Enhancing Indoor Inertial Odometry with WiFi

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Outline

1. Background

2. Motivation

3. Technique

4. Implementation and Evaluation

5. Conclusion

1. Background : Inertial Odometry

Odometry : Estimating change in position over time *i.e* distance

Robotics

UAVs

Fitness

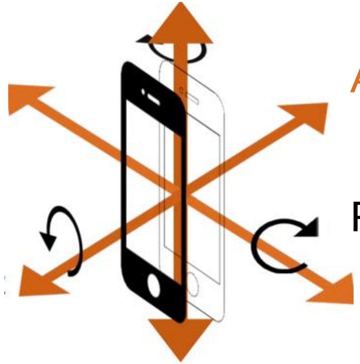
VR

Several Applications

1. Background : Inertial Odometry

Inertial Odometry : Odometry using IMUs (Accelerometer + Gyro)

- Power Efficient
- Ubiquitous
- Inexpensive (~2 USD)
- Scalable

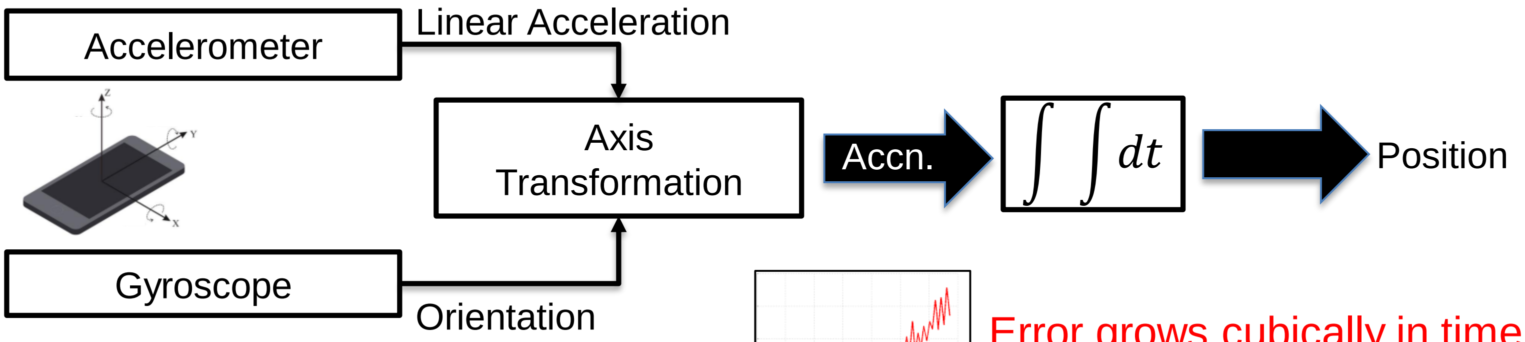


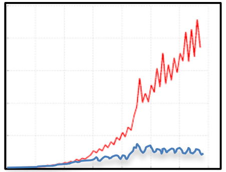
Acceleration

Rotation

1. Background : Inertial Odometry

Inertial Odometry : Odometry using IMUs (Accelerometer + Gyro)





Error grows cubically in time

Solution : Sensor Fusion (e.g GPS)

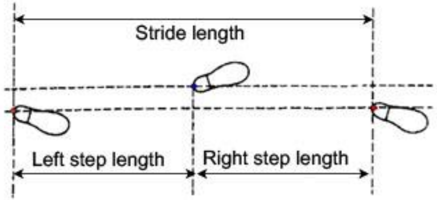
1. Background : Inertial Odometry

Error grows cubically in time

Outdoors : Sensor Fusion (GPS + IMU)

Indoors :

- PDR
  - Limited to Step Counts
  - Learning Stride Lengths
  - Only Humans



- Other Modalities (IR, Ultrasound, Vision, LIDAR)
  - Limited range or LoS only
  - Reduced Ubiquity
  - Inconsistent indoor localization accuracy

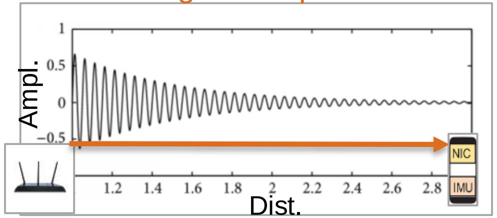
Is there a more ubiquitous modality for accurate indoor inertial odometry ?

