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# Experiences & Challenges with Server-Side WiFi Indoor Localization Using Existing Infrastructure

## Introduction

There has been a long and rich history of **WiFi-based indoor localization** research.
Each works have trade-off. So, to reduce limitation and increase advantage, Many studies have used various combinations.

| | | | | |
|---|---|---|---|---|
| Client-base Localization | Server-base Localization | Fingerprint Localization | Model-base Localization | Etc. |

Dheryta Jaisinghani, Rajesh Krishna Balan, Vinayak Naik, Archan Misra, Youngki Lee
2018, Experiences & Challenges with Server-Side WiFi Indoor Localization Using Existing Infrastructure

# Introduction

## Introduction

**Client-base Localization**

Client-base methods tend to have the highest accuracy. Users can actively send out RF(Radio-Frequency) signal to locate them when they want to.
But, It have to install specific programs to a user's device or modify OS.

**Server-base Localization**

Server-base methods tend to have more inaccuracy then client-base. But, It don't need to modify user's devices.
The system can only 'see' sended unmodified signal. So, It works with passive way.

# Introduction

## Introduction

**Fingerprint Localization**

Fingerprint methods is pre-mapping the real space and specific data(ex: RF-signal). And matching the map and a newly accepted signal data to find where the signal located.
This way is easy to integrate compared with model-base. But, It need to pre-mapping before process.

**Model-base Localization**

Model-base method analyzes signals that are complex parameters and based on them, perform localization.
This method analyzes a signal that combines the time the signal reaches, the strength of the signal, and so on in many ways to derive a general result.
This way is hard to implement. Because constructing model and analyzing signal is too complex.

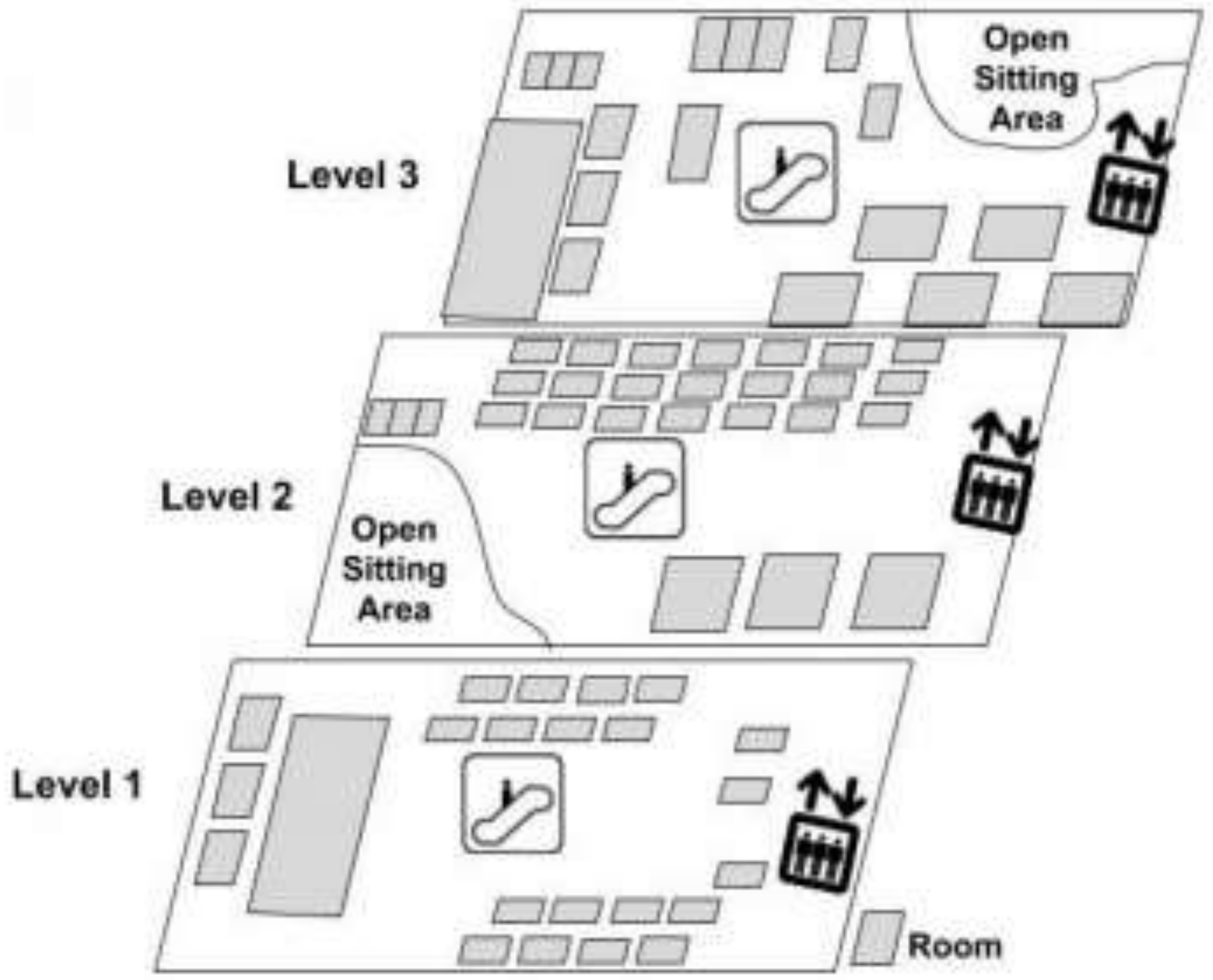
# Introduction

## Introduction

In this paper, they try to highlight challenges and propose easy to integrate solutions to build a universal indoor localization system – without any modifications whether client or server.
They adopted fingerprint infrastructure base solution.

Server-base Localization

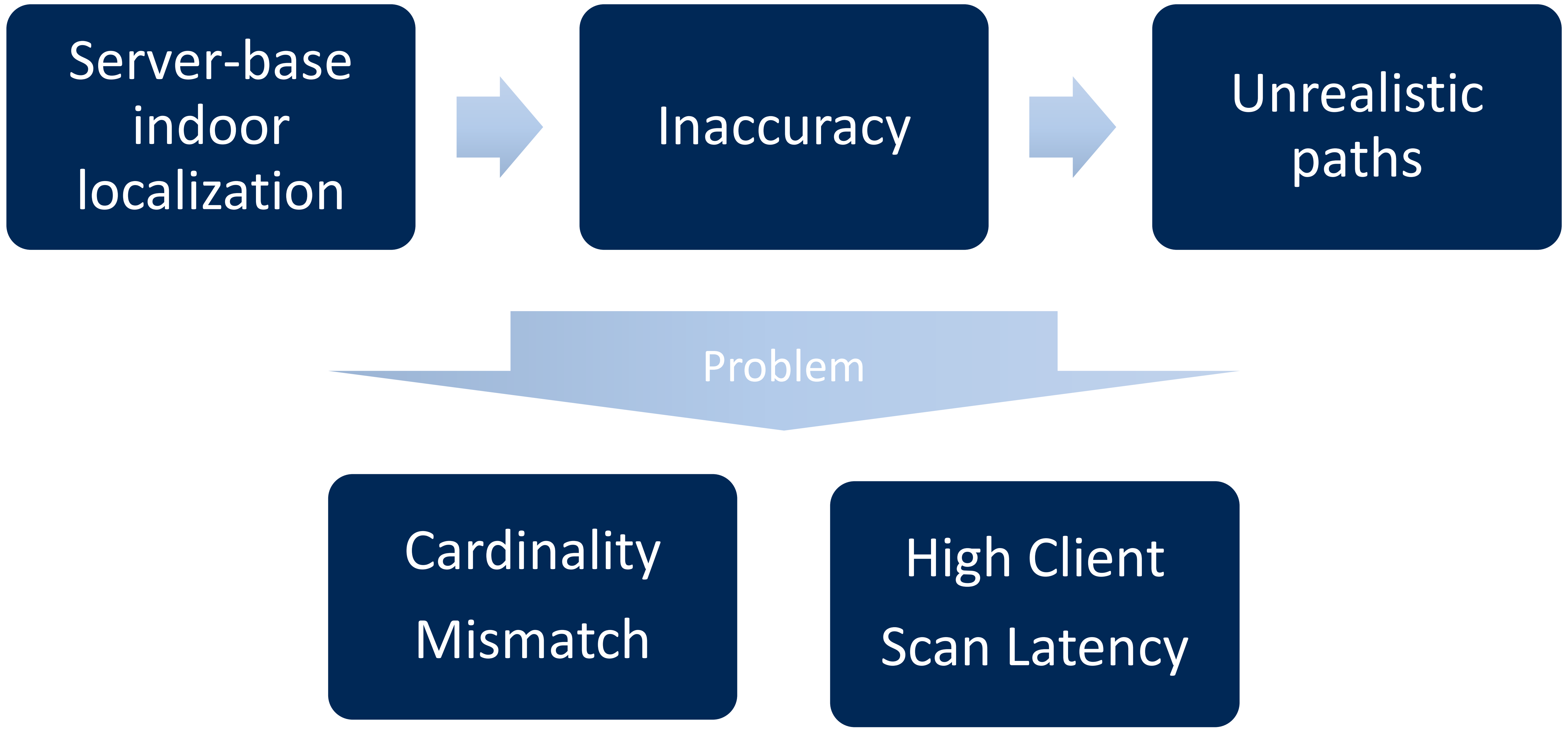
Fingerprint Localization



# Introduction

## Problem

Server-base indoor location tracking system have limitations in terms of **accuracy** comparing to tradition client-base tracking system.
In this paper, It focus two unique challenges ‘Cardinality Mismatch’ and ‘High Client Scan Latency’ associated with it’s approach.



# Introduction

Two challenges to overcome

Cardinality Mismatch

**Cardinality** means the number of AP(Access Point)s which reported a client located at a specific landmark.
Cardinality Mismatch is different Cardinality with offline fingerprints and online fingerprints.
Due to dynamic power of client and client management performed by a centralized controller in commercial grade WiFi networks.

