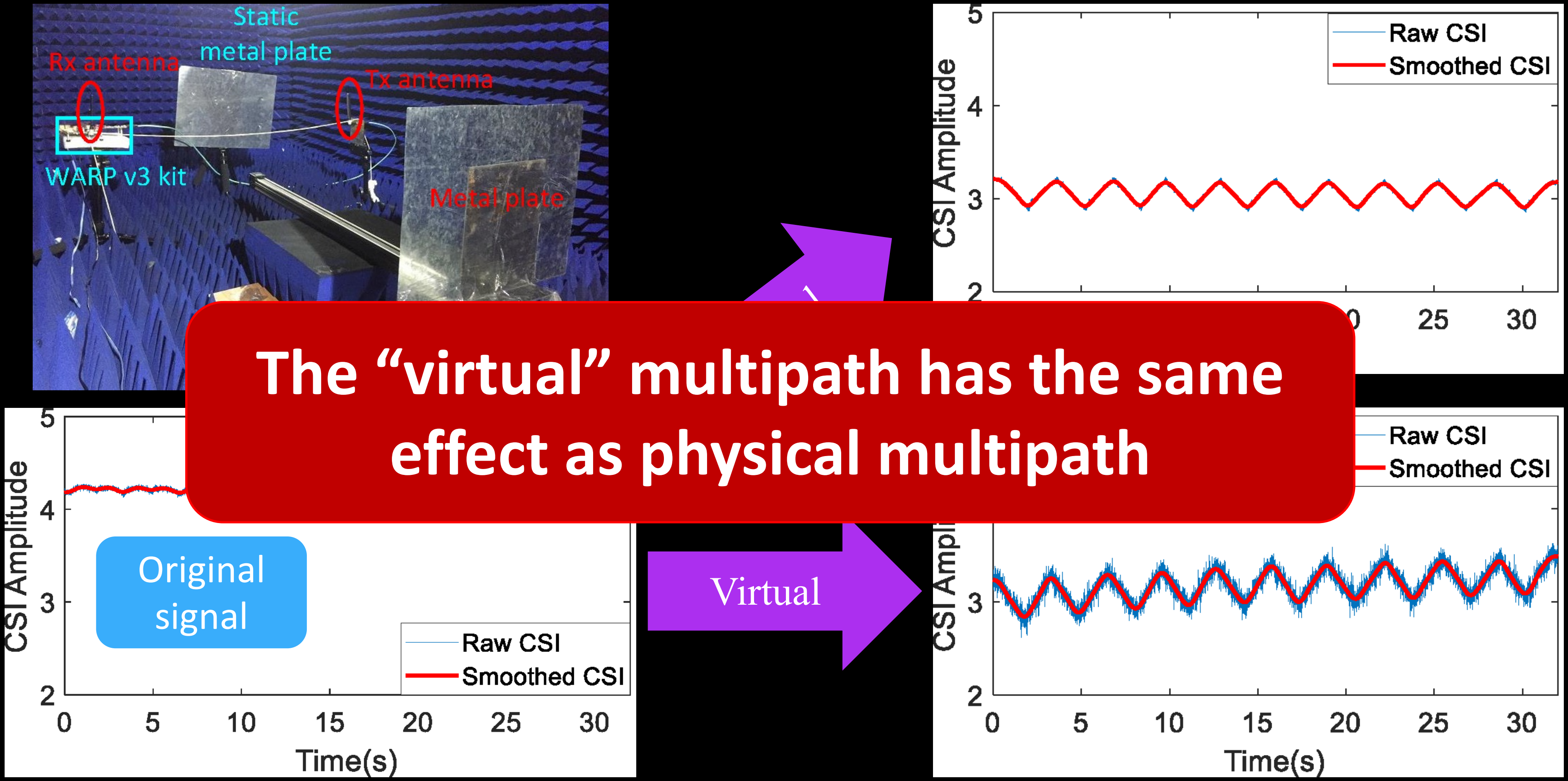
“Virtual” Multipath

$$S_0 = (H_{t1}, H_{t2}, \ldots, H_{tN})$$

$$H_m = |H_m| e^{-i\theta_m}$$

$$S_m = (H_{t1} + H_m, H_{t2} + H_m, \ldots, H_{tN} + H_m)$$

How to add a multipath?



The "virtual" multipath has the same effect as physical multipath

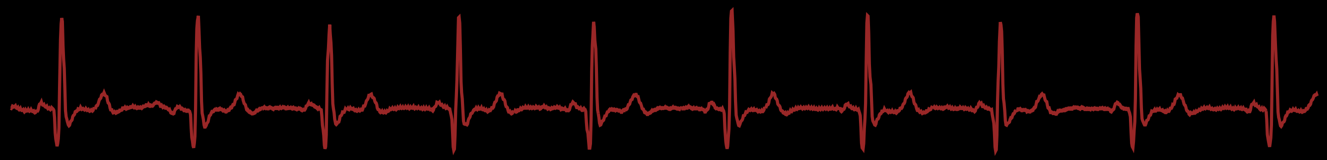
Emotion sensing using radio!

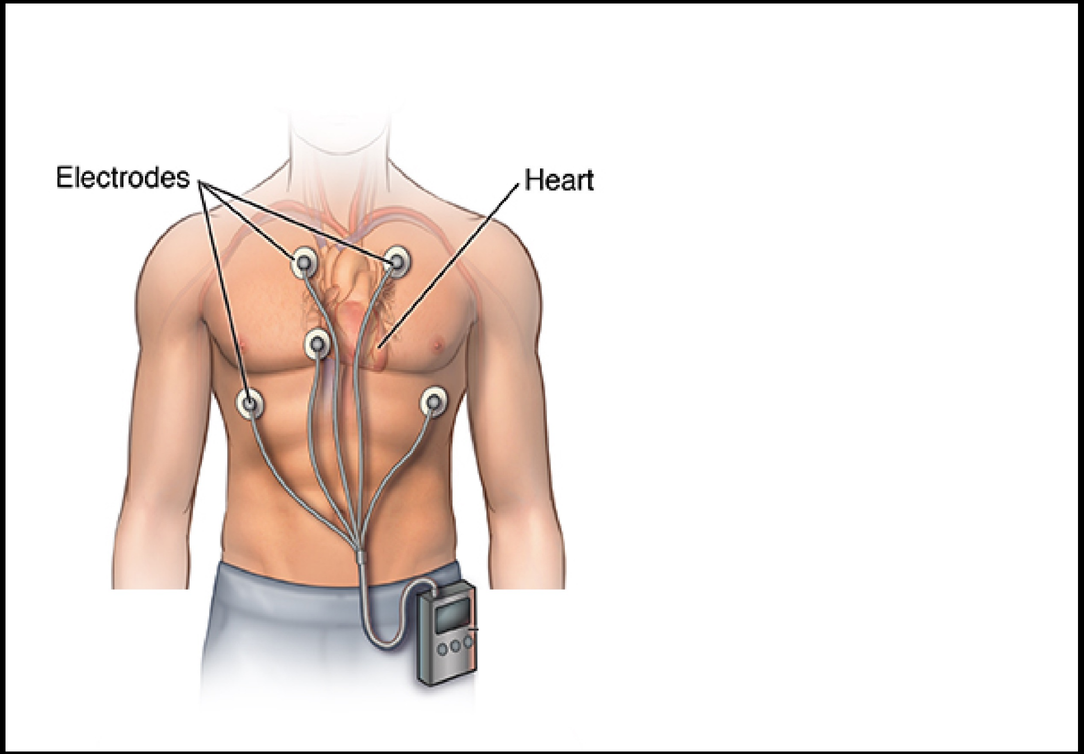
Does my advisor like my research?

How can we tell people's emotions even if they don't show up on their faces?