2. Motivation : WiFi assisted Inertial Odometry

- Most handhelds : IMU + WiFi NIC.
- WiFi Communication:
  - Power Efficient
  - Ubiquitous
- Measurements from WiFi communication : CSI
- Device Motion => Doppler Shift in CSI
- CSI =>Doppler Shift => Device Speed => IMU Fusion

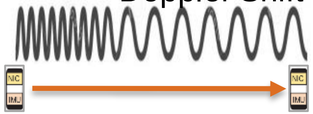
Challenge : Doppler Shift ≠ Device Speed

CSI : Change in Amplitude + Phase



CSI : $0.01e^{40\times 2\pi}$

Doppler Shift



2. Motivation : WiFi assisted Inertial Odometry

Problem Statement :

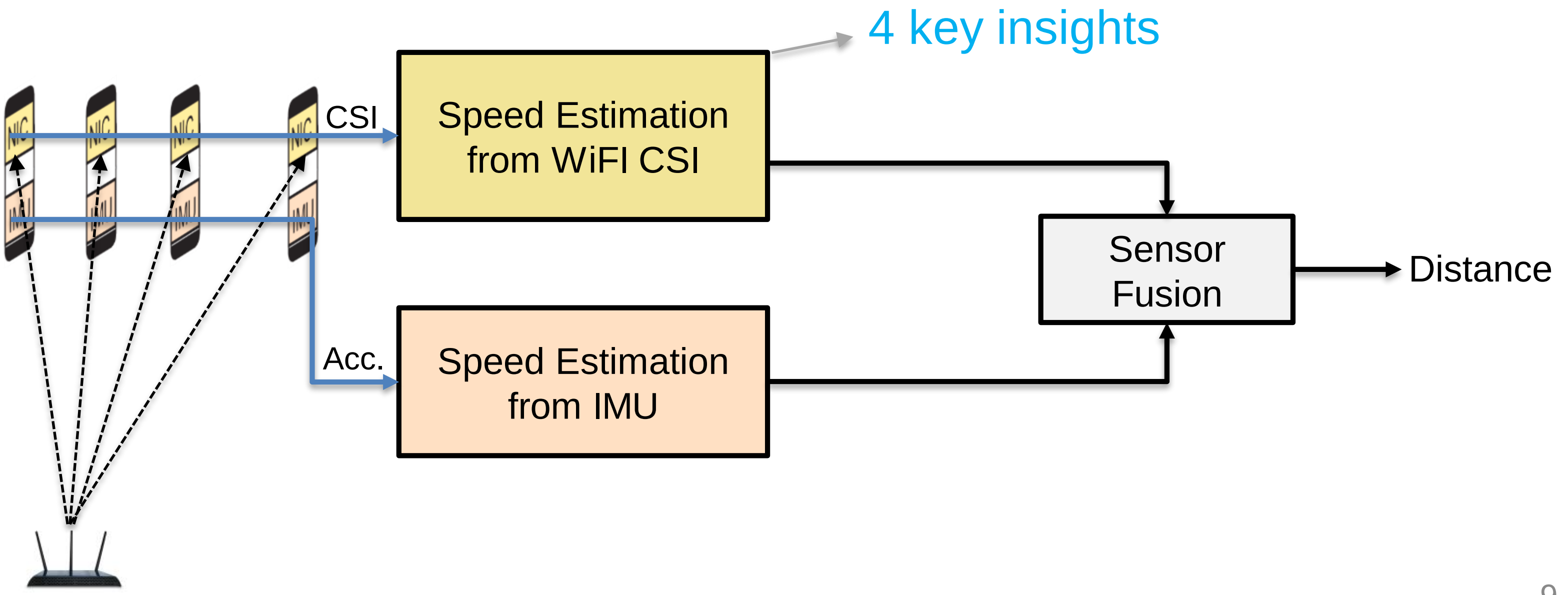
Derive speed from the Doppler Shifts in WiFi signals from a single AP to correct the drift errors in inertial odometry

Requirements:

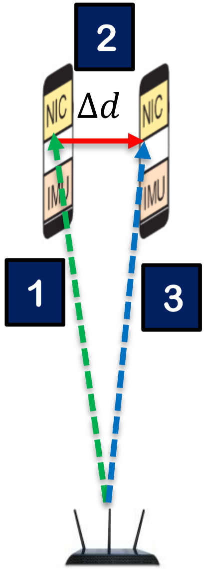
1. Not require fingerprinting
2. Commodity WiFi Devices
3. Resilient to background human movements
4. Single AP, no hardware/firmware modifications
5. Deployable on robots and humans