High Client Scan Latency

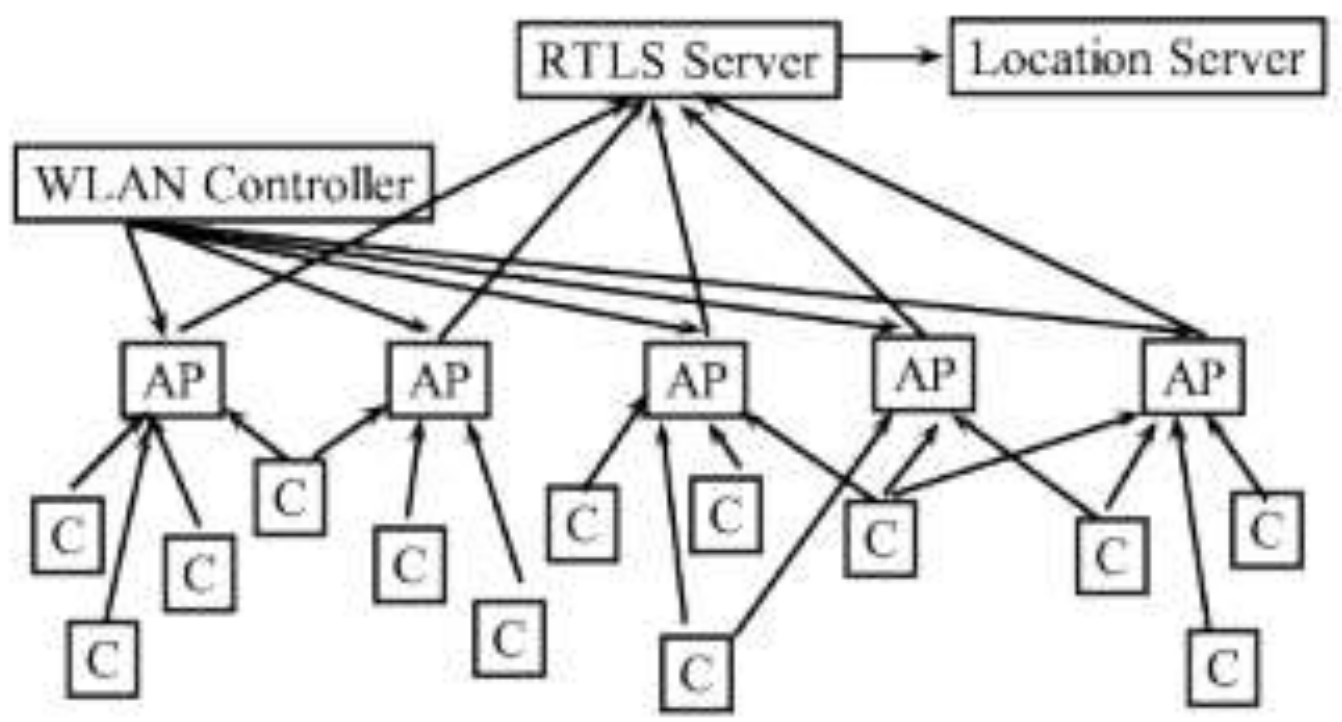
If Client-side localization techniques where clients actively scan the network when they need location fix.
But in Server-side, the system can only 'see' sended signal.
In this paper's report, **90%** of client scan interval to be **20 minutes**.
So, there is a situation of 'teleporting' of clients across the location.

# System Architecture and Data Collection

## System overview

Each AP send **RTLS(Real Time Location System)** data feeds every 5seconds to the RTLS Server.
The Location Server analyzes these RTLS data feeds for the signal strengths reported by different APs to estimate the location of a client.

The below table presents all the fields contained in an RTLS data feed per client.




System overview

| Field | Description |
|---|---|
| Timestamp | AP Epoch time (milliseconds) |
| Client MAC | SHA1 of original MAC address |
| Age | #Seconds since the client was last seen at an AP |
| Channel | Band (2.4/5 GHz) on which client was seen |
| AP | MAC address of the Access Point |
| Association Status | Client's association status (associated/unassociated) |
| Data Rate | MAC layer bit-rate of last transmission by the client |
| RSSI | Average RSSI for duration when client was seen |

Data of RTLS

# System Architecture and Data Collection

## Fingerprints

**Offline Pinger-print**

In Offline fingerprinting, two-dimensional map is prepared for each landmark on the per-floor basis.
For each landmark, the device(dual-band Android phones) collected data for **5 minutes**.
While the clients scan, APs collate RSSI reports for the client and send their measurements as RTLS data feeds to the Location Server.
L : Landmark, B : 2.4 or 5 GHz, AP : specific ID of AP, RSSI : the RSSI value of that RTLS data

$$< L_i, B, AP_1 : RSSI_1; \ldots; AP_n : RSSI_n; >$$

**Online Pinger-print**

In Online fingerprinting, Localization of a client is done with online fingerprints.
On localization estimation, match online fingerprint with offline fingerprints of each landmark to calculate the location of signal space.
By difference of Signal strength(RSSI), It can estimate the difference of distance with landmarks.

$$< B, AP_1 : RSSI_1; \ldots; AP_m : RSSI_m; >$$

# System Architecture and Data Collection

## Pre-processing of the data

Filter the raw RTLS data feed for latest values, with age less than or equal to 15 sec, RSSI should greater than or equal to -72 dBm. When client loses association when RSSI is below -72 dBm.
For analysis, Classify MAC layer frames in two classes.

(a)Scanning-Frames : High power and low bit rate probe requests.
(b)Non-Scanning-Frames : All other MAC layer frames.

Offline Fingerprints are derived from the scanning frames, which are known to provide accurate distance estimates as they transmitted at full power.
Online Fingerprints are mixed of scanning and non-scanning frames. Due to It is real world device operation.

So, It need to match by different type of frame.
But, in RTLS data feeds don’t report the type of frame.

# System Architecture and Data Collection

## Pre-processing of the data

So, They design controlled experiments, a)send scanning frames only and b)send non-scanning frames only.

**Scanning frame only**

All report RTLS data is Unassociated.
Data rates fixed 1,6, 24 Mbps, probe response rate.

**Non-Scanning frame only**

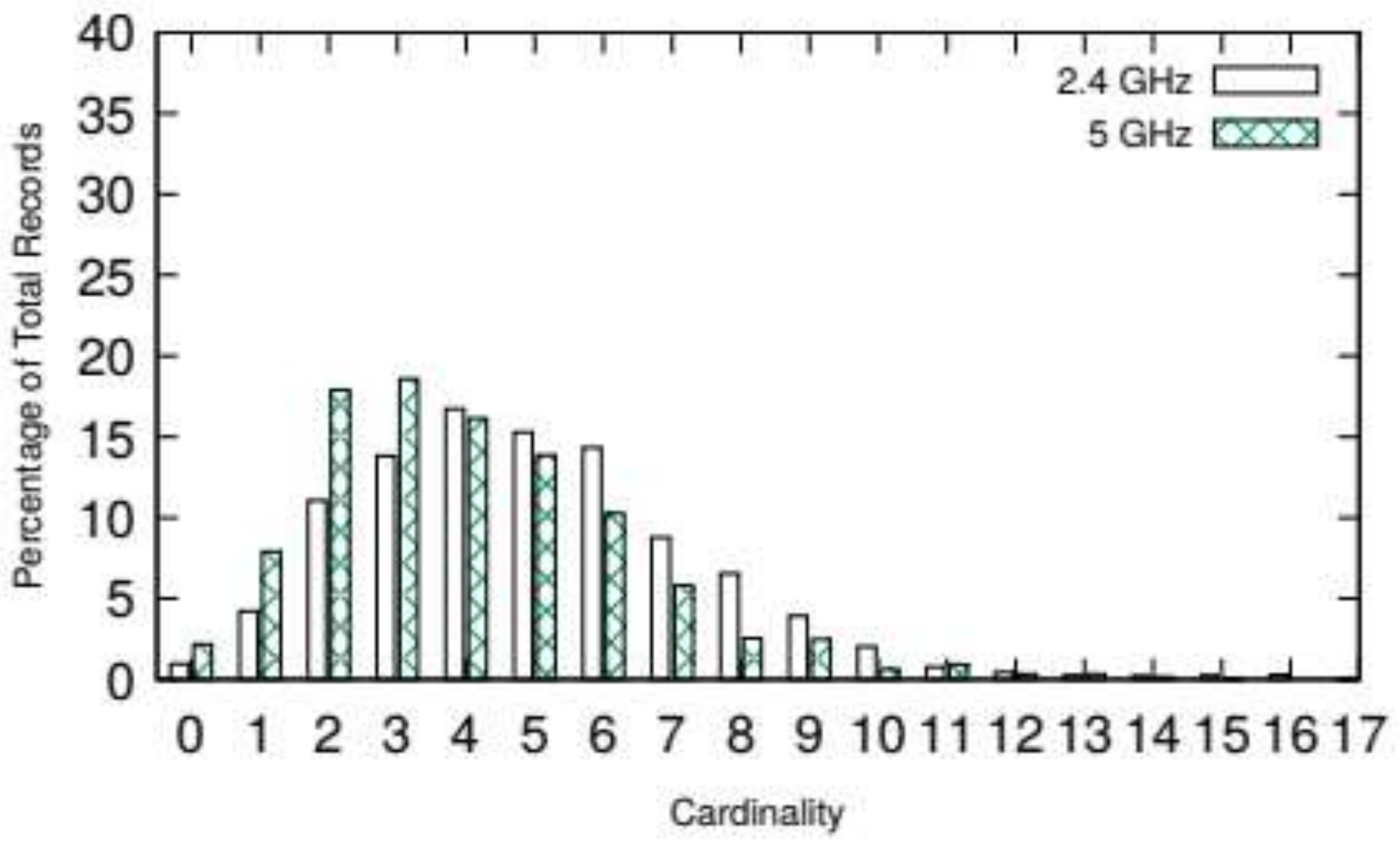
There is associated report RTLS data.
Data rates various rate. Ex) 1, 2, 5.5, … ,54 Mbps.