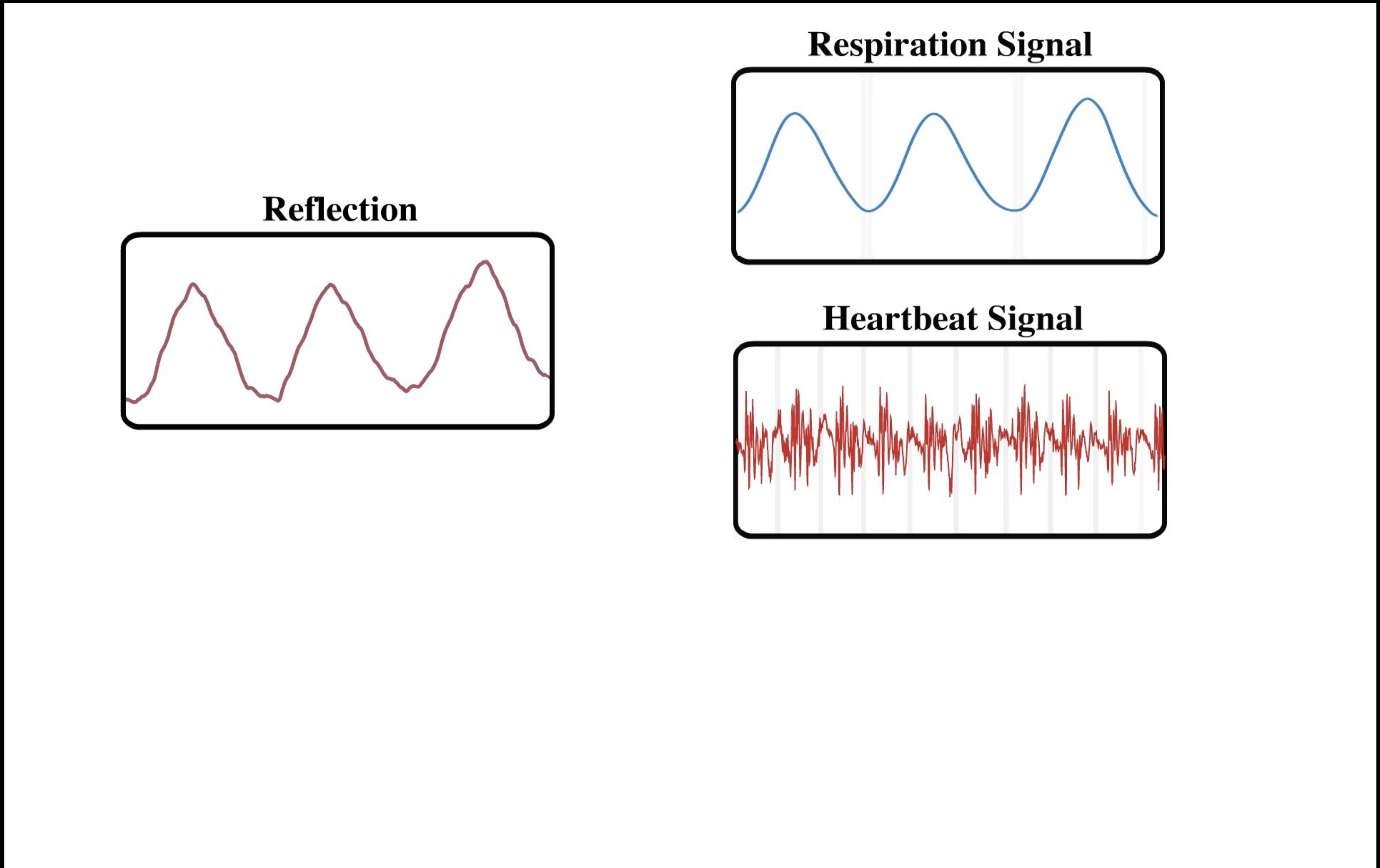
Existing approaches measure vital signs

Use ECG to get very accurate heartbeats



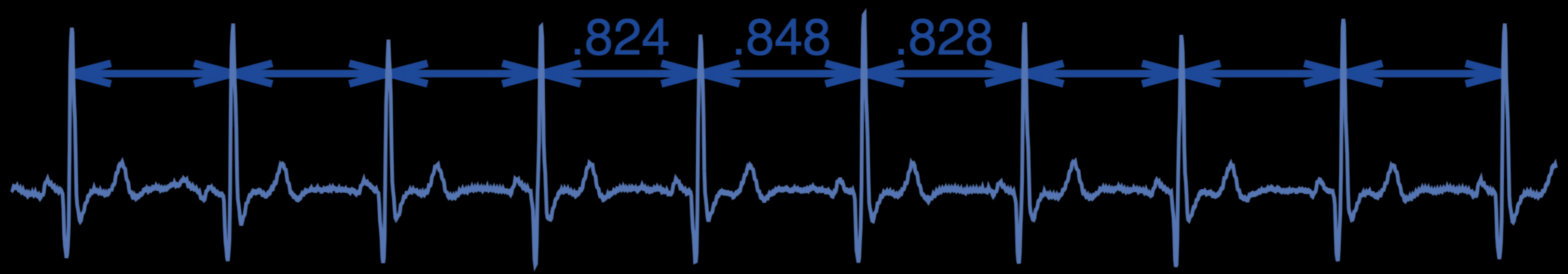


Key idea



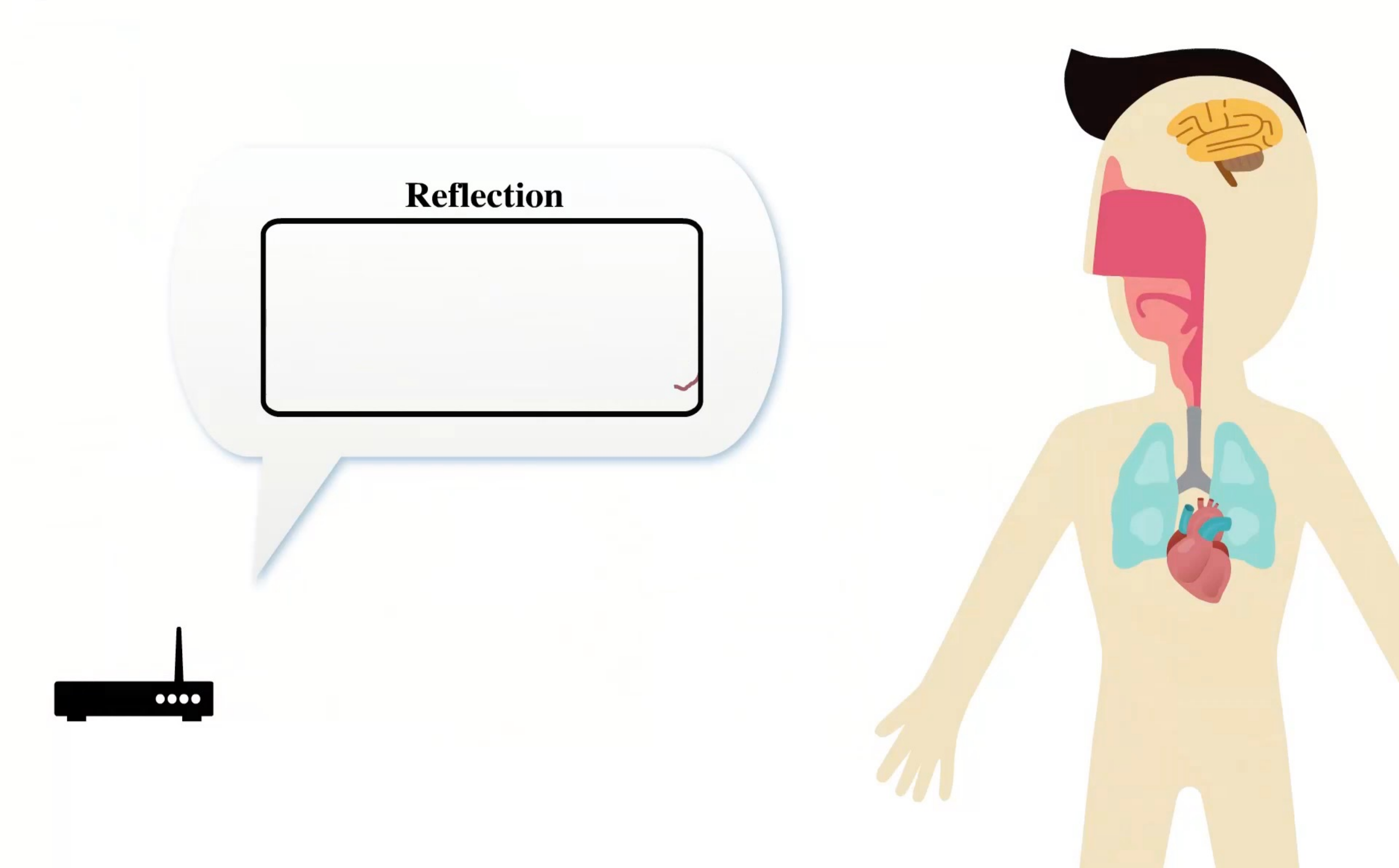
Heartbeat information is the key

- Emotion recognition needs accurate measurements of the length of every single heartbeat

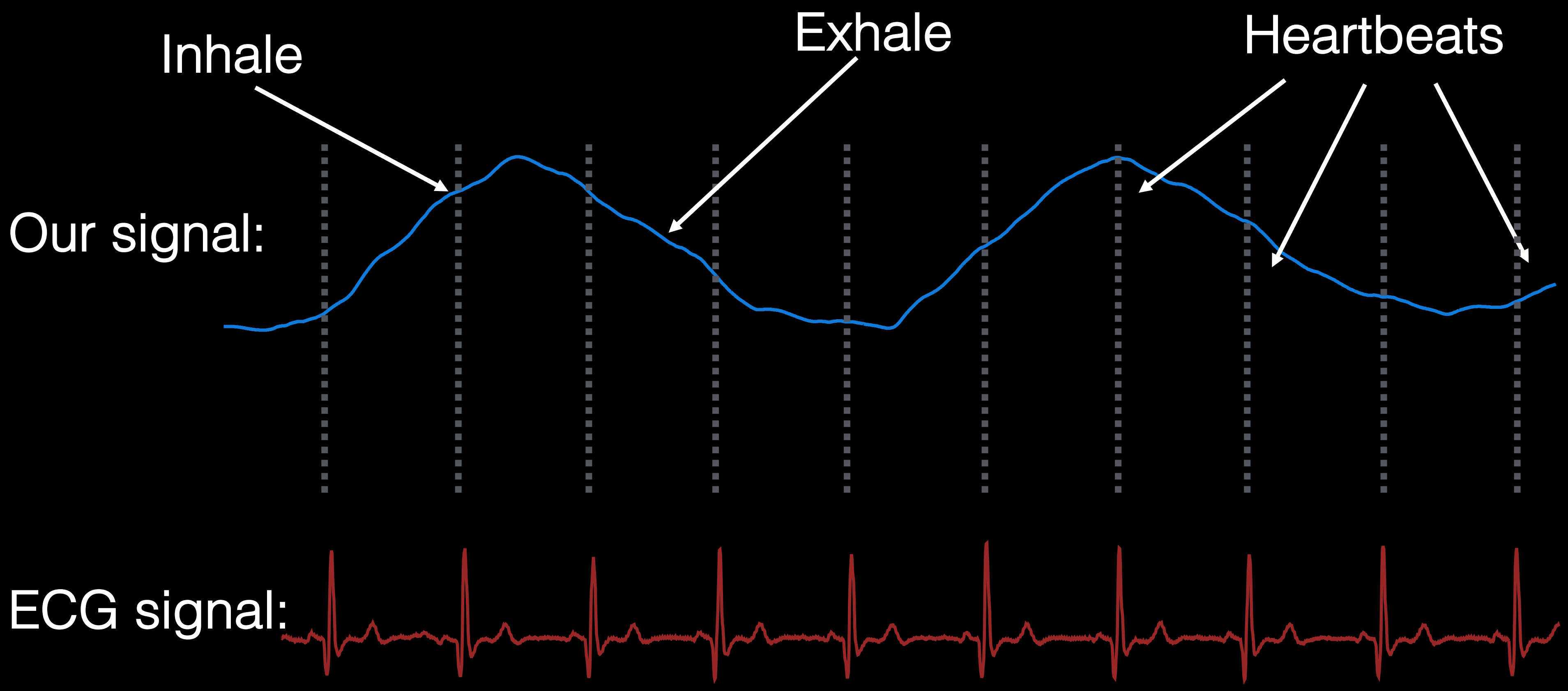


We need to extract IBI (Inter-beat-interval) with accuracy over 99%

Input: wireless signal reflected from human target

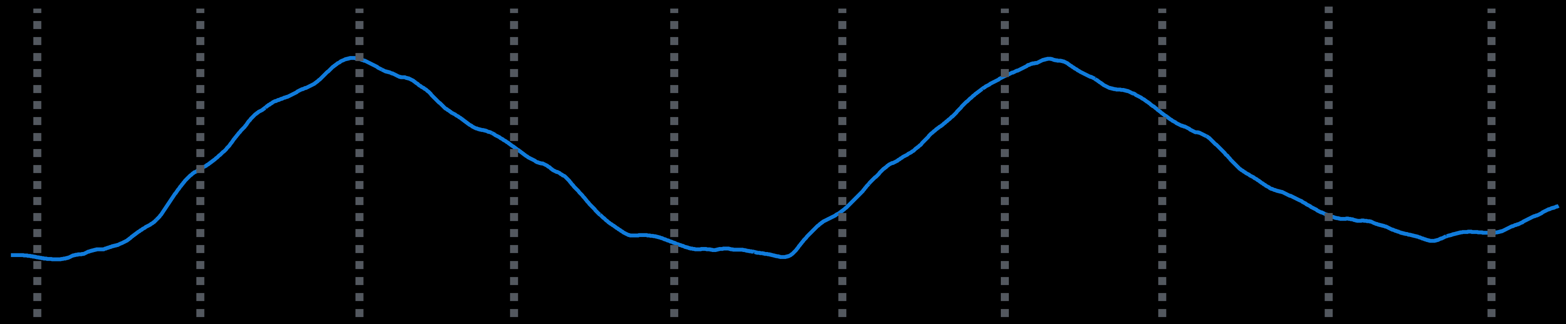


Input: wireless signal reflected from human target



How do we extract accurate IBI?