3. Technique : Overview

Idea : *Measure device movement speed from WiFi channel measurements and correct IMU Speed Drift*



3. Technique : WiFi CSI as a speed sensor

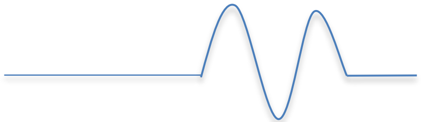


Insight 1 : Path Length Change => Sinusoid in CSI Power

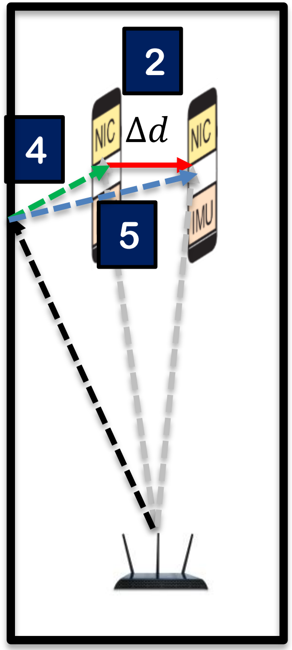
1. L_0 : Signal Path Length @ $t = 0$
2. Device moves Δd in time Δt
3. L_1 : Signal Path Length @ $t = \Delta t$

Path Length Change Speed : $\boldsymbol{v} = \frac{|L_1 - L_0|}{\Delta t}$

CSI Power : $A * \cos\left(\frac{2\pi\, \boldsymbol{v}\Delta t}{c/f} + \frac{2\pi L_0}{c/f} + \varphi_{sk}\right)$



3. Technique : WiFi CSI as a speed sensor



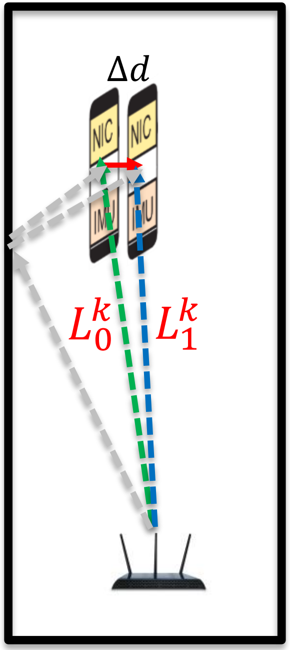
Insight 2 : Different Multipaths => Different sinusoids in CSI Power

4	$L_0{}'$: Signal Path Length @ $t = 0$
2	Device moves Δd in time Δt
5	$L_1{}'$: Signal Path Length @ $t = \Delta t$

Path Length Change Speed : $v' = \frac{|L_1{}' - L_0{}'|}{\Delta t}$

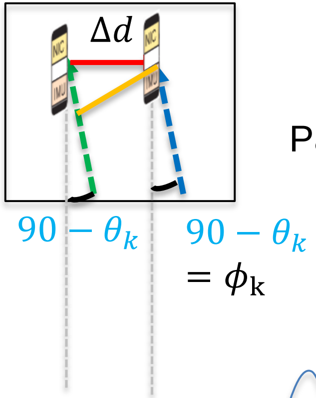
CSI Power : $A' * \cos\left(\frac{2\pi\, v' \Delta t}{c/f} + \frac{2\pi L_0{}'}{c/f} + \varphi'_{sk}\right)$

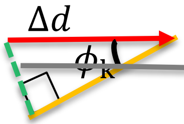
3. Technique : WiFi CSI as a speed sensor



$(\Delta d <<L_0^k)$ ^ $(\Delta d <<L_1^k)\ \forall k$

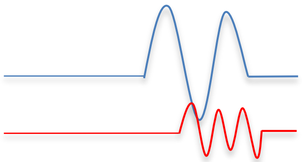
Insight 3 : If Δd << length of all k multipaths, path length change speed => a relation of Δd





Path Length Change Speed : $v^k = \frac{|L_0^k{}' - L_0^k{}'|}{\Delta t} = \frac{|\Delta d \cos \theta_k|}{\Delta t}$