By this two fact, It can classify with high probability.

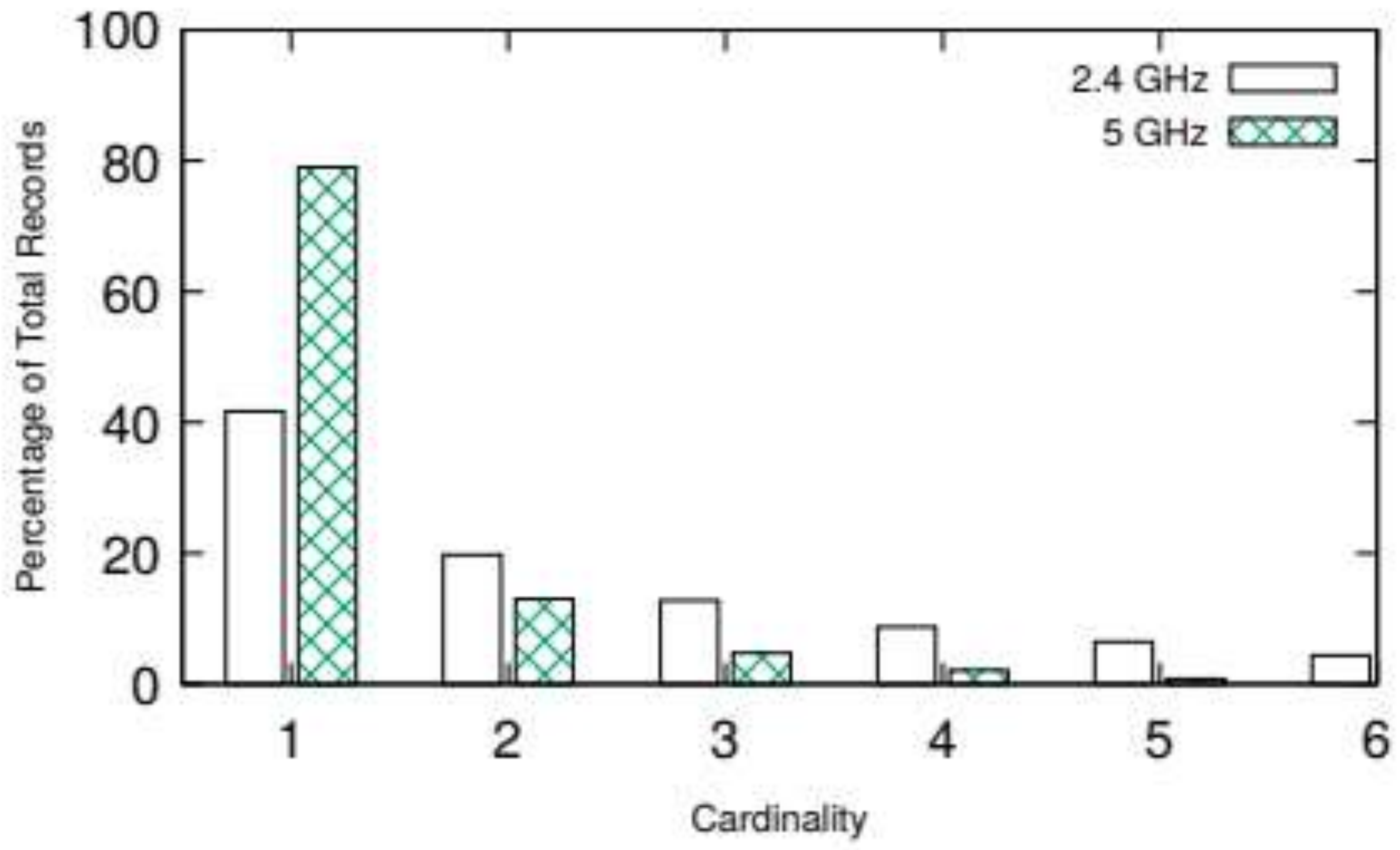
# Challenges Discovered

## Evidence of the Issues

This graphs shows the Cardinality Mismatch on Offline and Online Phases.
Also, the Cardinality is different with Band.
Across all the cardinalities, 2.4 GHz has 57.30% mismatches and 5 GHz has 30.6% mismatches.
5 GHz band is more affected by the Cardinality Mismatch issue because it experiences lower cardinality, which increases the chances of error.
2 GHz band is traveling more distance and transmitting more scanning frames. So, High number of Cardinality is recorded then 5 GHz band.




(a) Offline Phase




(b) Online Phase

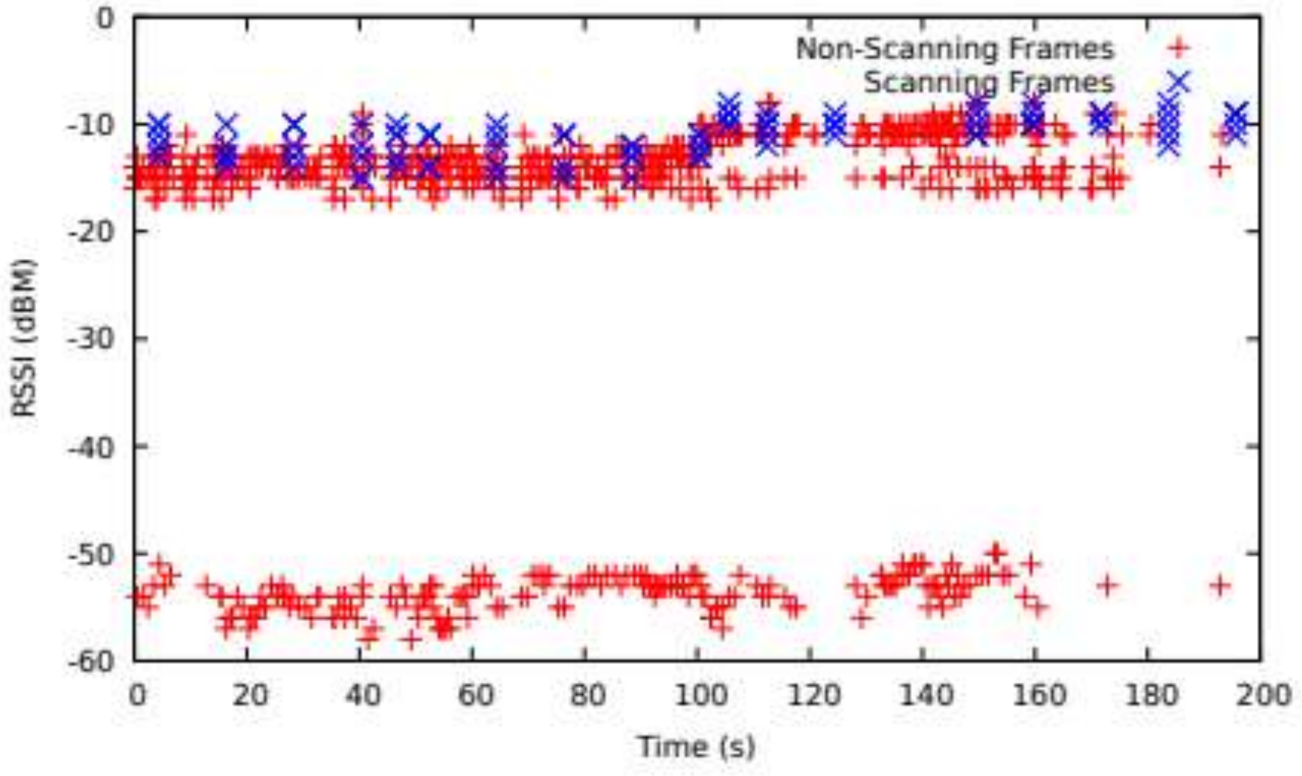
# Challenges Discovered

## Evidence of the Issues

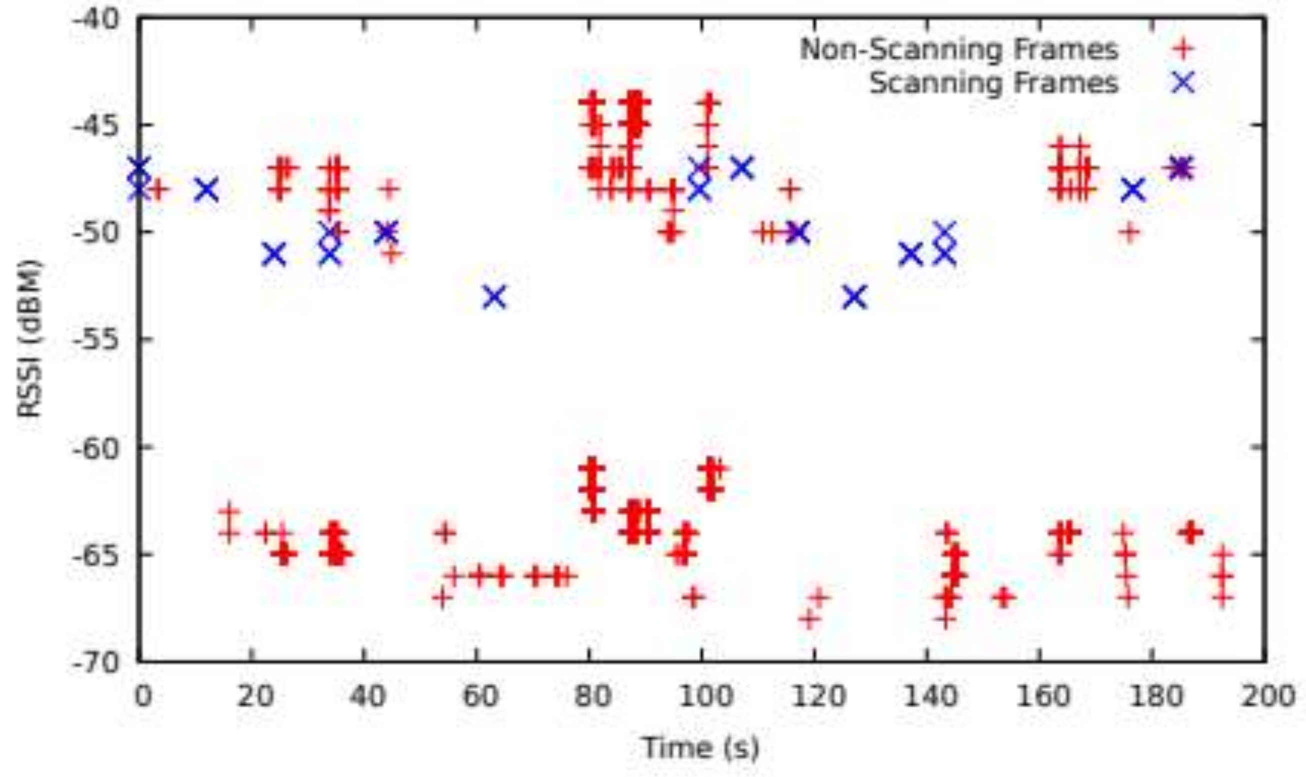
1. Experiment of find difference of RSSI strength with close to AP and far from AP.
2. Experiment of difference of Scanning Frequency by Band and RSSI strength for 6 hours.