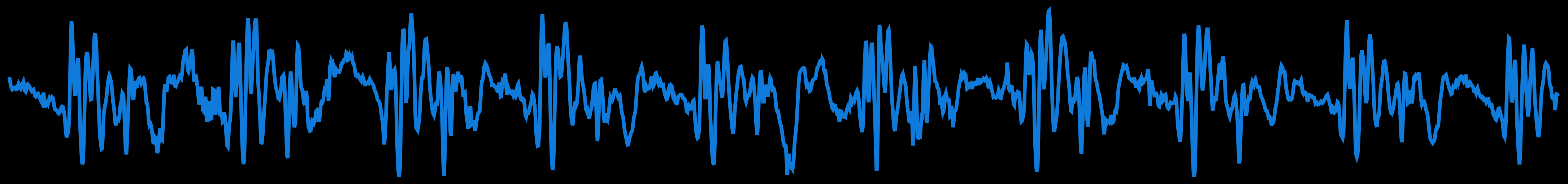
Step 1: Remove breathing signal



- Breathing masks heartbeats
- We use a filter
  - Heartbeat involves rapid contraction of muscle
  - Breathing is slow and steady

Heartbeat signal

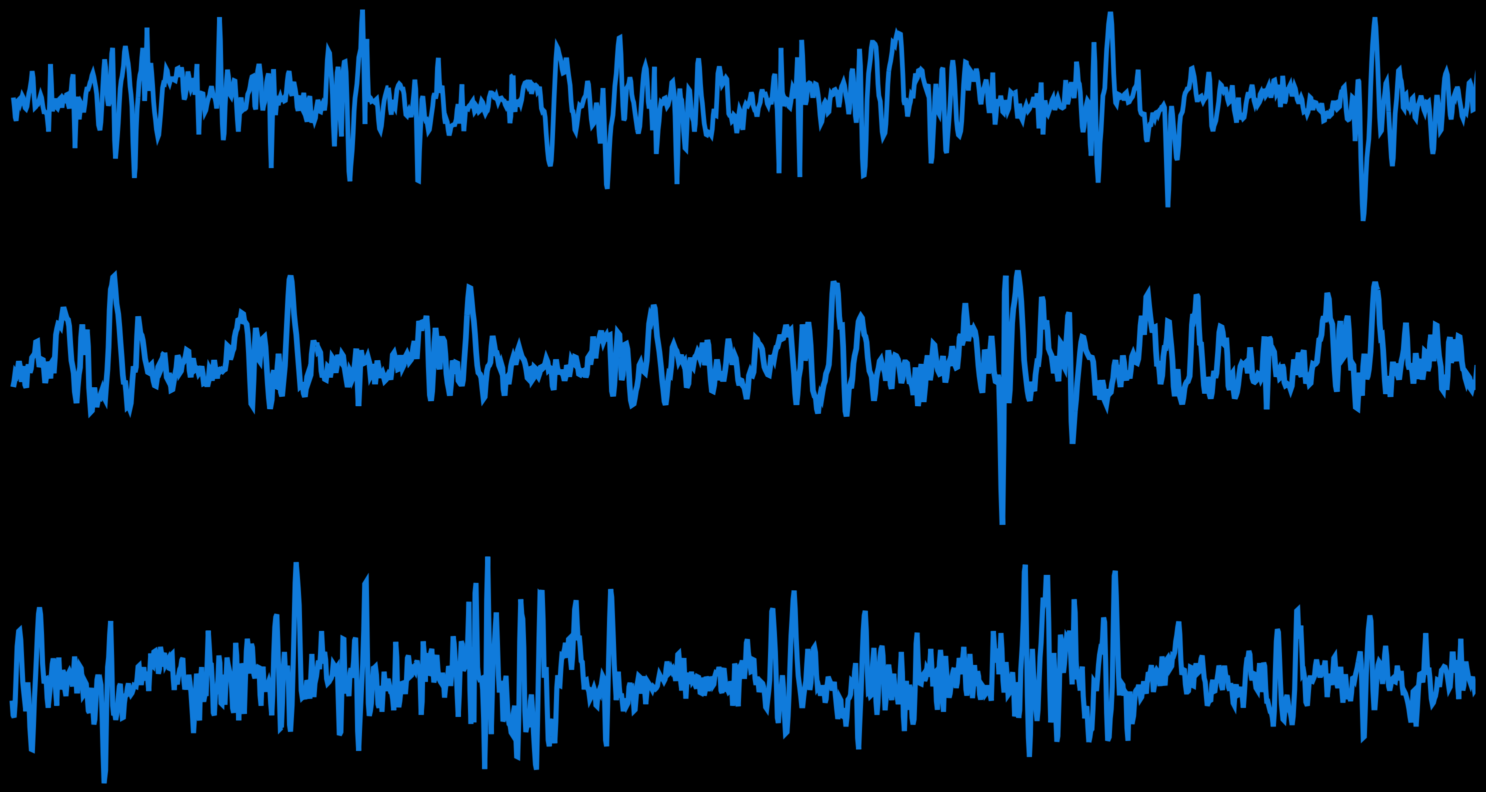
- Output of acceleration filter



- ECG signal

Heartbeat signal

- Other typical examples:



Step 2: Heartbeat segmentation

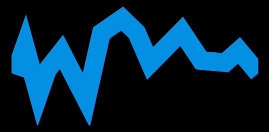
- **Intuition**: heartbeat repeats with certain shape (template)

- If we can somehow discover the template, then we can segment into individual heartbeats

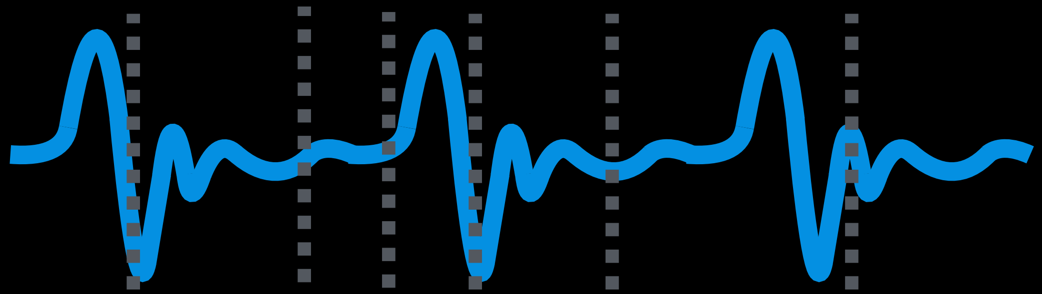
Step 2: Heartbeat segmentation

- **Intuition**: heartbeat repeats with certain shape (template)

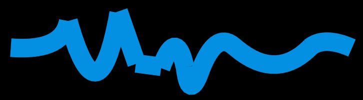
Random template:



Segmentation Update



Template Update



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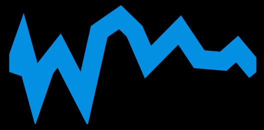

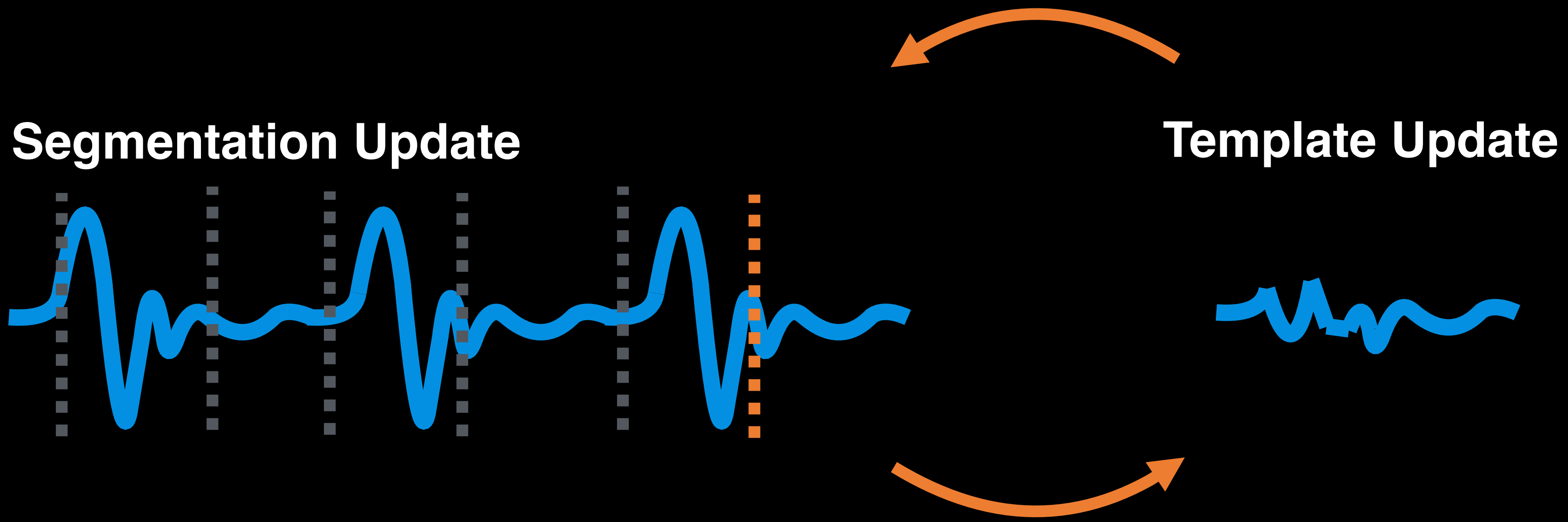

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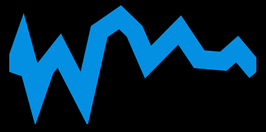
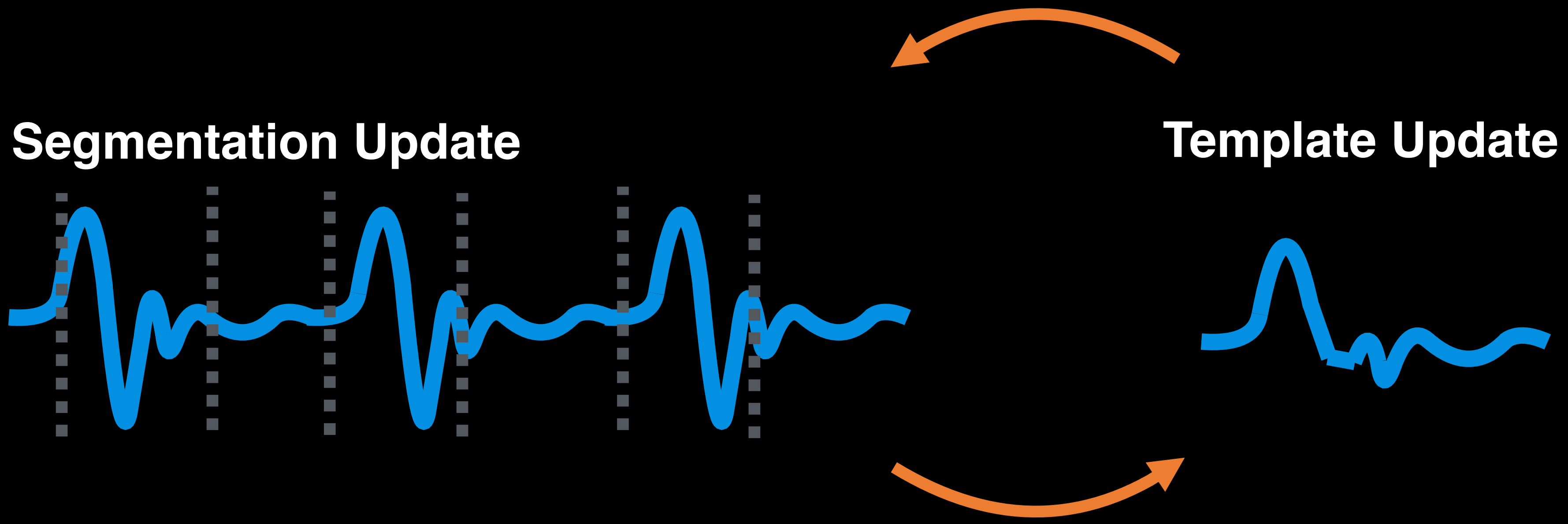
Random template: 