3. Technique : WiFi CSI as a speed sensor



Insight 1 : Path Length Change => Sinusoid in CSI Power

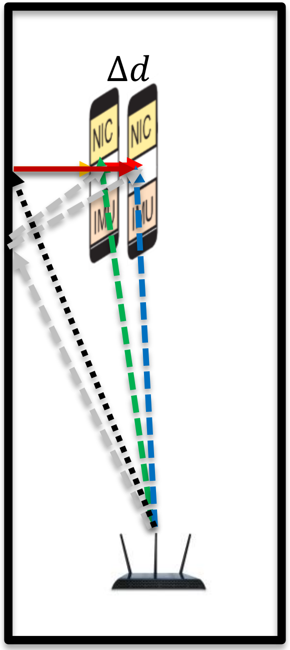
Insight 2 : Different Multipaths => Different sinusoids in CSI Power

Insight 3 : Freq. of sinusoid => $f\ (\Delta d\ ,\ \cos\theta_k\ )$

$$\frac{|\Delta d \cos \theta_k|}{\Delta t}$$

Challenging to accurately find θ_k on Commodity WiFi!

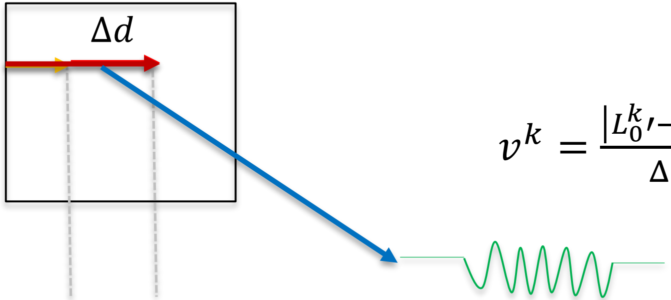
3. Technique : WiFi CSI as a speed sensor



Insight 4 :

Multipath *k* most parallel to the direction of motion

i.e $\theta_k = 0$ or $\theta_k = \pi$ => highest path length change speed



$$v^k = \frac{|L_0^k{}' - L_0^k{}'|}{\Delta t} = \frac{|\Delta\, d \cos 0|}{\Delta t}$$

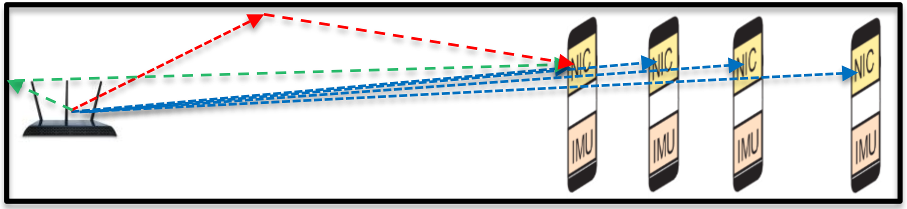
Freq (Highest Frequency Sine) × Wavelength ≈ Device Speed

$$v^k \approx F^k \lambda \quad => \Delta d \approx v_k \Delta t \quad => \quad \Delta d \approx F^k \lambda \Delta t$$

$\lambda = 5.2cm\ @5.8Ghz$!

3. Technique : WiFi CSI as a speed sensor

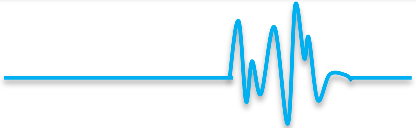
Putting it all together:



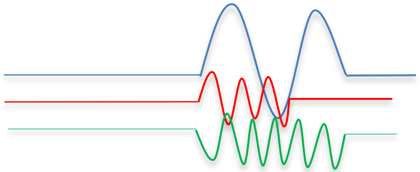
Every Δt :

1) CSI Power Time Series :

** Noise & Human interference removal*



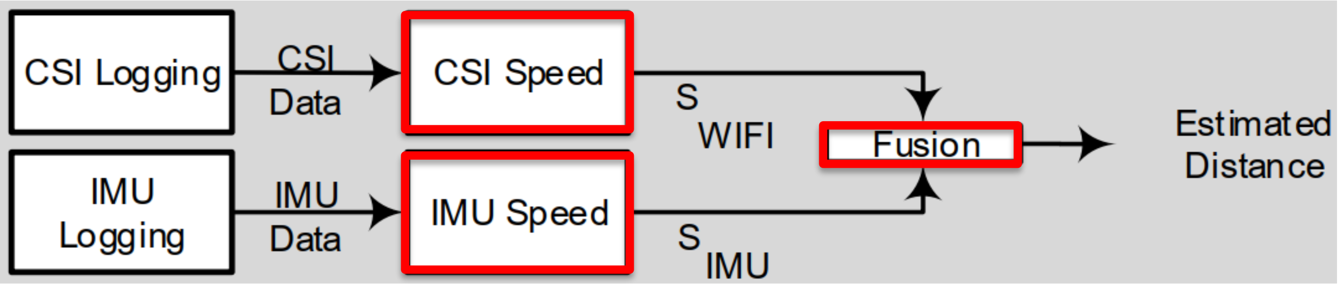
2) STFT :