Scanning frame has only 10 dB gap in close to AP and 5 dB gap in far from AP.
Non-scanning frame has 50 dB gap in close to AP and 30 dB gap in for from AP.
It shows Scanning frame is more reliable indicator.

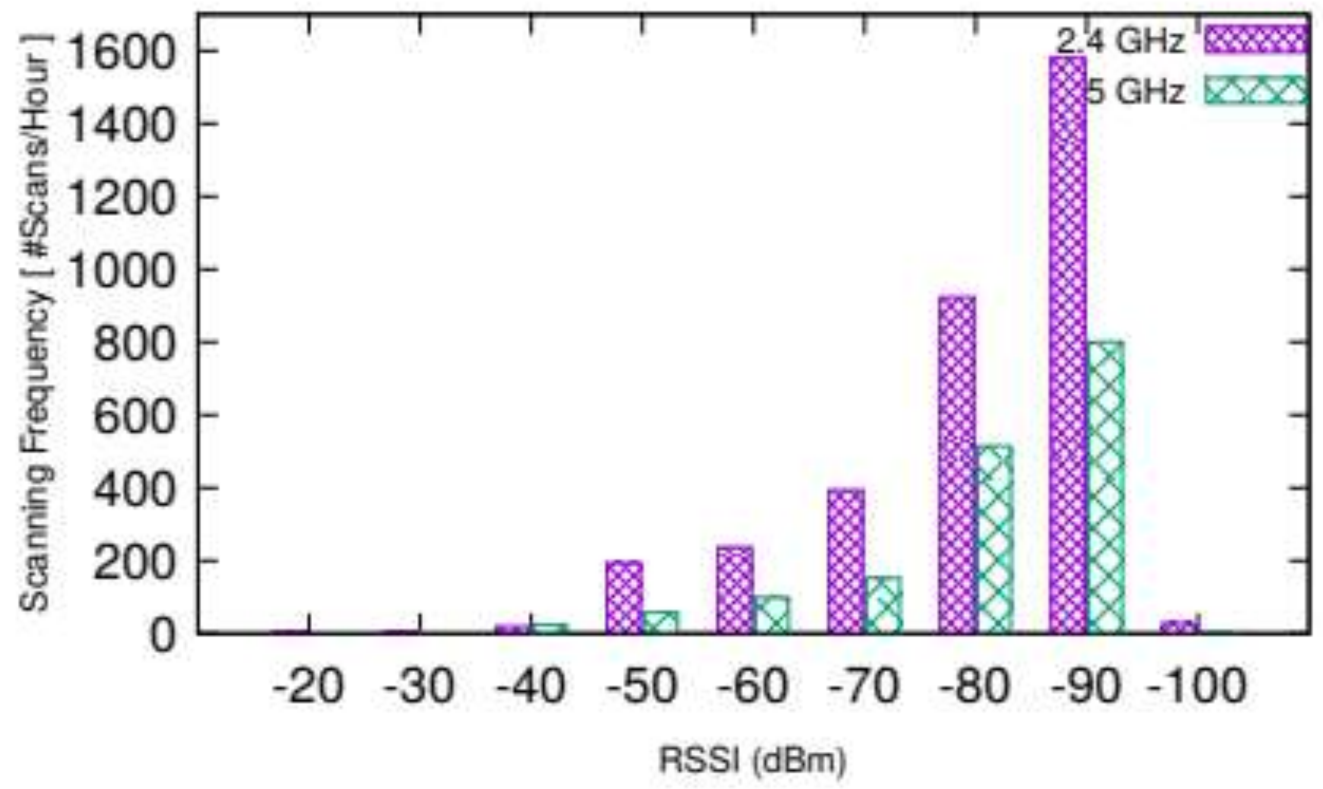
90% of scanning intervals is in the order of few 1000 sec.




(a) Client Close To AP




(b) Client Far From AP



# Challenges Discovered

## Evidence of the Issues

By experiment, a stationary client RSSI recorded at the RTLS server data for 1hour.
Difference with RSSI strength is 2.4 GHz has more gap.

The table shows summary of all experiments data.

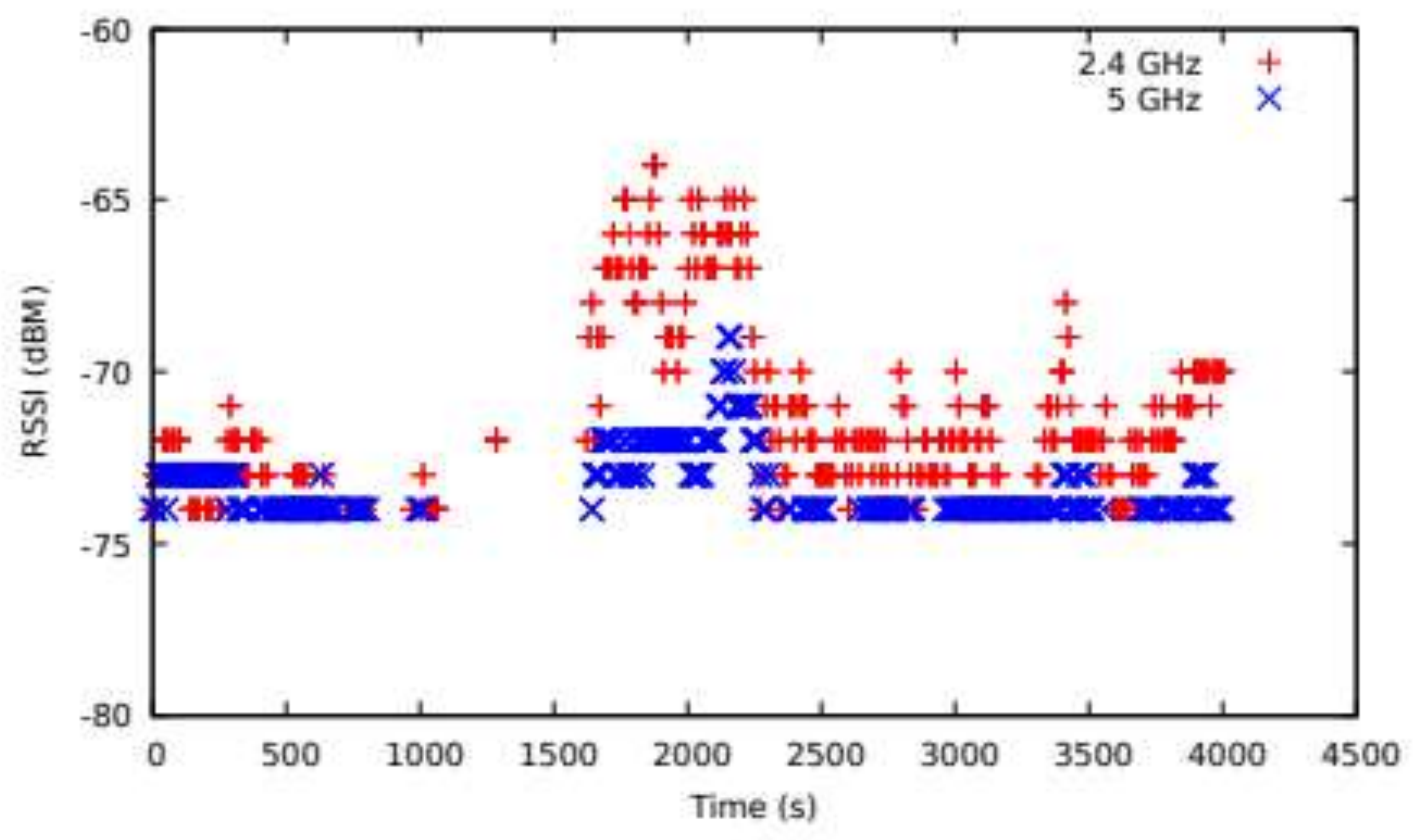



**Table 2: A summary of the causes and their impact (✓- Reduces Localization Errors, ✗- Increases Localization Errors). Causes conflict with each other, making server-side localization non-trivial.**

| **Frames** | **Transmission Distance** | **RSSI Variation** | **Frequency of Transmission** |
|---|---|---|---|
| Scanning | *High* – ✓ | *Low* – ✓ | *Low* – ✗ |
| Non-Scanning | *Low* – ✗ | *High* – ✗ | *High* – ✓ |
| **Band** | **Transmission Distance** | **RSSI Variation** | **Frequency of Scanning** |
| 2.4 GHz | *High* – ✓ | *High* – ✗ | *High* – ✓ |
| 5 GHz | *Low* – ✗ | *Low* – ✓ | *Low* – ✗ |