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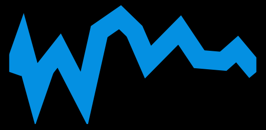
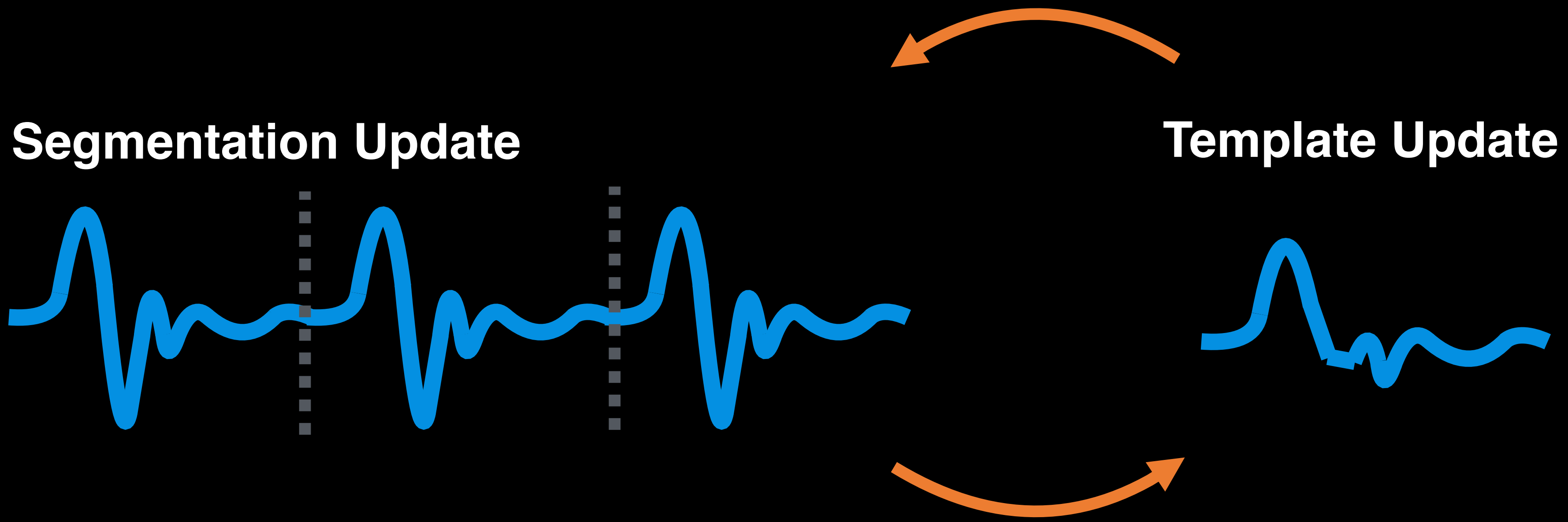
Random template: 



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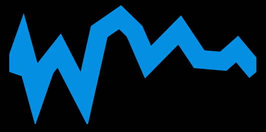
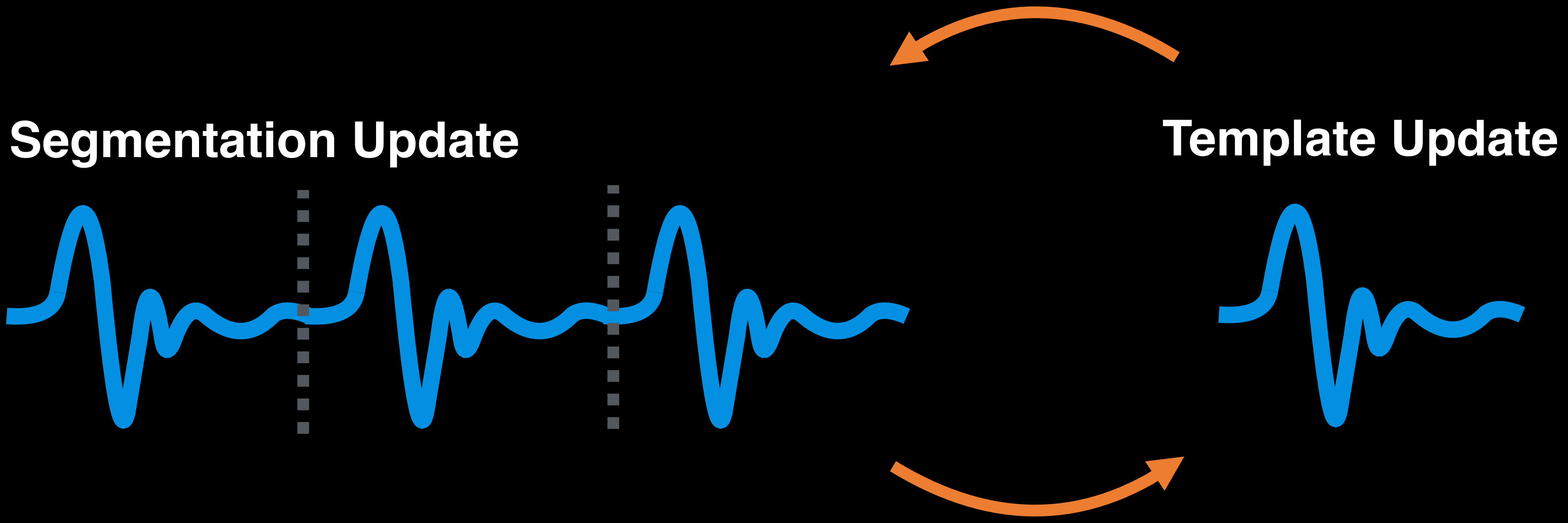
Random template: 



From vital signs to emotions

Physiological Features for Emotion Recognition

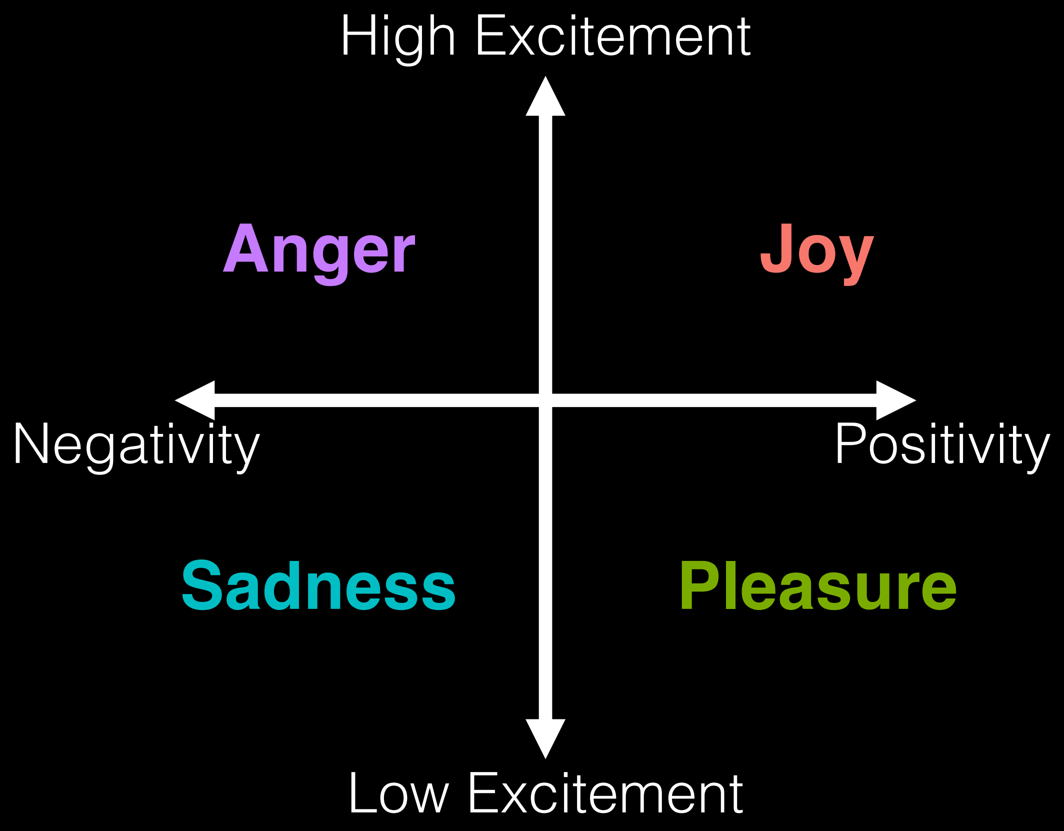
- 37 Features similar to ECG-based methods
  - Variability of IBI
  - Irregularity of breathing

Emotion Classification

- Recognize emotion using physiological features
- Used L1-SVM classifier
  - Select features and train classifier at the same time

Emotion Model

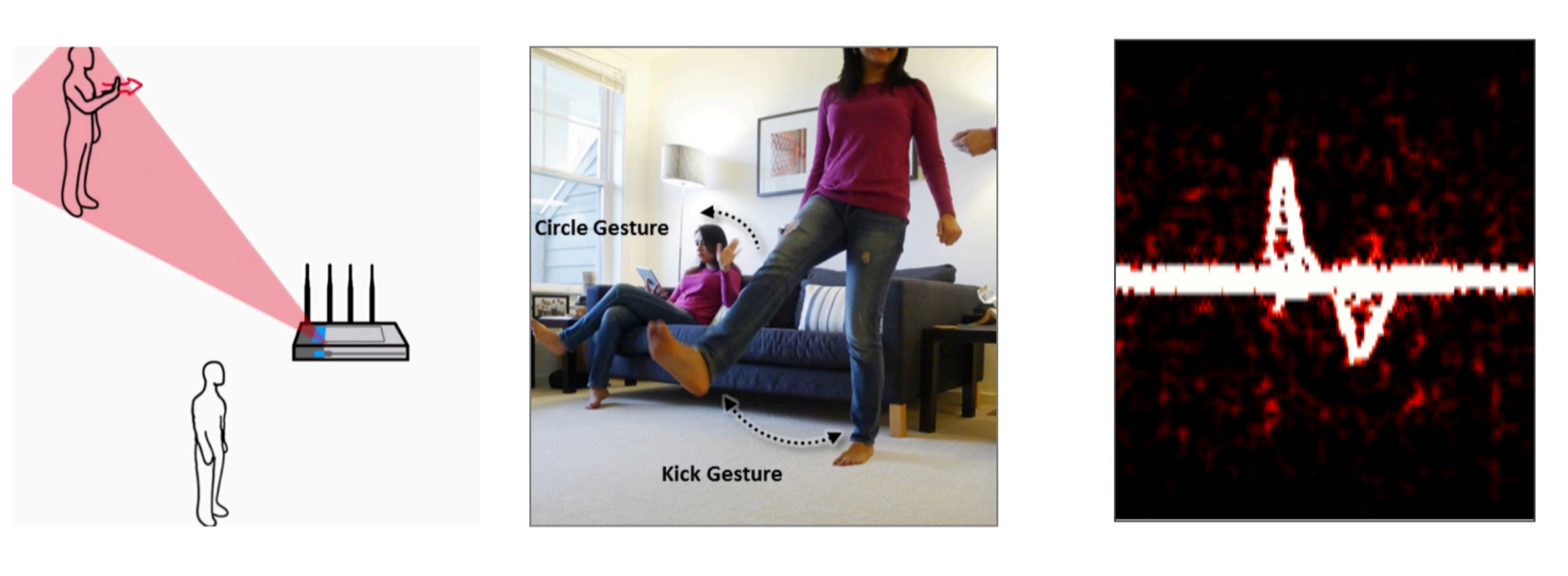
- Standard 2D emotion model
- Classify into **anger**, **sadness**, **pleasure** and **joy**