3) WiFi Speed = 1.0166 $F^k\lambda$

*e.g 1.0166 * 5 hz* 5.2cm = 26.413 cm/s*

3. Technique : WiFi CSI as a speed sensor



1) Bias Computation
2) Bias Elimination
3) IMU Speed = $\sqrt{v_x^2 + v_y^2 + v_z^2}$

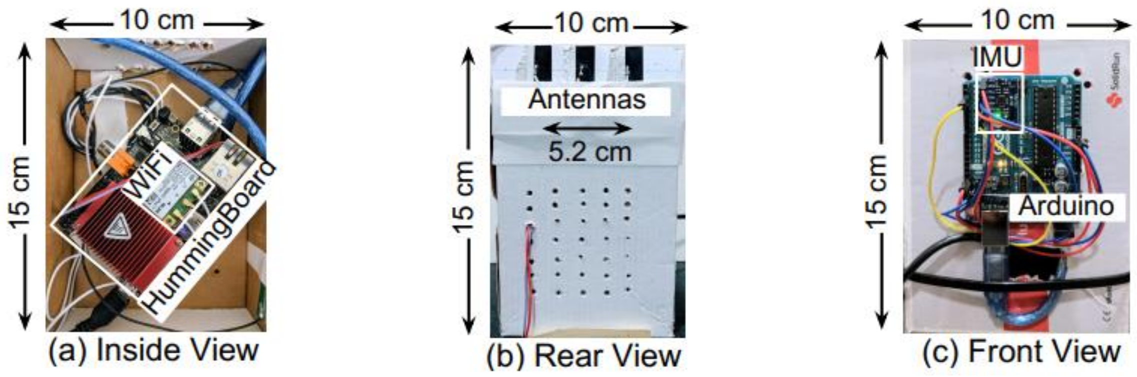
Kalman Filter

1) Process Var : IMU Speed
2) Measurement Var : CSI Speed
3) Compute optimal middle ground estimate

4. Implementation and Evaluation

Testing Platform : Custom Handheld device (10cm x 15cm x 5cm box)

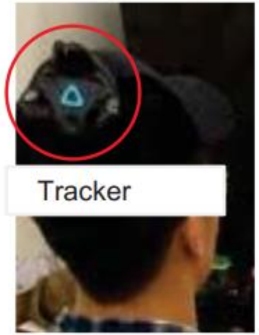
Inside : HummingBoard Pro running Ubuntu 14 + Intel WiFi Chipset
Outside: Rear : 3 Omnidirectional Antennas (HalfWave ULA) → θ_k
Front : Arduino Uno + Invensense MPU-6050 IMU + USB