# Conclusion

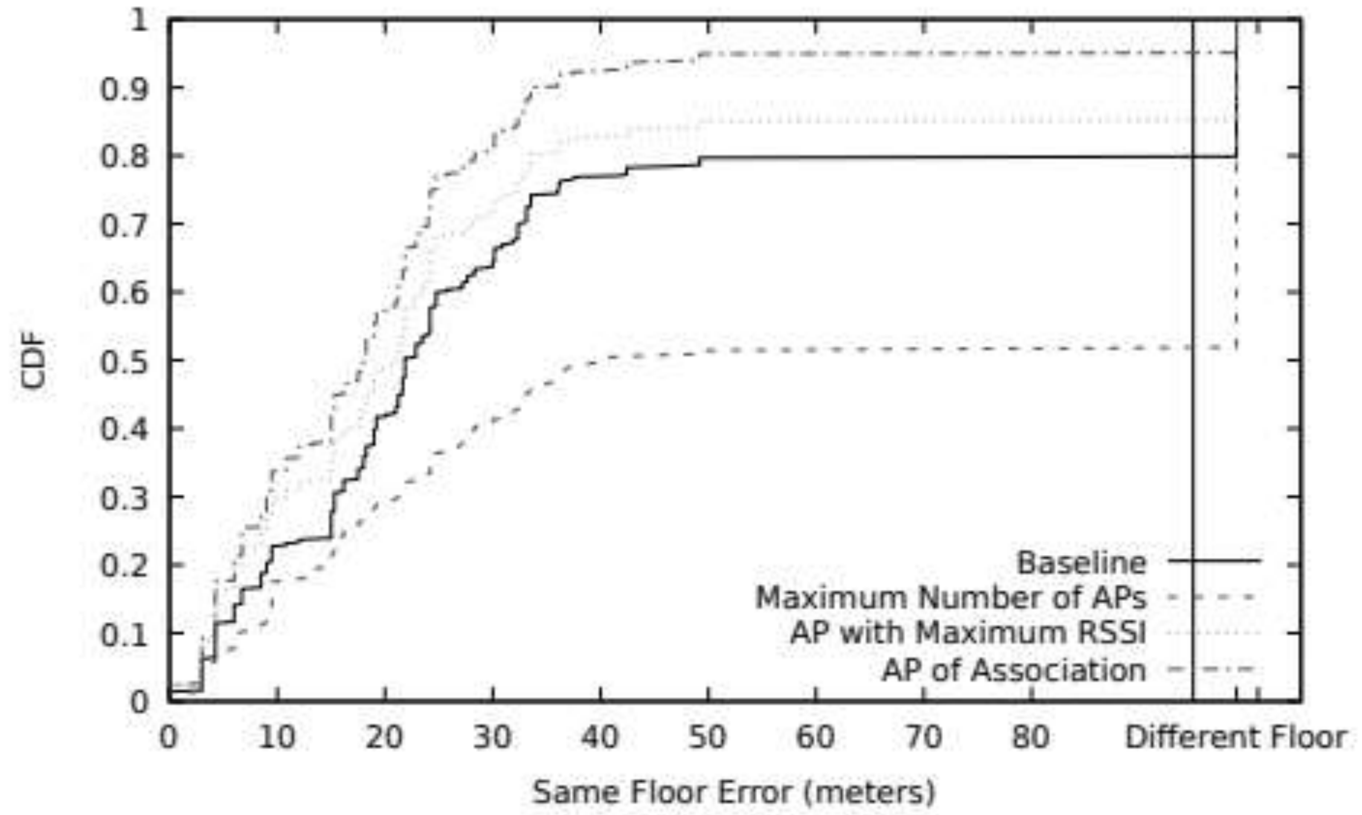
## Impact of Causes on Localization Errors

The algorithm first selects a floor and then shortlists all the APs that are located on the same floor. And then matching with offline fingerprints.
There are three methods it explored.
(a)Maximum Number of APs – the floor for which the maximum APs are reporting the client.
(b)AP with Maximum RSSI – the floor from which the strongest RSSI is received.
(c)AP of Association – the floor of AP to which the client is presently associated with.

The (c) shows most accurate tendency, and in 5 GHz shows more accurate tendency.

**Table 3: Localization errors with different floor detection heuristics ($C$ - Cardinality, SF - Same Floor [$85^{th}$%ile (meters)], DF - Different Floor [%], $NA$ - Not Applicable). Cardinalities >3 are not applicable to 5 GHz due to cardinality mismatch. Lowest localization errors obtained using AP of Association.**

| | Baseline | | | | Maximum Number of APs | | | | AP with Maximum RSSI | | | | AP of Association | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 2.4 GHz | | 5 GHz | | 2.4 GHz | | 5 GHz | | 2.4 GHz | | 5 GHz | | 2.4 GHz | | 5 GHz | |
| $C$ | SF | DF | SF | DF | SF | DF | SF | DF | SF | DF | SF | DF | SF | DF | SF | DF |
| 1 | >50 | 20.00 | 29.50 | 03.10 | >50 | 48.00 | 29.60 | 03.49 | 49.20 | 14.70 | 28.30 | 02.09 | 32.30 | 04.90 | 27.60 | 01.28 |
| 2 | >50 | 18.30 | 26.80 | 02.00 | >50 | 33.33 | 27.00 | 05.60 | 24.20 | 05.60 | 27.00 | 03.46 | 21.60 | 00.70 | 25.80 | 01.48 |
| 3 | >50 | 33.15 | 20.12 | 00.00 | >50 | 40.00 | 24.00 | 00.00 | 36.00 | 14.70 | 20.12 | 00.00 | 22.80 | 05.50 | 20.12 | 00.00 |
| 4 | >50 | 18.49 | $NA$ | $NA$ | 33.00 | 13.40 | $NA$ | $NA$ | 24.00 | 11.00 | $NA$ | $NA$ | 18.90 | 04.40 | $NA$ | $NA$ |
| 5 | 19.20 | 10.25 | $NA$ | $NA$ | 26.00 | 14.60 | $NA$ | $NA$ | 17.49 | 00.00 | $NA$ | $NA$ | 17.49 | 00.00 | $NA$ | $NA$ |
| 6 | 23.00 | 04.17 | $NA$ | $NA$ | 22.00 | 00.00 | $NA$ | $NA$ | 16.00 | 00.00 | $NA$ | $NA$ | 22.00 | 00.00 | $NA$ | $NA$ |




2.4Ghz Cardinality 1

# Conclusion

## Limitation and Conclusion

First, they only used fixed set of devices(one iPhone and one Android Phone).
By difference tendency with various devices, It is most big limitation of fingerprinting method.
Second, they collected the data for lightly(few people situation) and heavily loaded(many people situation).
But, in test, they only tested in lightly loaded situation.

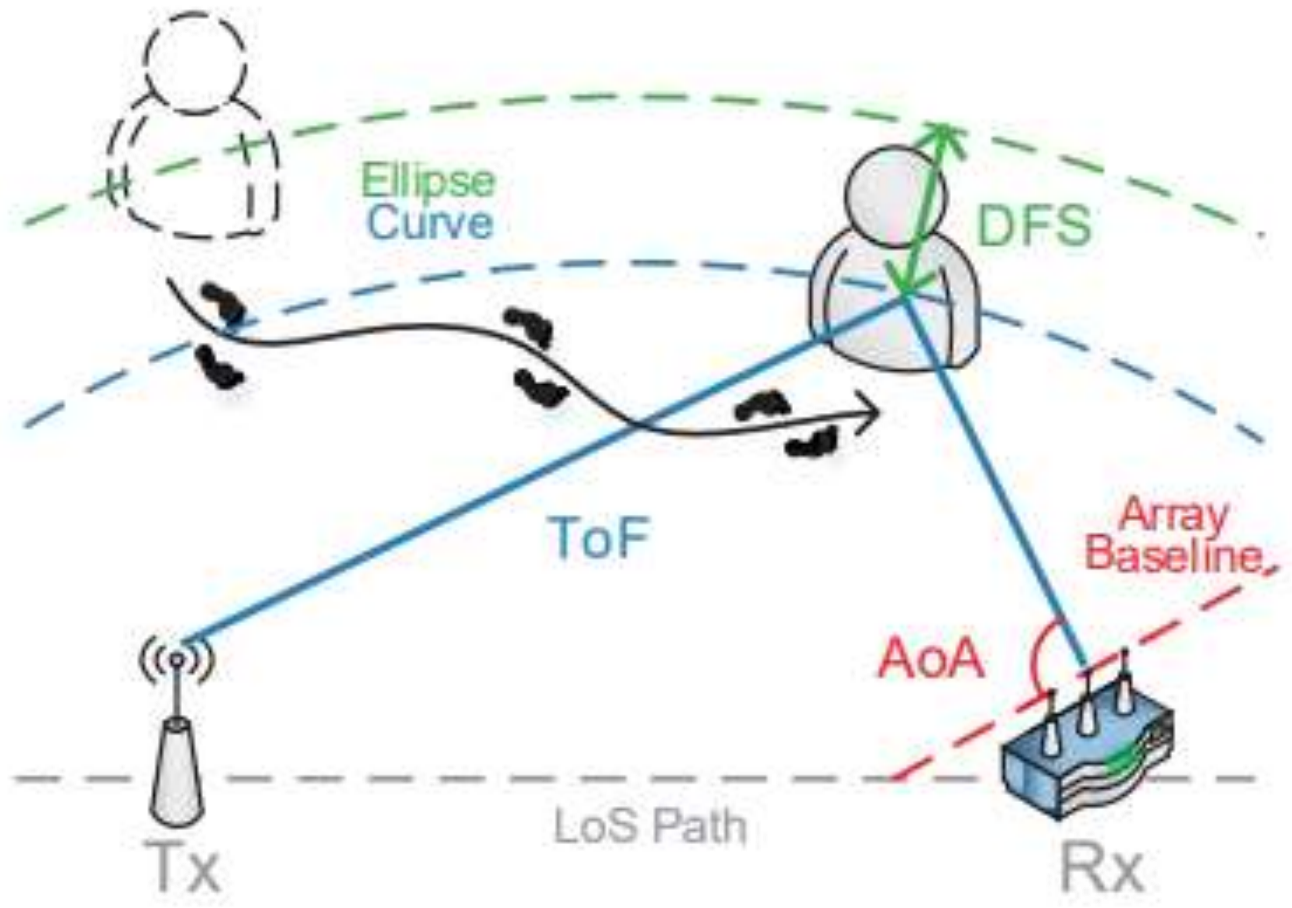
To conclude, In this paper, they presented two major issues.
Most of this work provides real-world evidence of “where” and “what” may go wrong for practically localizing clients in a device agnostic manner.