Sensing Human Gestures with Wi-Fi

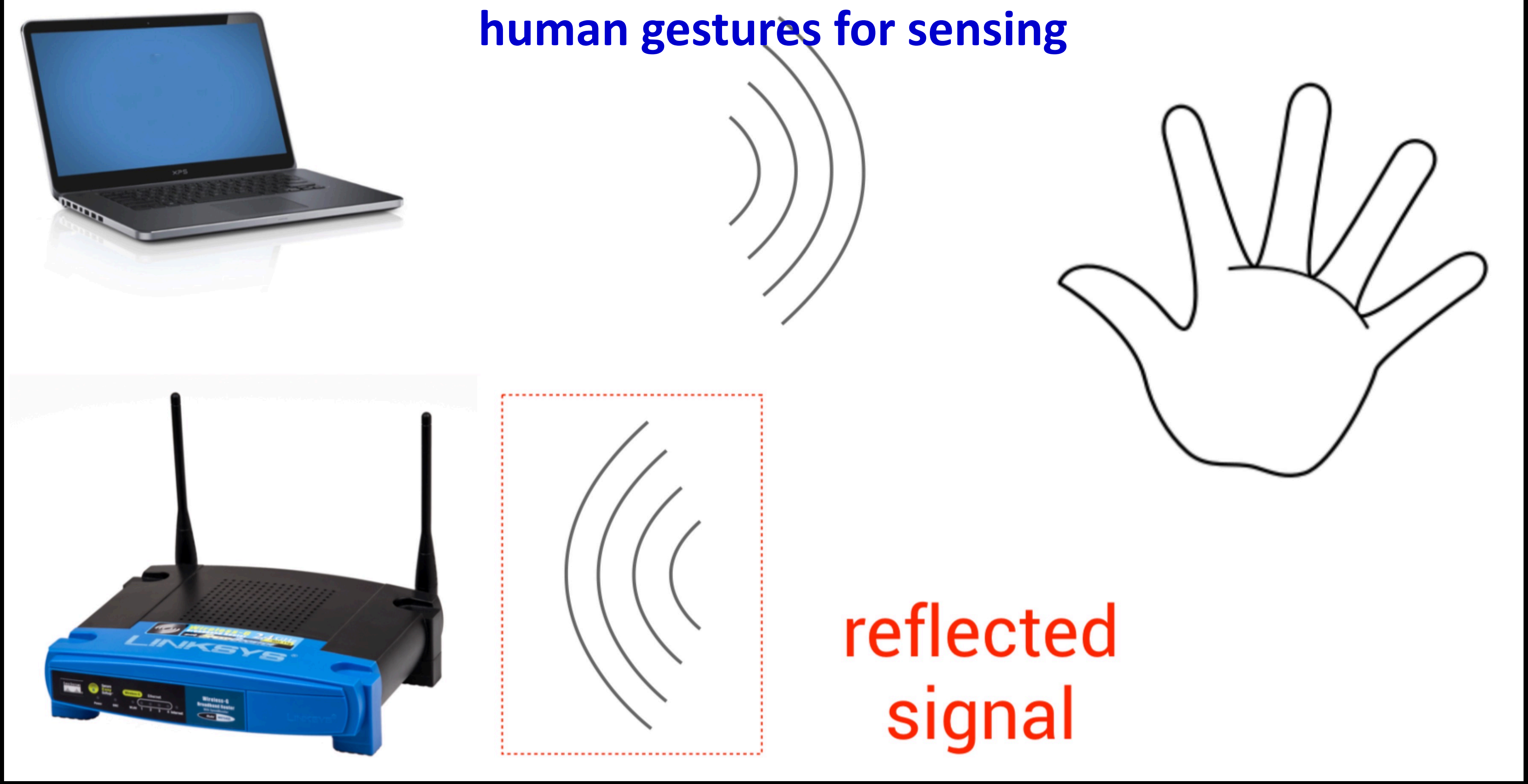
WiSee: Whole-Home Gesture Recognition Using Wireless Signals

Qifan Pu, Sidhant Gupta, Shyam Gollakota, Shwetak Patel
Mobicom 2013



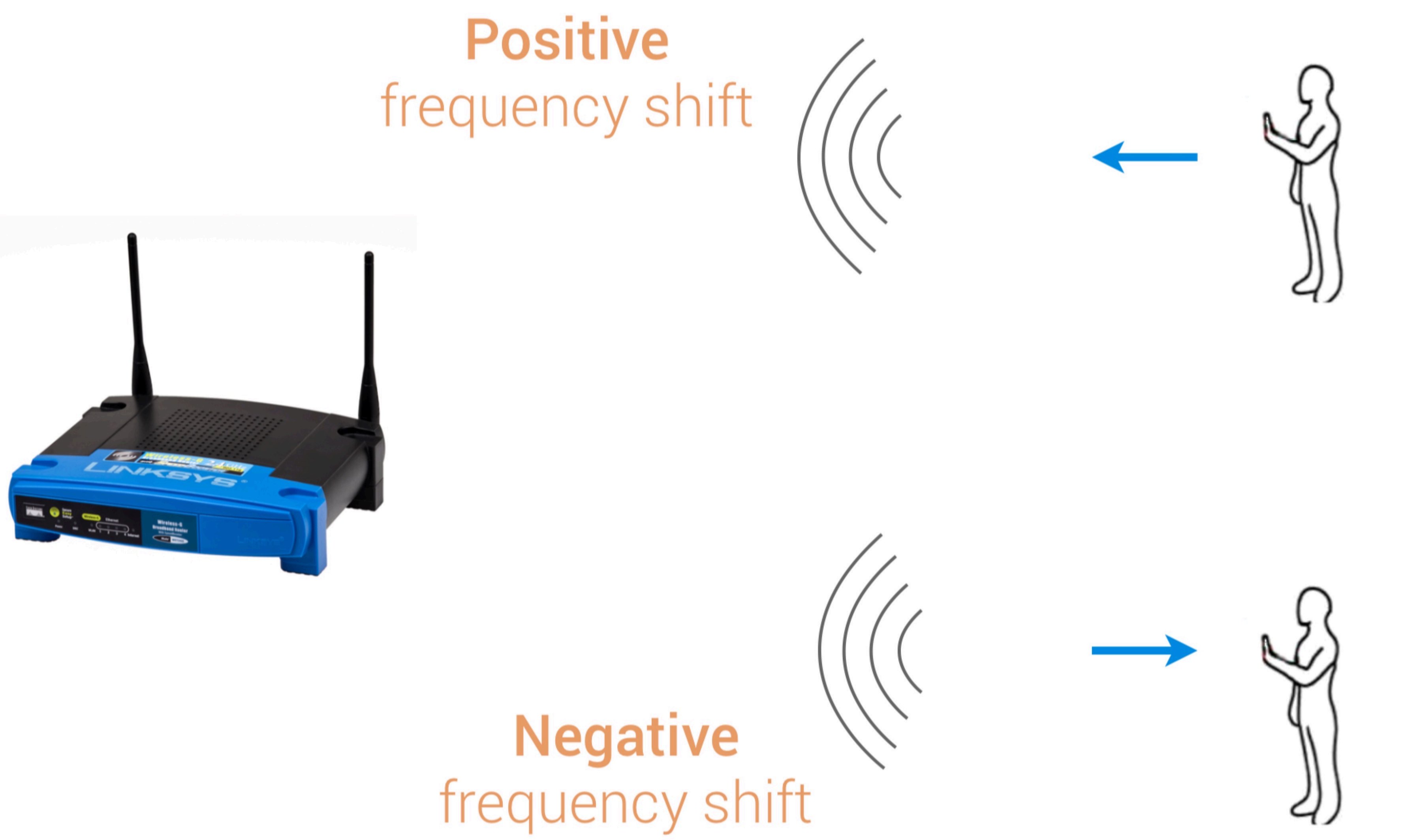
Wi-Fi based gesture recognition

Leveraging unique doppler shifts induced by human gestures for sensing



Wi-Fi based gesture recognition

Wi-Fi based gesture recognition



Wi-Fi based gesture recognition

- **Doppler Shift:** $\Delta f = \frac{f_c \cdot v_{radial}}{c}$
  - v_{radial} is the **radial** component of the receiver's velocity vector **along the path**
    - **Positive** Δf with **decreasing path length**, **negative** Δf **with increasing** path length

- For WiFi signal f_c = 2.4 GHz, v = 0.5m/s
  - **Doppler shift**: $\Delta f = 8\ Hz$

Wi-Fi based gesture recognition

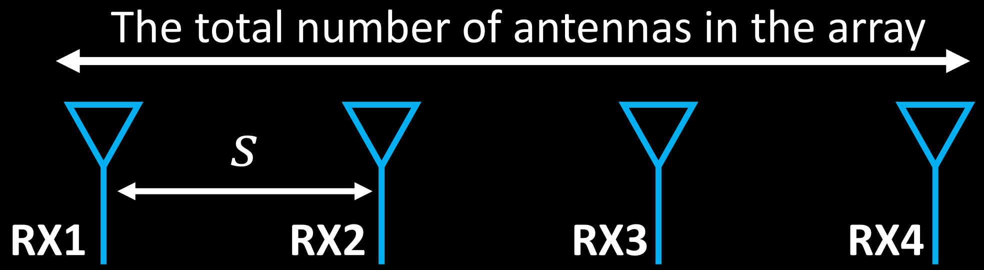
- The frequency bandwidth for WiFi is 20MHz
- We want to measure an 8 Hz change which is 0.00004 % of 20MHz

We need to obtain a fine-grained
Doppler shift

A few hertz

ToF and AoA: Resolution

AoA Sensor: antenna

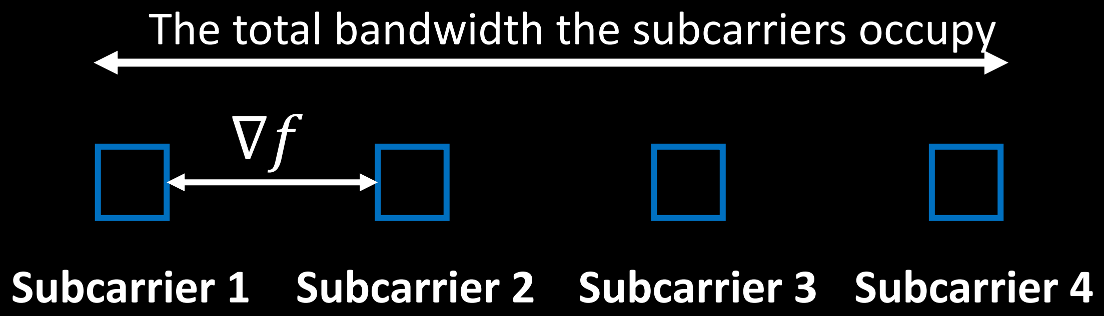


More antennas, higher spatial resolution

Increase the number of antennas

Any other solutions? ?

ToF Sensor: OFDM subcarrier



Increase the bandwidth

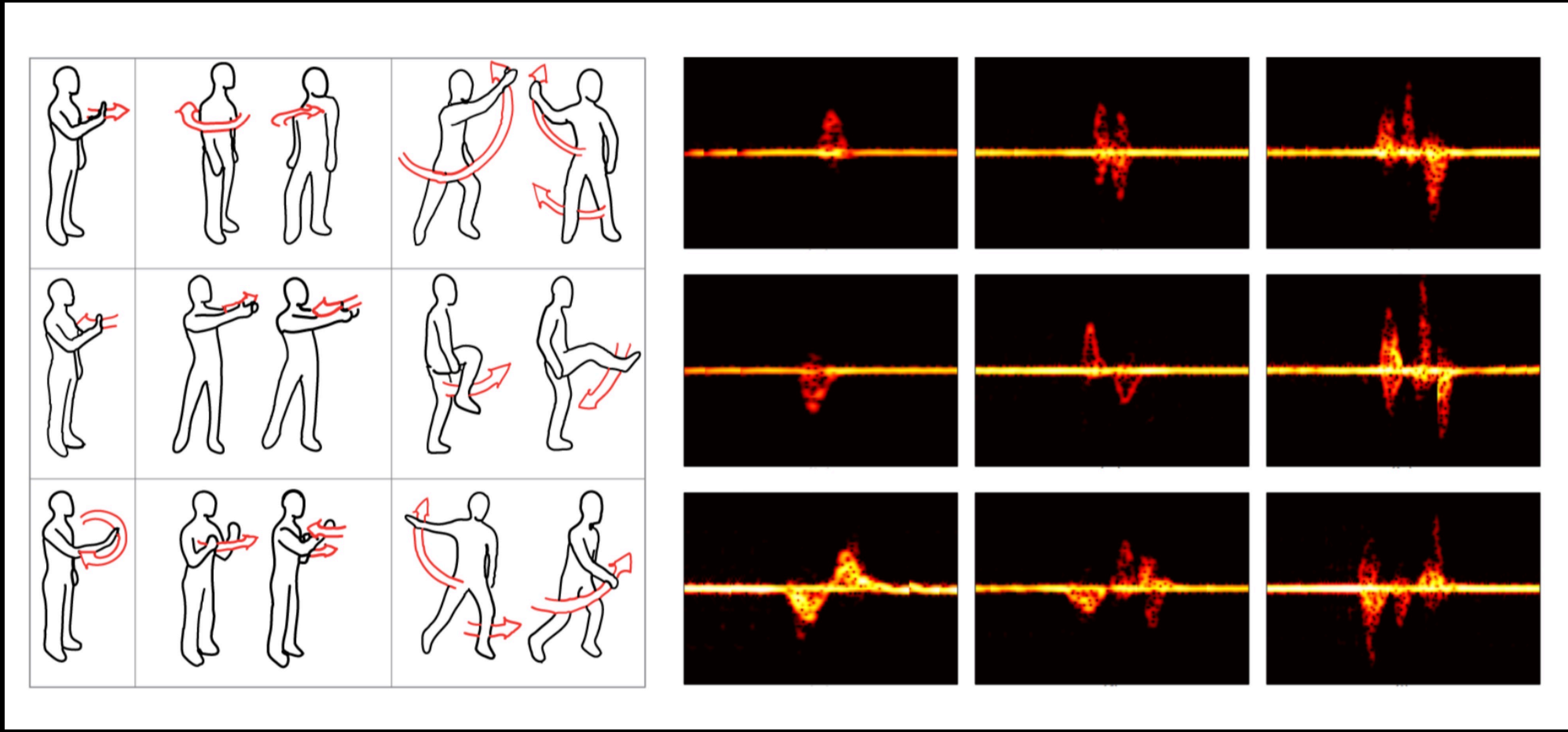
Larger bandwidth, higher time resolution