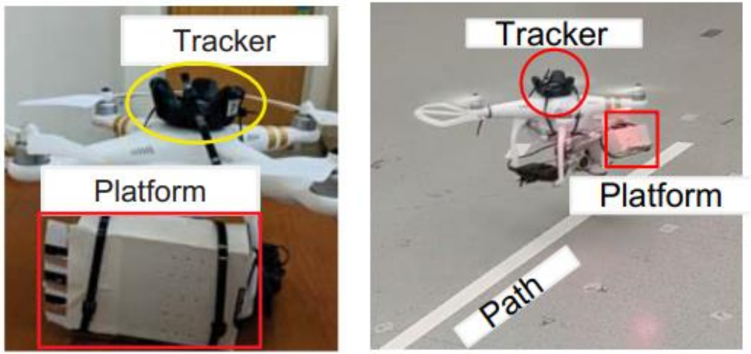
4. Implementation and Evaluation

Deployments : Humans (4M, 2F) + Drone

(a) Deployment in a vest pocket



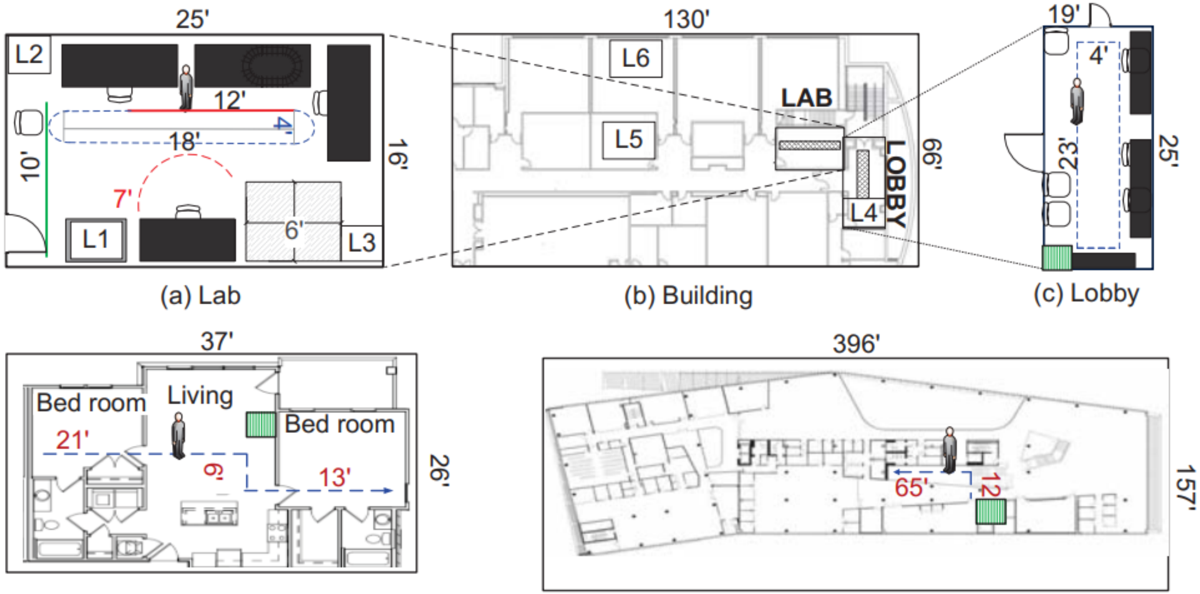
(b) Subject with HTC Vive Tracker



Drone with Vive Tracker

4. Implementation and Evaluation

Environments : 4

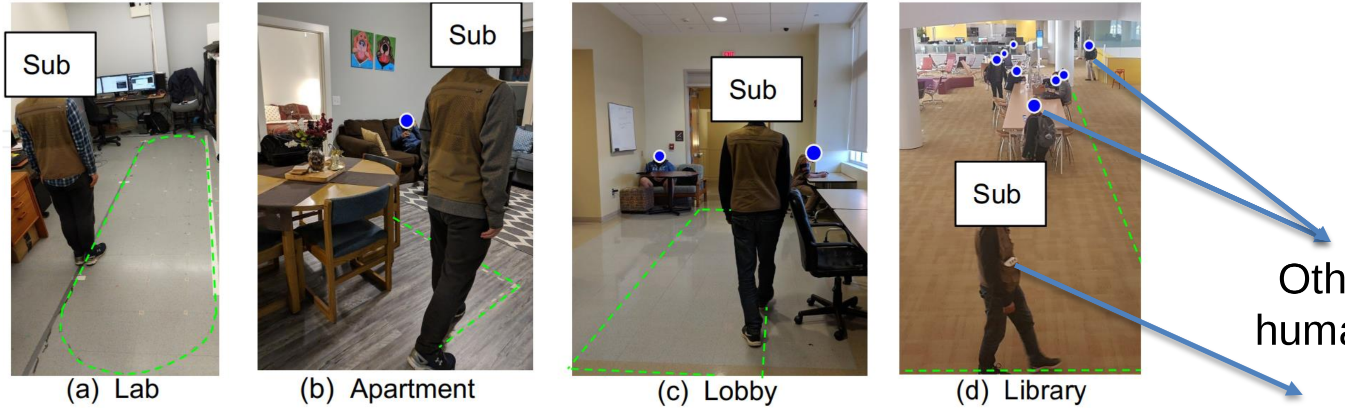


(a) Lab (b) Building (c) Lobby

(d) Apartment (e) University Library

4. Implementation and Evaluation

Environments : 4



(a) Lab (b) Apartment (c) Lobby (d) Library