# Widar2.0: Passive Human Tracking with a Single Wi-Fi Link

## Introduction

In this paper, They try to figure out human tracking without carrying device on human side.
Also, construct system with a single commercial Wi-Fi devices.

They adopted LOS(Line-Of-Sight) situation scenario and model-based localization.
Estimate the cluttering signal which reflected by human body.




Widar2.0 tracking with ToF(Time of Flight), AoA(Angle of Array) and DFS(Doppler Frequency Shift).

Kun Qian, Chenshu Wu, Yi Zhang, Guidong Zhang, Zheng Yang, Yunhao Liu
MobiSys '18 Widar2.0: Passive Human Tracking with a Single Wi-Fi Link

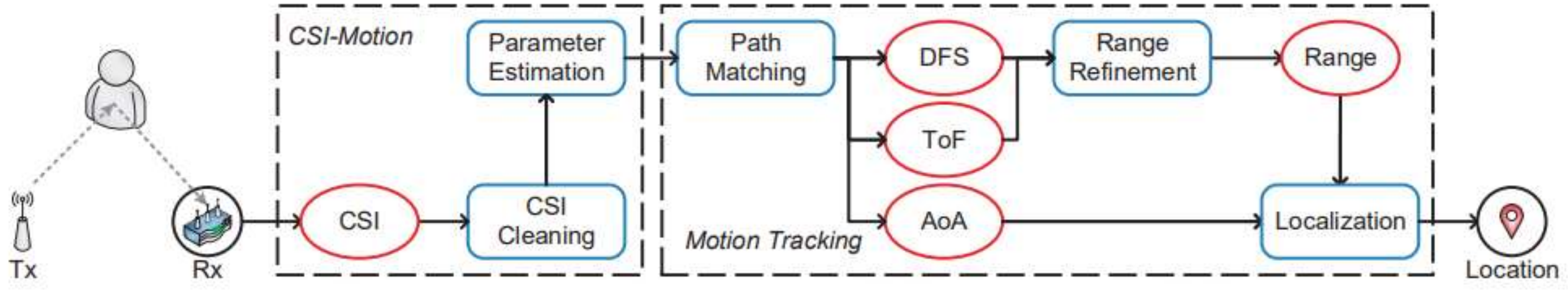
# Introduction

## System overview

First, they build a unified model for simultaneous and joint estimation of multiple parameters including ToF, AoA, DFS, and attenuation.

Second, they configure how to automatic calibrate CSI(Channel State Information) phase noises.

Third, The way of derive locations from unmatched parameters.



# Architecture and Algorithm

## CSI Model

Multipath problem : the received signal is multipath parameters are cluttered together.

$$\mathrm{H}(t,f,s) = \sum_{l=1}^{L} P_l(t,f,s) + N(t,f,s) = \sum_{l=1}^{L} \boldsymbol{\alpha}_l(t,f,s) e^{-j2\pi \underline{f\tau_l(t,f,s)}} + N(t,f,s)$$

$P_l$ is the signal of the l-th path. $\tau_l$ and $\boldsymbol{\alpha}_l$ is propagation delay and complex attenuation factor of l-th path.
N is the complex white Gaussian noise capturing
Wi-Fi NICs(Network Interface Controller) measure channel discretely in time(packet), frequency(subcarrier) and space(sensor).
i-th packet, j-th subcarrier and k-th sensor as H(i, j, k) and H(0, 0, 0) as reference.
The signal phase of the l-path in H(i, j, k) is transformed as :

$$f\tau_l(i,j,k) = f_c \underbrace{\tau_l}_{\text{ToF}} + \Delta f_c \Delta s_k \cdot \underbrace{\emptyset_l}_{\text{AoA}} - \underbrace{f_{D_l}}_{\text{DFS}} \Delta t_i$$

# Architecture and Algorithm

## Parameter Estimation

$\theta_l = (\alpha_l, \tau_l, \emptyset_l, f_{D_l})$ denoted multidimensional l-th path signal parameter.

$\Theta = (\theta_l)_{l=1}^{L}$ is multidimensional multipath signal parameter.

And the log-likelihood function of big theta is : $\gamma(\Theta; h) = -\sum_m |h(m) - \sum_{l=1}^{L} P_l(m; \theta_l)|^2$

And the MLE of big theta is the solution that maximizes Λ:

$$\Theta\hat{}_{ML} = argmax_{\Theta}\{\Lambda(\Theta;h)\}$$

# Architecture and Algorithm

## CSI Cleaning

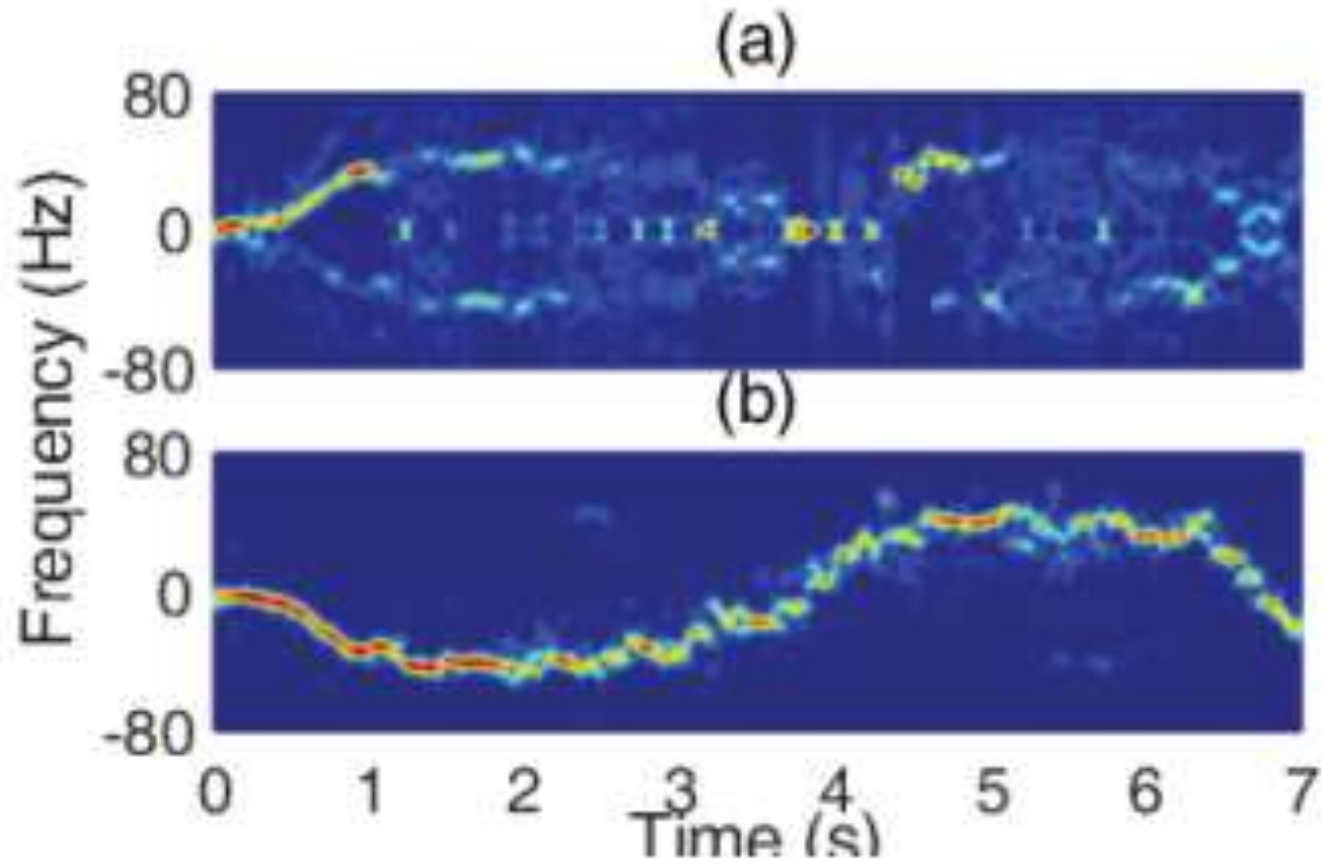
CSI contains not only channel response, but also various unknown phase noises.
The erroneous version of CSI measurement $H^{\sim}$ (m) is:

$$H^{\sim}(m) = H(m)e^{2\pi(\Delta f_j \epsilon_{t_i} + \Delta t_i \epsilon_f) + \zeta_{s_k}}$$

$\zeta_{s_k}$ is the initial phase of the receiver sensor. So, It constant every time the receiver starts up.
But, time offset $\epsilon_{t_i}$ and carrier frequency offset $\epsilon_f$ vary between packets.
So, It is impossible to directly estimate signal parameters from raw CSIs.
So, in this work, they adopted different solution which is conjugate multiplication.