Wi-Fi based gesture recognition

- Increase the observation time to increase the resolution

If we increase the observation time to 1 second, we can achieve 1Hz resolution which is enough to detect a few Hz of doppler shift

Unique Doppler shifts caused by different gestures



Demo: Pioneer WiFi-based gesture recognition

The state-of-the-art human sensing with WiFi

Sensing Human with Visible Light

- Tianxing Li, Chuankai An, Zhao Tian,
- Andrew T. Campbell, and Xia Zhou

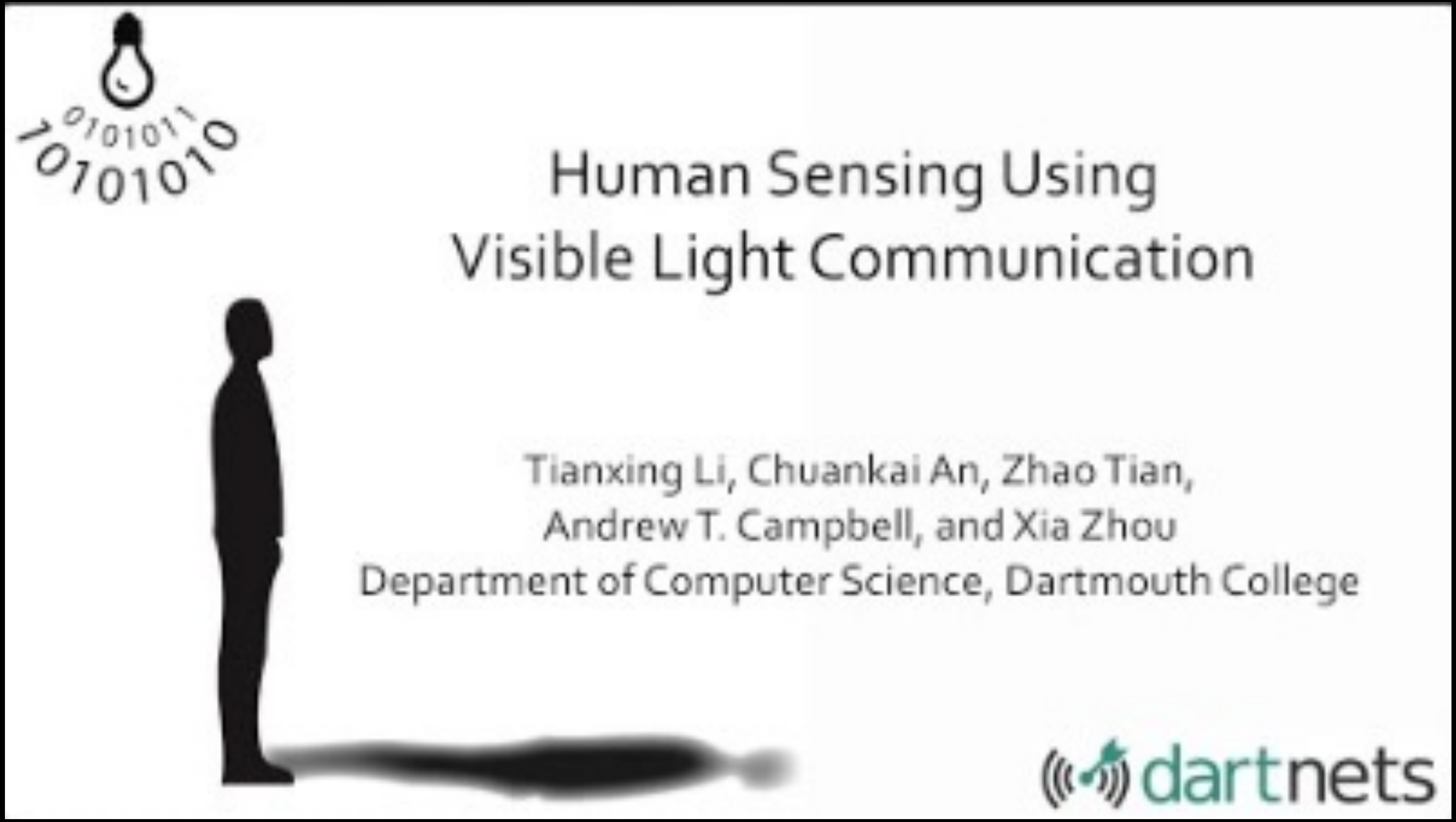
- *Department of Computer Science*
  Dartmouth College

dartnets

Sensing Human with Visible Light

- Leverage the ubiquitous light around us to sense what we do

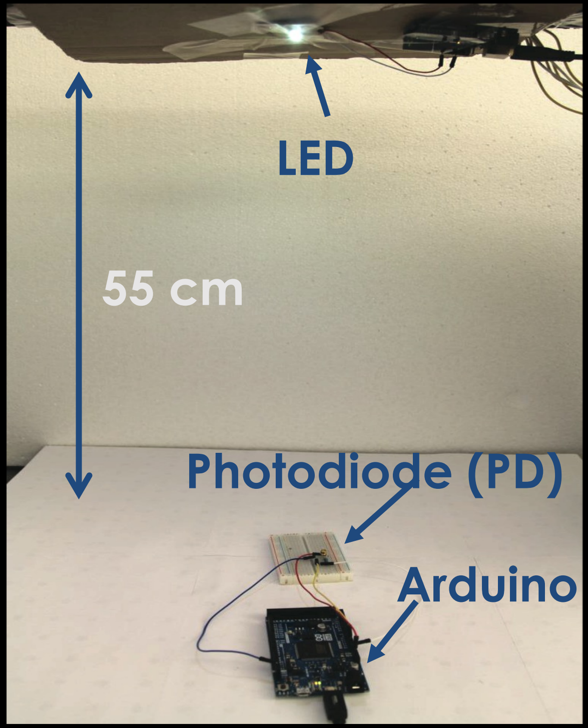
Sensing Human with Visible Light



Sensing Human with Visible Light

Key ideas: shadows!

Sensing Human with Visible Light

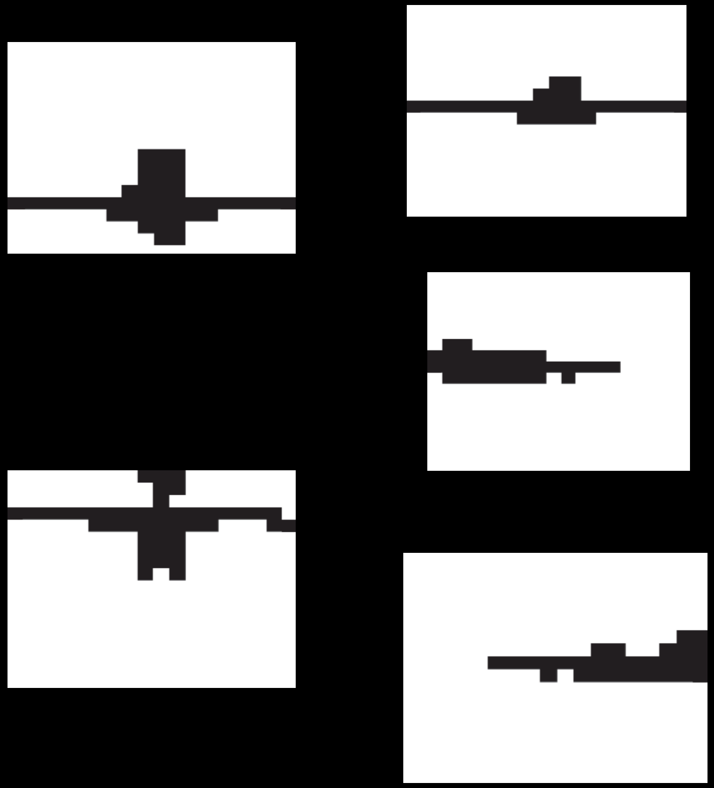


Not That Simple

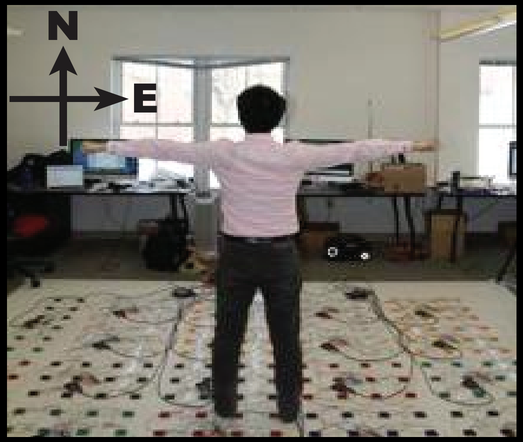
Challenge #1: Diluted and complex shadow under multiple light sources

Not That Simple

Challenge #2: Reconstruct a 3D posture from 2D low-resolution (18 x 18) shadows



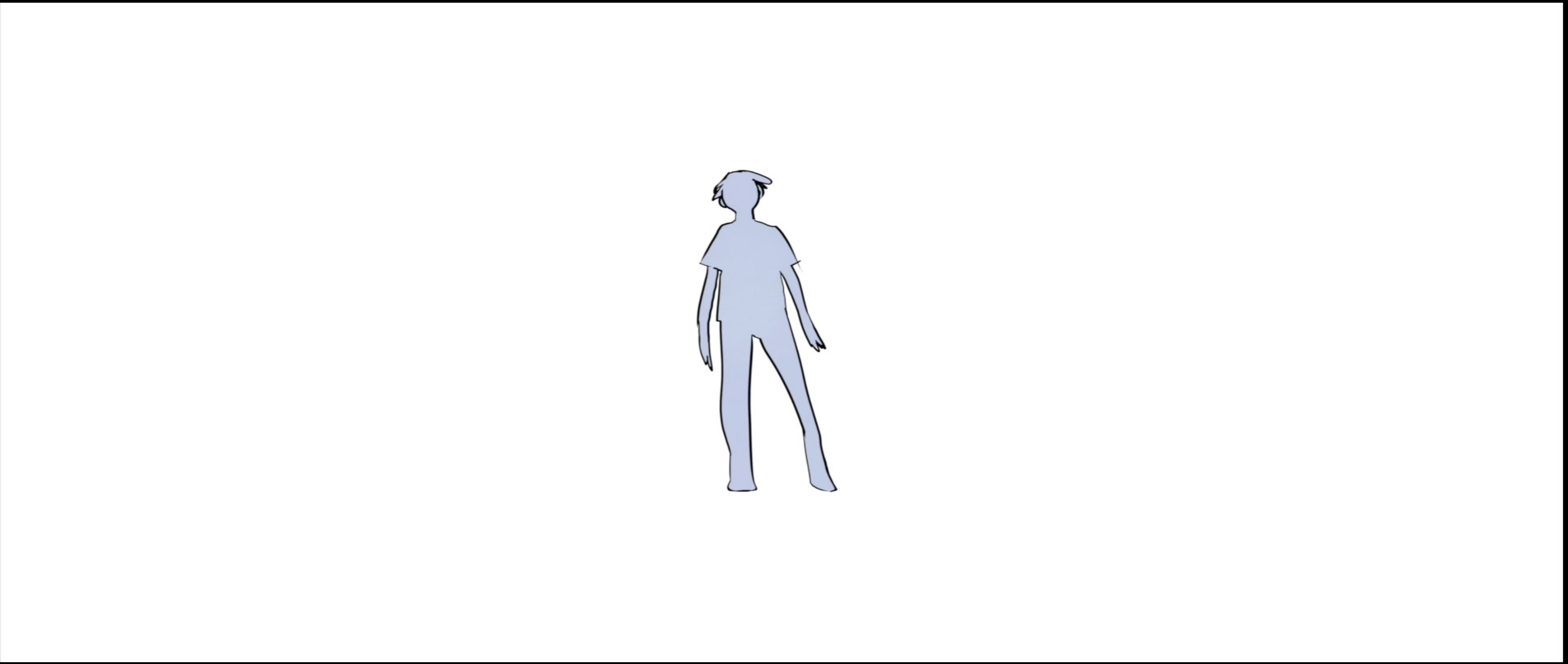
?