Other humans

Platform

4. Implementation and Evaluation

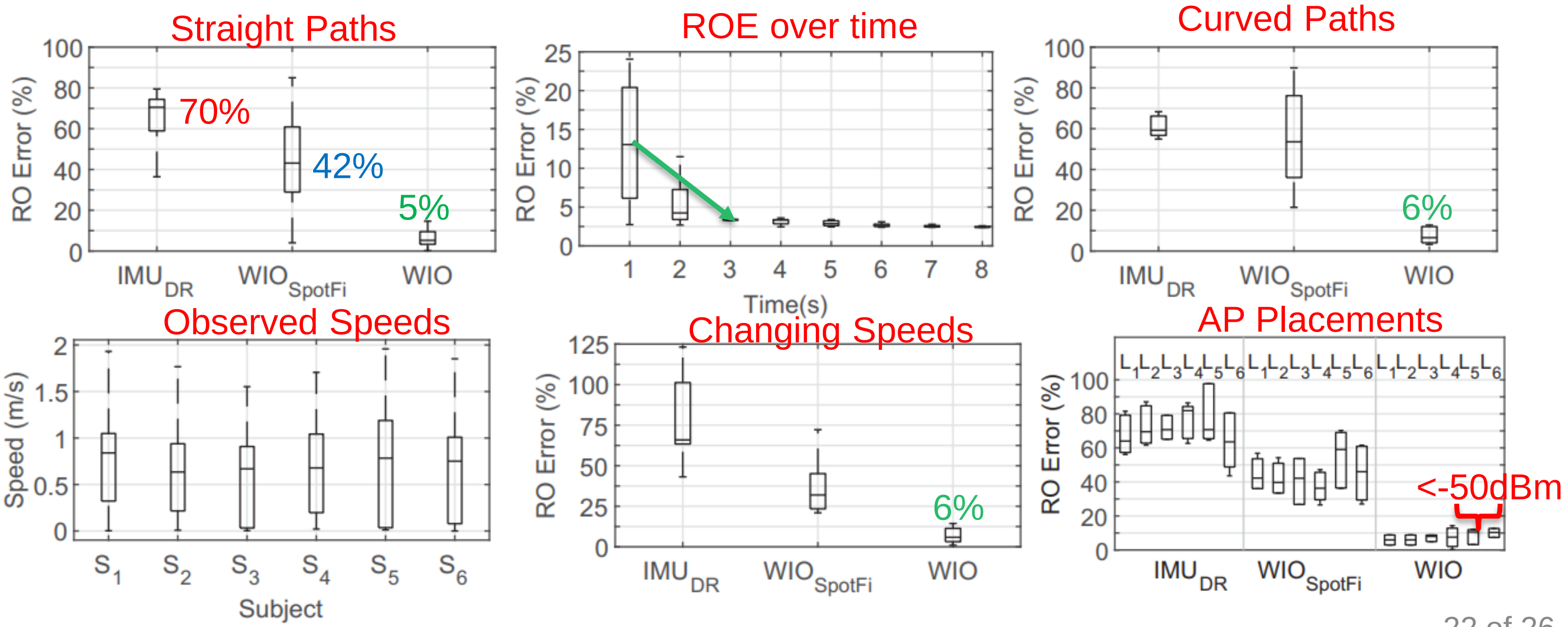
Evaluation Metric :

$$\text{RO Error} = \frac{|\text{ Estimated Distance} - \text{Actual Distance}|}{\text{Actual Distance}}$$

- $\mathrm{IMU_{DR}}$ — Distance computed from IMU double integration
- $\mathrm{WIO_{SpotFi}}$ — Distance computed from Most Parallel Path using a state-of-the-art SuperResolution AoA Method (θ_k Insight 3)
- WIO — Distance computed from Insight 4 (*HF sinusoid*)