a) linear calibration

b) conjugate multiplicatio



# Architecture and Algorithm

Conjugate Multiplication

They observe phase noises is only changes with time and frequency.
So, choose one antenna as reference and conjugate multiplication between reference and other antenna each.

$$C(m) = \tilde{H}(m) * \tilde{H}^{*}(m0) = H(m) * H^{*}(m0)$$

Further, classify multipath into static signals ($f_D = 0$) and dynamic signals ($f_D \neq 0$).
S is static d is dynamic.

$$C(m) = \sum_{n1,n2 \in P_s} P_{n_1}(m) P_{n_2}^{*}(m_0)$$
$$+ \sum_{l \in P_d,\, n \in P_s} P_l(m) P_n^{*}(m_0) + P_n(m_0)\, P_l^{*}(m_0)$$
$$+ \sum_{l1,\, l2 \in P_d} P_{l_1}(m) P_{l_2}^{*}(m_0)$$

Target

$$|P_n(\mathbf{m}) P_l^{*}(\mathbf{m}_0)| = (|\alpha_n| - \beta)|\alpha_l|$$
$$<< |\alpha_l|(|\alpha_n| + \gamma) = |P_l(\mathbf{m}) P_n^{*}(\mathbf{m}_0)|$$

# Architecture and Algorithm

Conjugate Multiplication

This target term can be formulate :

$$P_l\ (m_0)\ P_n^*(m_0) = \alpha_l \alpha_n^* e^{-2\pi\Delta f_j(\tau_l-\tau_n)-\underline{2\pi f_c \Delta s_k \cdot \emptyset_l}+2\pi f_{D_l}\Delta t_i}$$

Other remain term is

$$P_n\ (m_0)\ P_l^*(m_0) = \alpha_n \alpha_l^* e^{-2\pi\Delta f_j(\tau_n-\tau_l)-\underline{2\pi f_c \Delta s_k \cdot \emptyset_n}+2\pi f_{D_l}\Delta t_i}$$

Omit

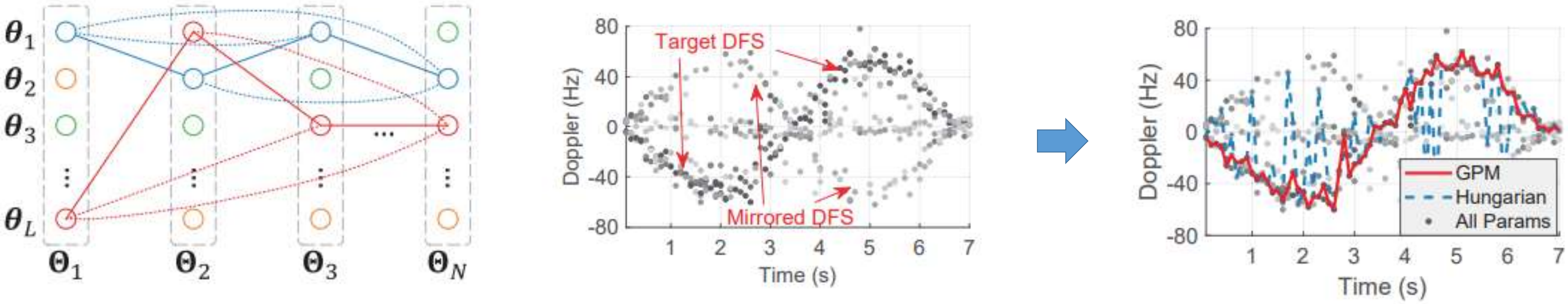
When m ≠m0 :

$$|P_n(\boldsymbol{m})P_l^*(\boldsymbol{m}_0)| = (|\alpha_n| - \beta)|\alpha_l| \ll |\alpha_l|(|\alpha_n| + \gamma) = |P_l(\boldsymbol{m})P_n^*(\boldsymbol{m}_0)|$$

# Architecture and Algorithm

## Path Matching

The graph has all multipath parameters are cluttering together.
So, It have to estimate right way.
Early estimation part we have $\Theta = (\theta_l)_{l=1}^{L}$
To overcome interference, by Graph Path Matching, we matching these cluttered data.
Weight of graph is distance between multipath parameters.
By searching minimal overall weight, In this work, successfully search for an optimal assignment.

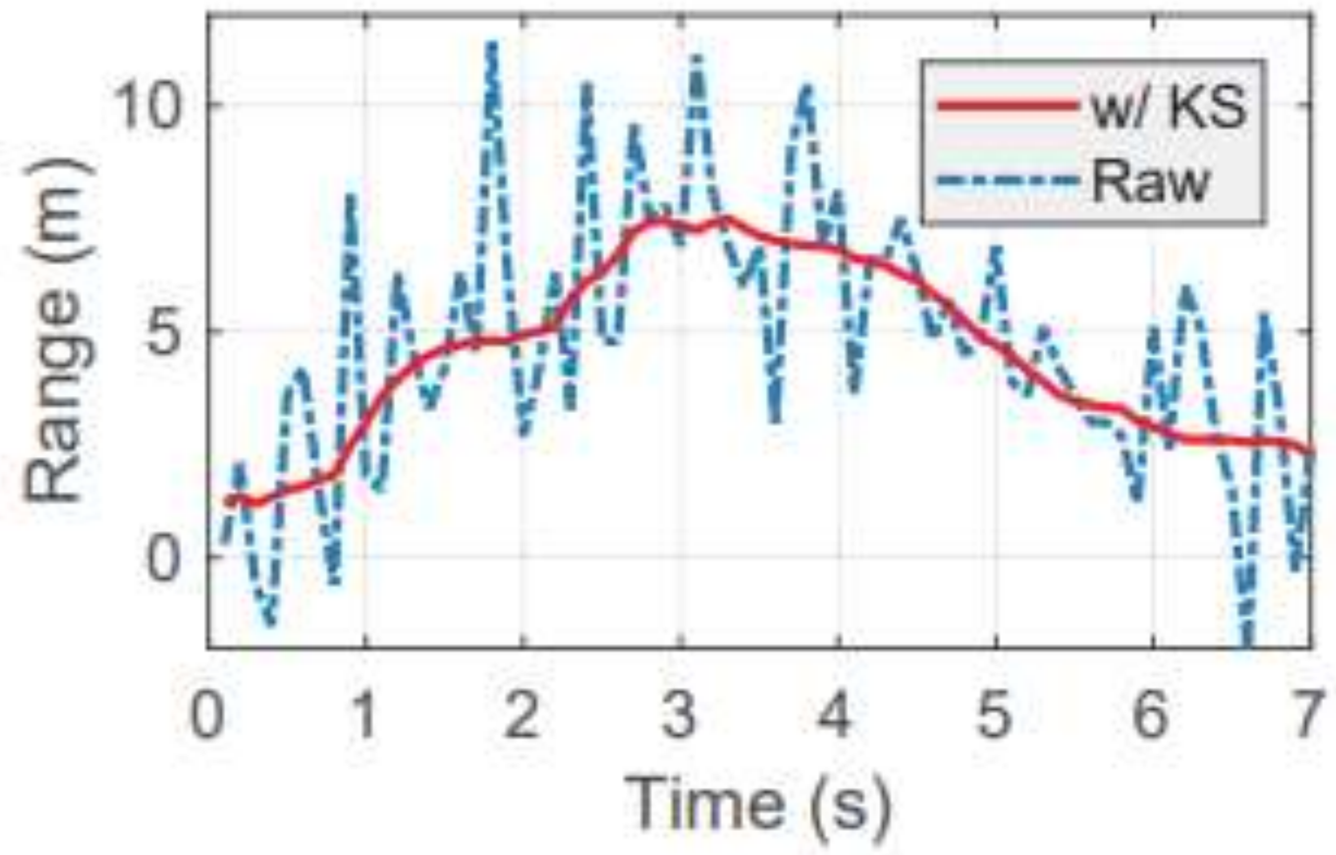


# Architecture and Algorithm

## Range Refinement

Theoretically, the relative range between the reflection path and the LoS path can be calculated by multiplying estimated ToF with the speed of light.
But, It has many fluctuation only using estimated ToF.

It apply Kalman Smoother to refine ranges from ToF estimations with the change rates of path range from DFS estimations.