Sensing Human with Visible Light

Challenge #1: Multiple light sources

Separate light rays via light beacons

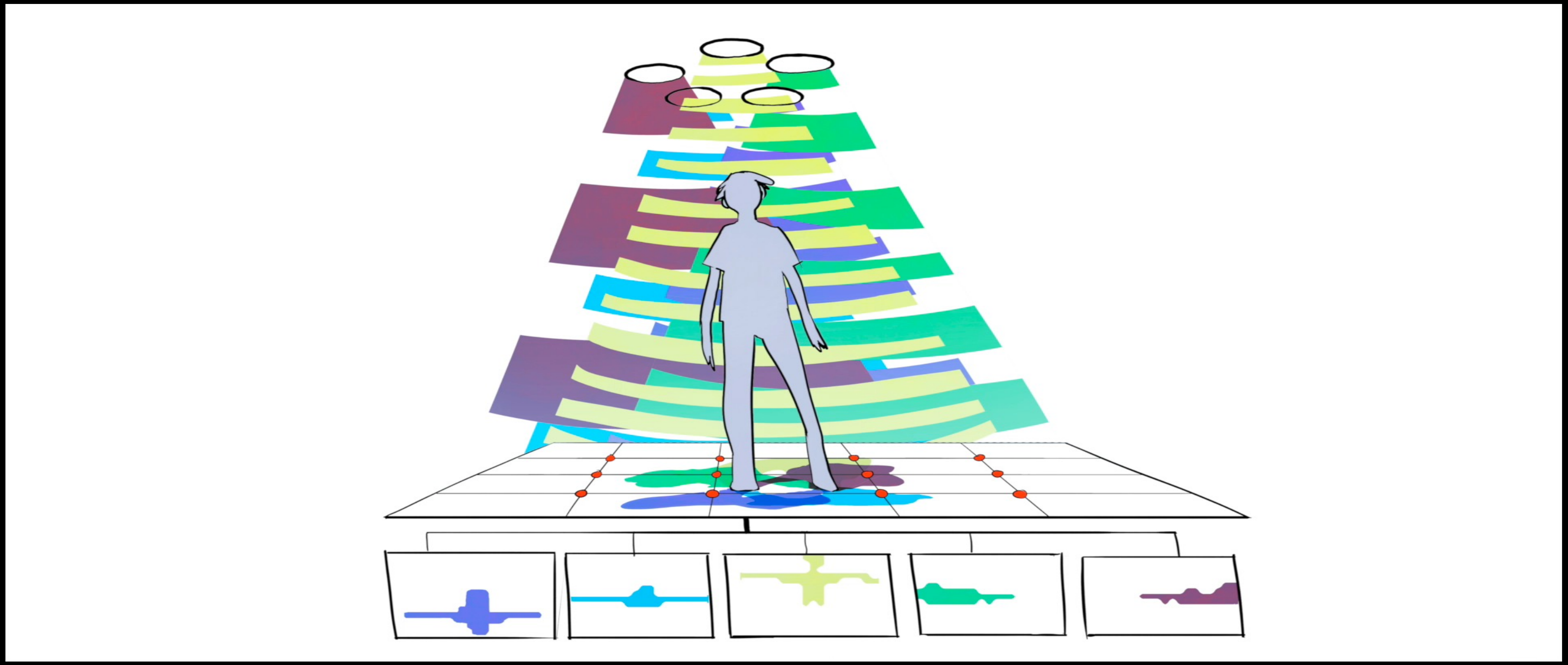


Sensing Human with Visible Light

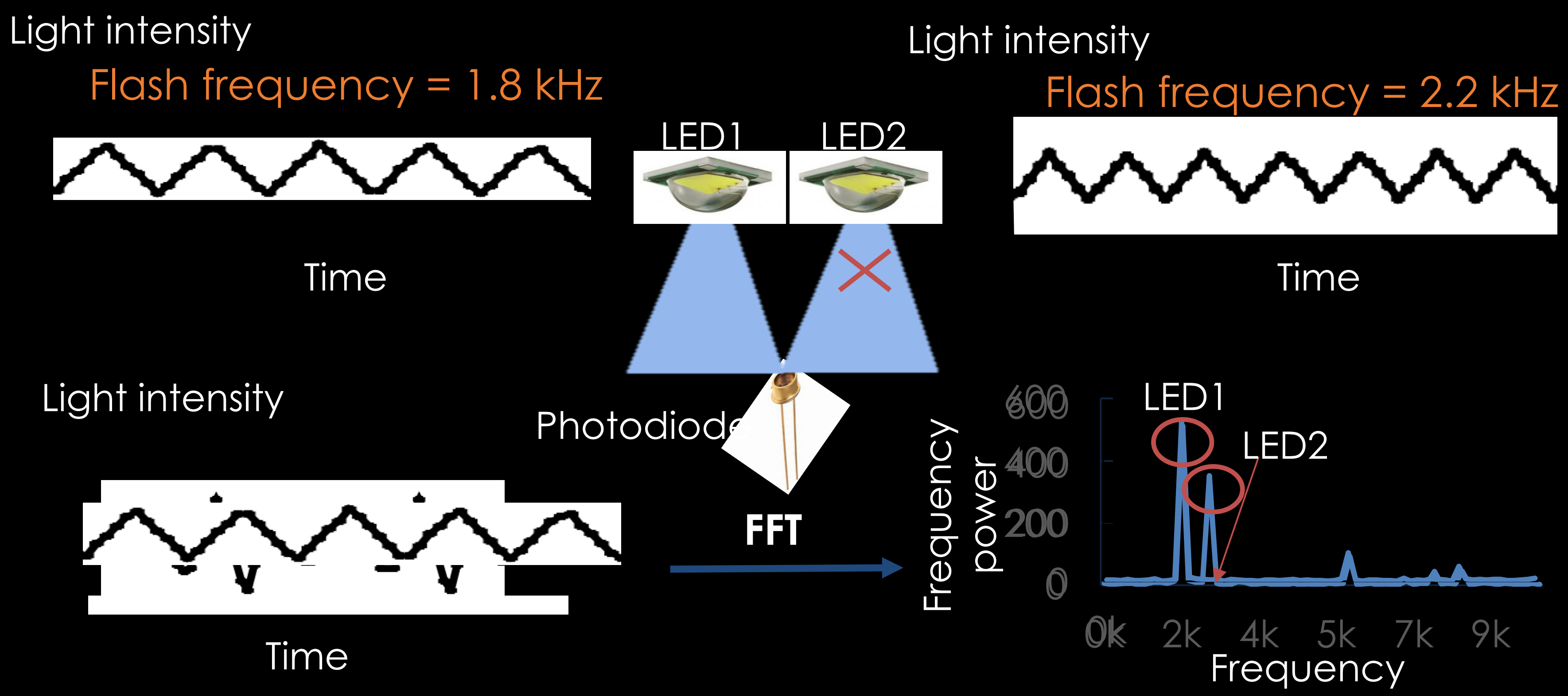
Challenge #2:
Reconstruct a 3D posture from 2D shadows