4. Implementation and Evaluation

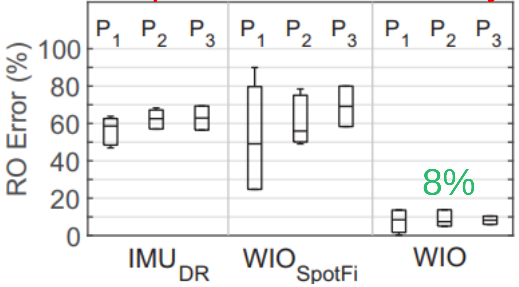
1. Human Deployments

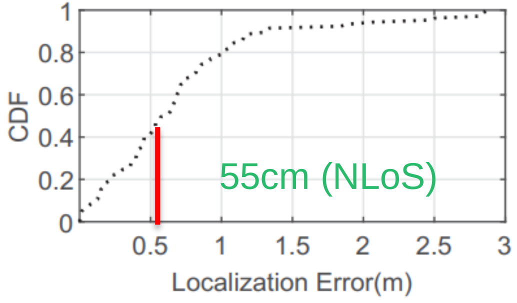


4. Implementation and Evaluation

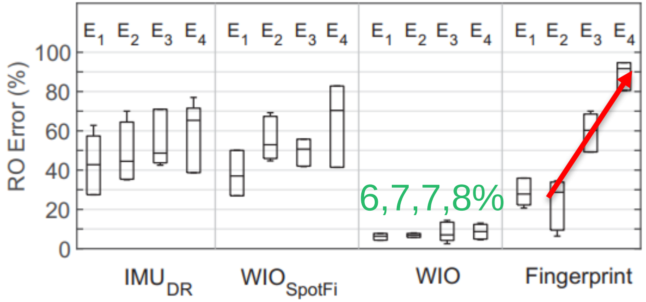
1. Human Deployments

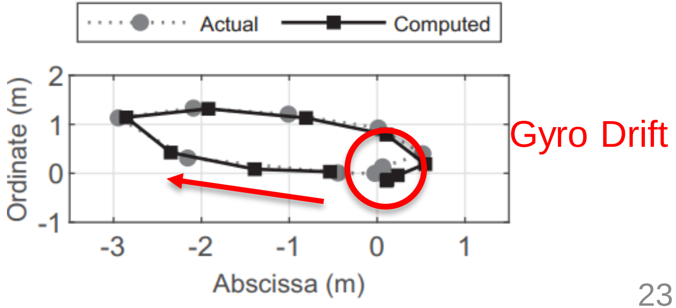
Multiple Human Odometry





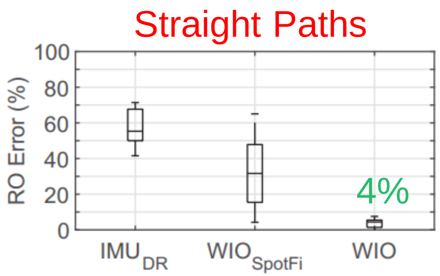
Error across Envs.

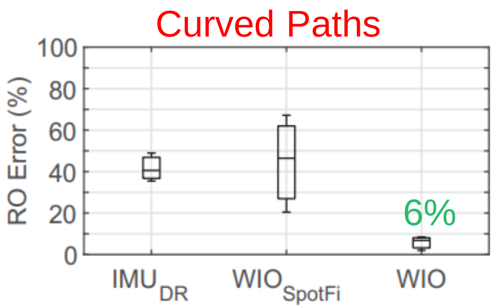


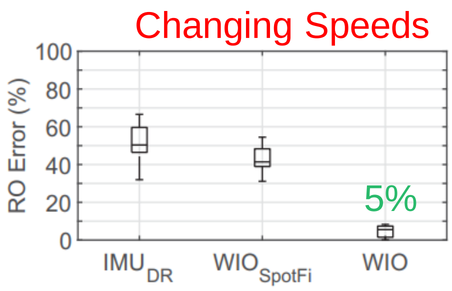


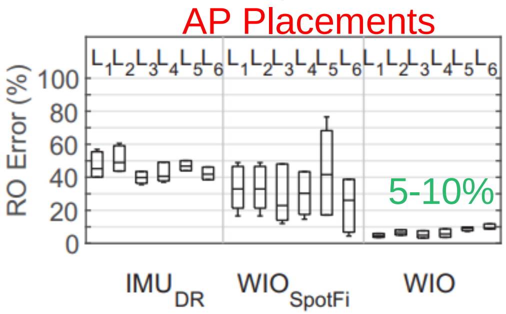
4. Implementation and Evaluation

2. Drone Deployment









5. Conclusion

- Proposed a novel WiFi-assisted inertial odometry technique
- The key novelty of using the WiFi signals as the auxiliary source of information that works in indoor environments, w/o fingerprinting, and resilient against changes in environment
- Median RO error of just 6.87% and 5.7% respectively for human subjects and a drone across all scenarios, and at least 3x more accuracy compared to pure Inertial Odometry

Thank You!