↓

Seek a posture best fitting shadows cast in multiple directions

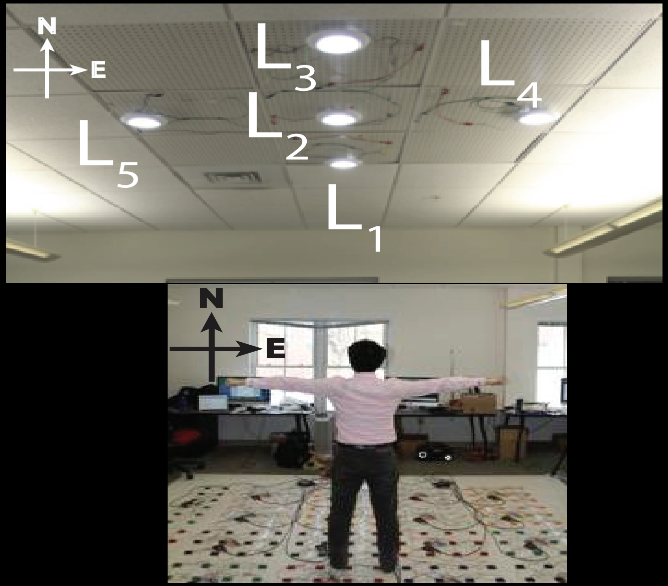


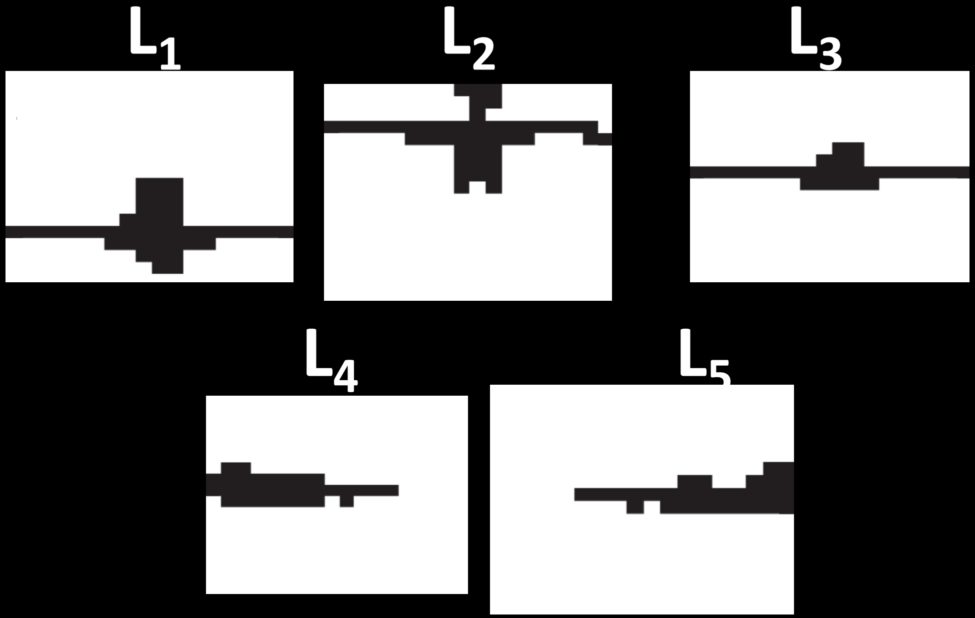
Light Beacons



Recover Shadow Maps

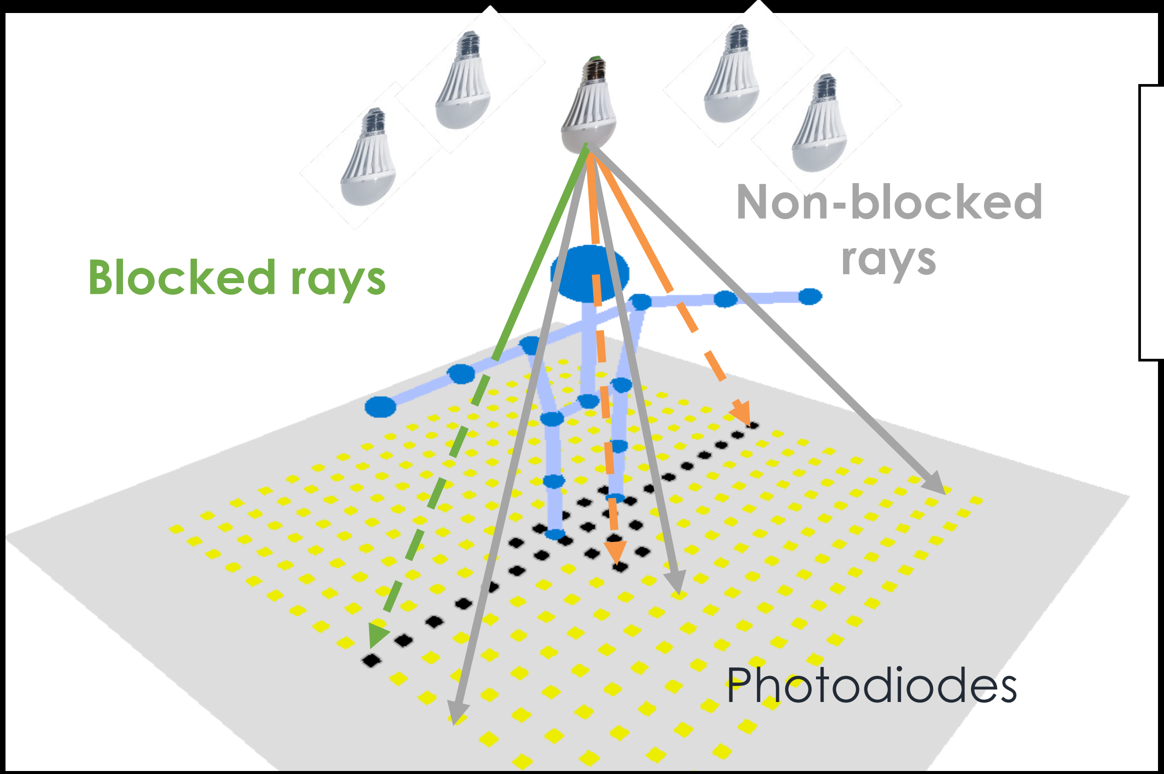
- Infer a binary shadow map cast by each single LED light





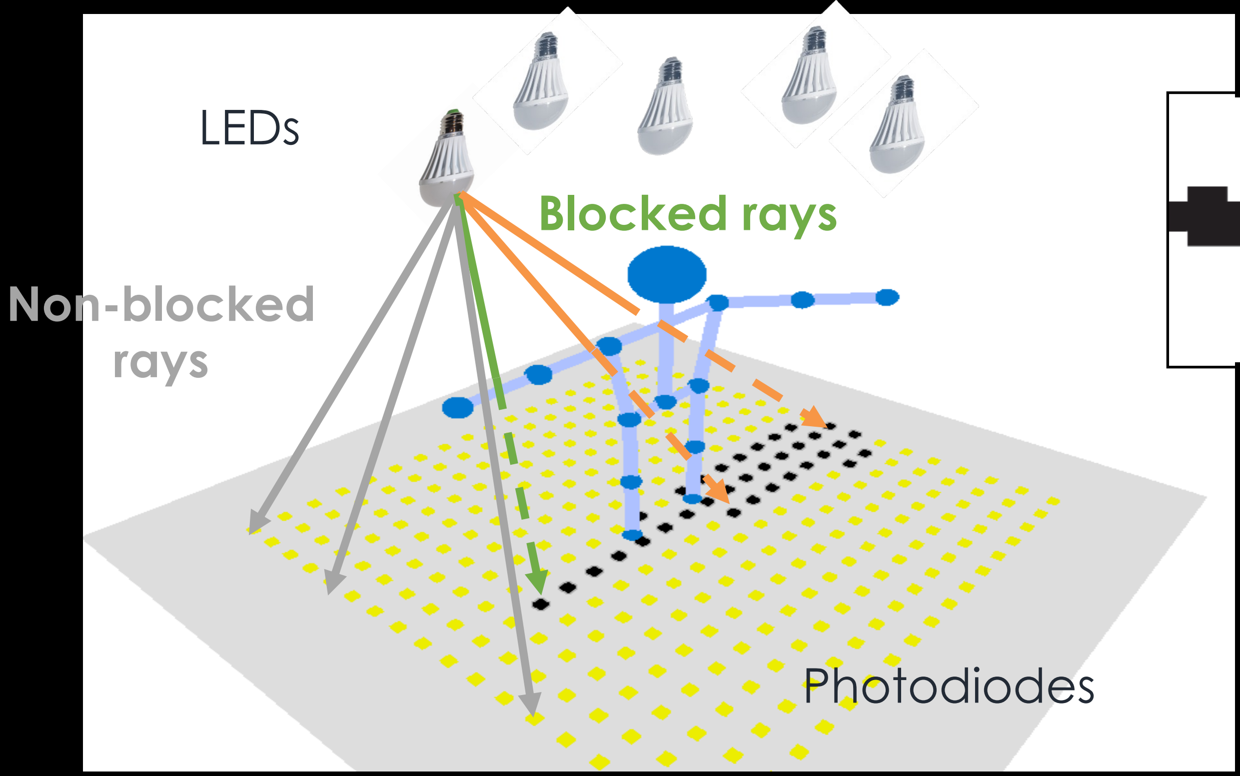
Sensing Human with Visible Light

- Search for the skeleton best matching observed shadow maps



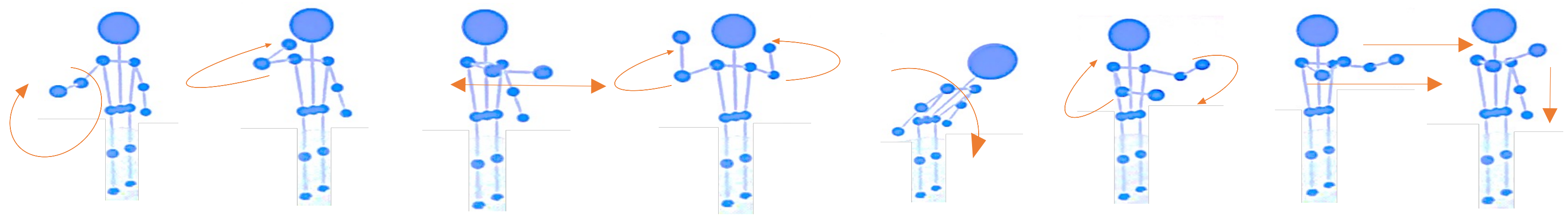
Sensing Human with Visible Light

- Search for the skeleton best matching observed shadow maps

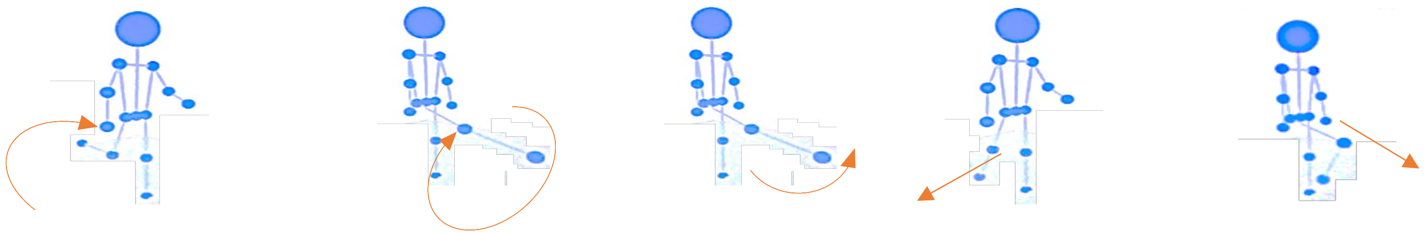


Testing Gestures

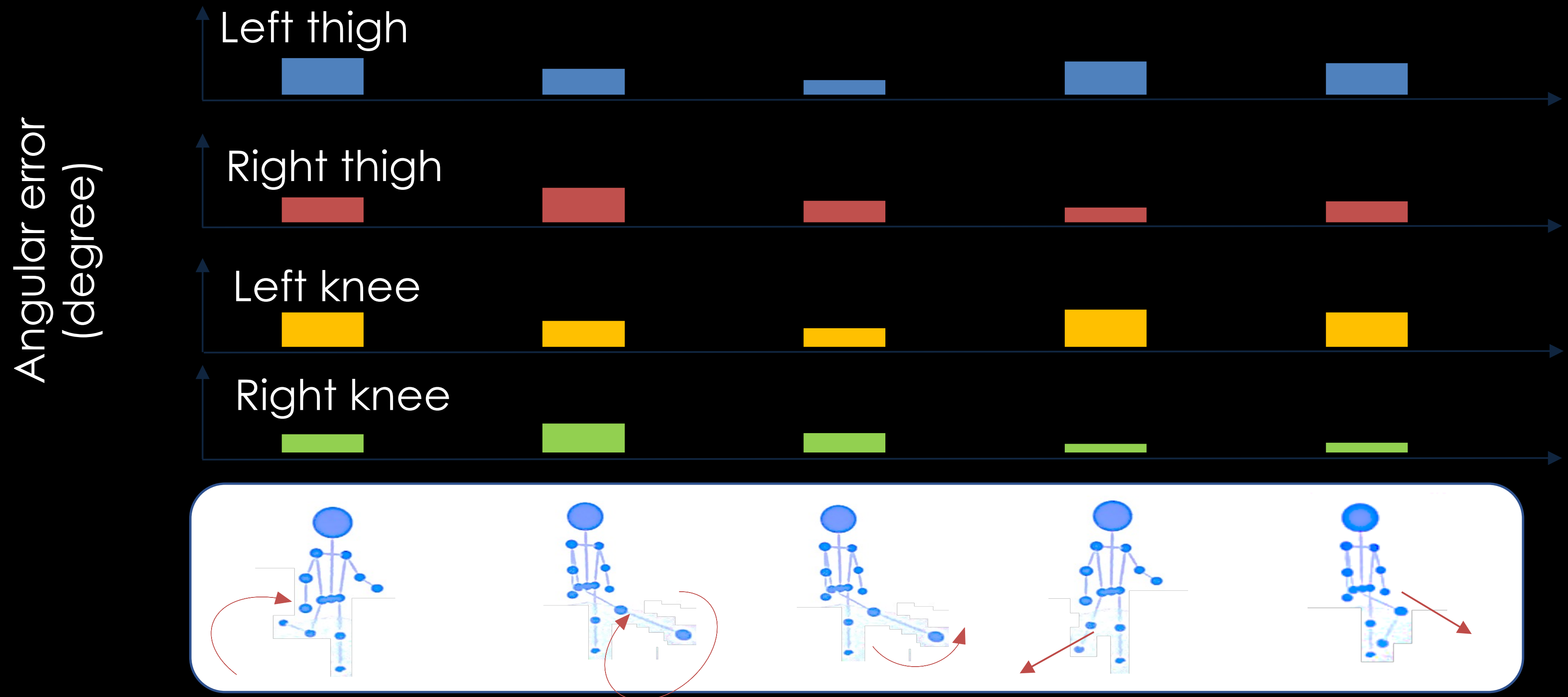
- 20 upper-body gestures



- 5 lower-body gestures



Testing Gestures



11-degree mean angular error for four lower-body joints