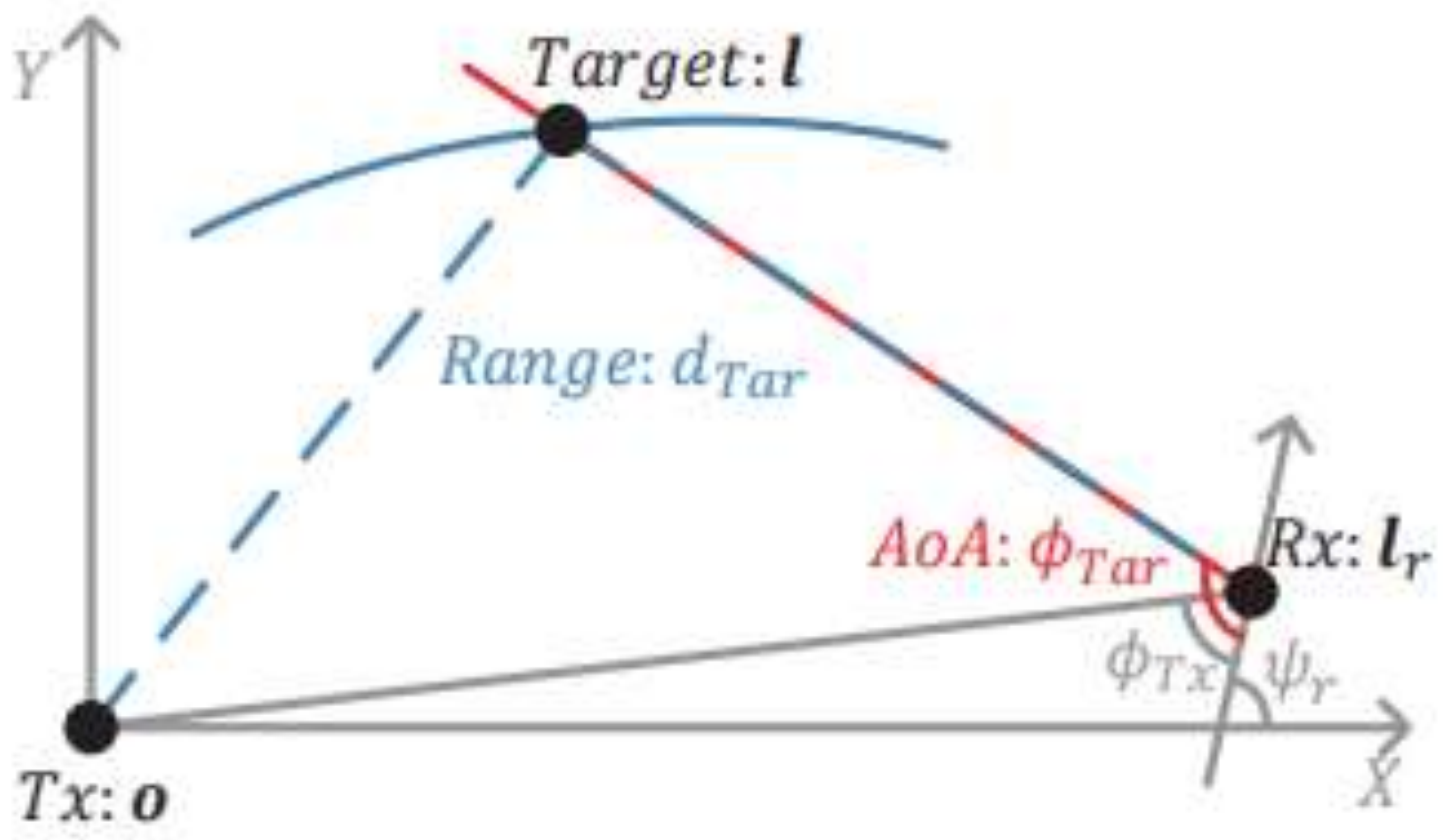
# Architecture and Algorithm

## Localization

They find the range which refined and angle of the receiver and target.
So, By calculating inversely, Finally it can estimate the target's location.

$$\begin{cases} \sqrt{x^2+y^2}+\sqrt{(x-x_r)^2+(y-y_r)^2}=d_{Tar} \\ (y-y_r)\cos(\psi_r-\phi_{Tar})=(x-x_r)\sin(\psi_r-\phi_{Tar}) \end{cases}$$

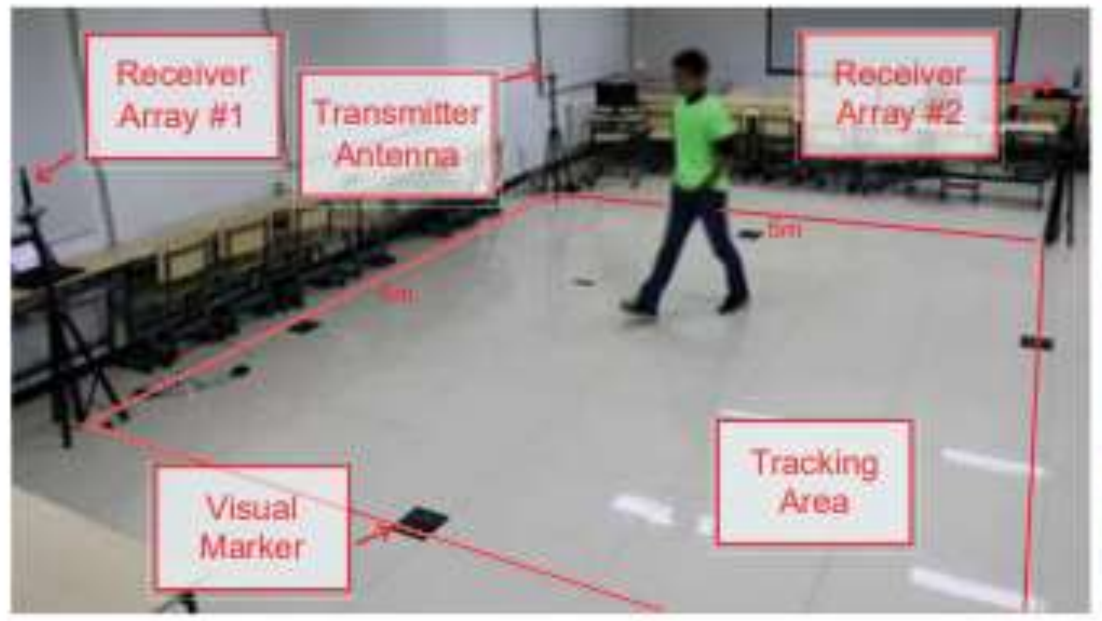
$$\begin{cases} x=\frac{1}{2}\frac{d_{Tar}^2+2s_r d_{Tar} x_r \sec\varphi + x_r^2\sec^2\varphi-(x_r\tan\varphi-y_r)^2}{x_r+y_r\tan\varphi+s_r d_{Tar}\sec\varphi} \\ y=\tan\varphi(x-x_r)+y_r \end{cases}$$



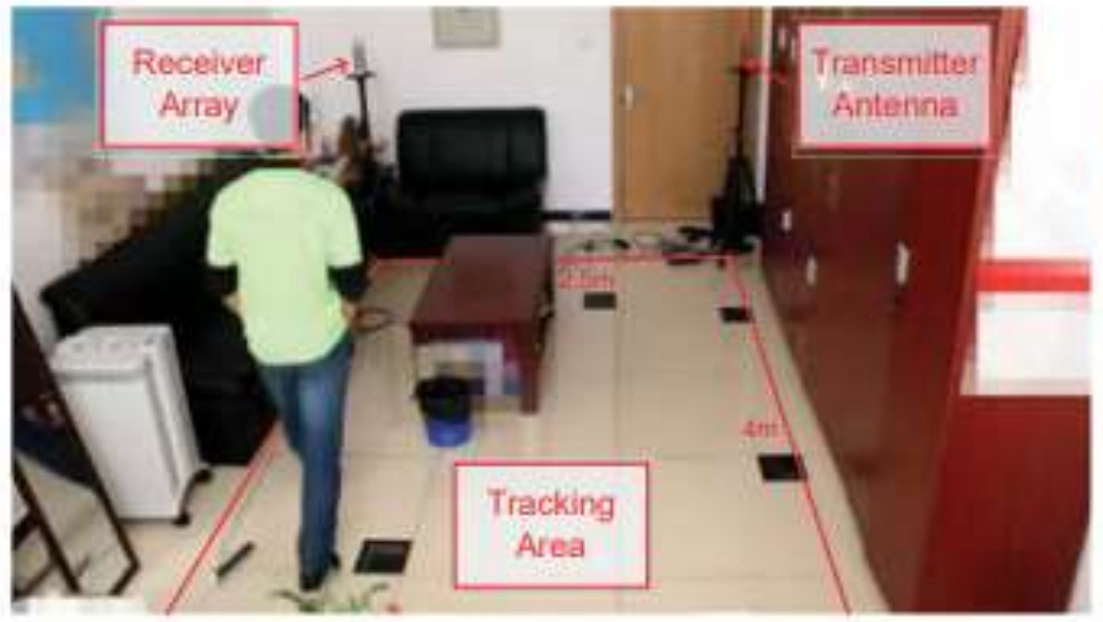
# Experiment

## The way of experiment

3 scenarios : Classroom, Office, Corridor

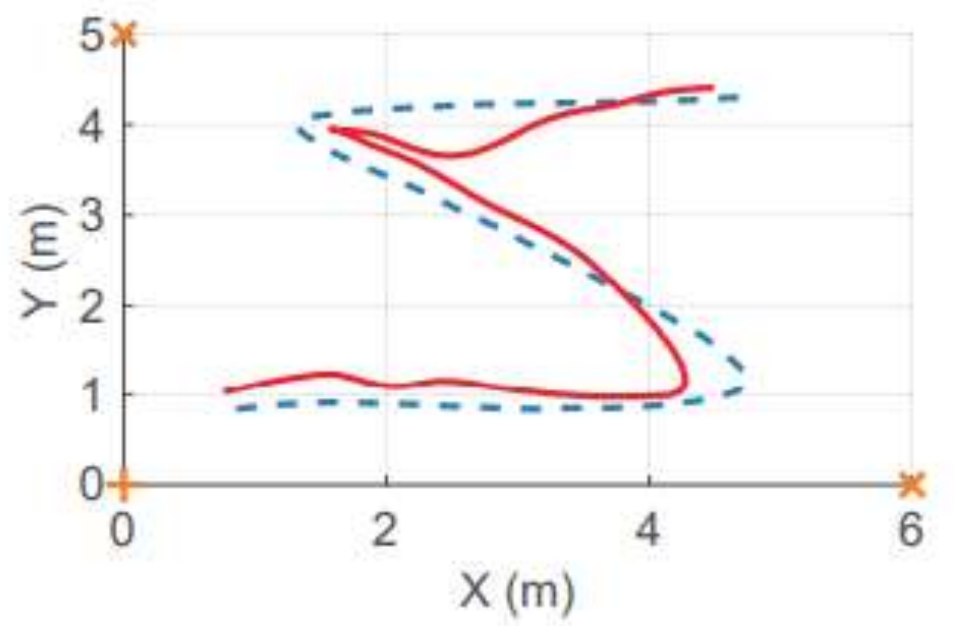



(a) Classroom

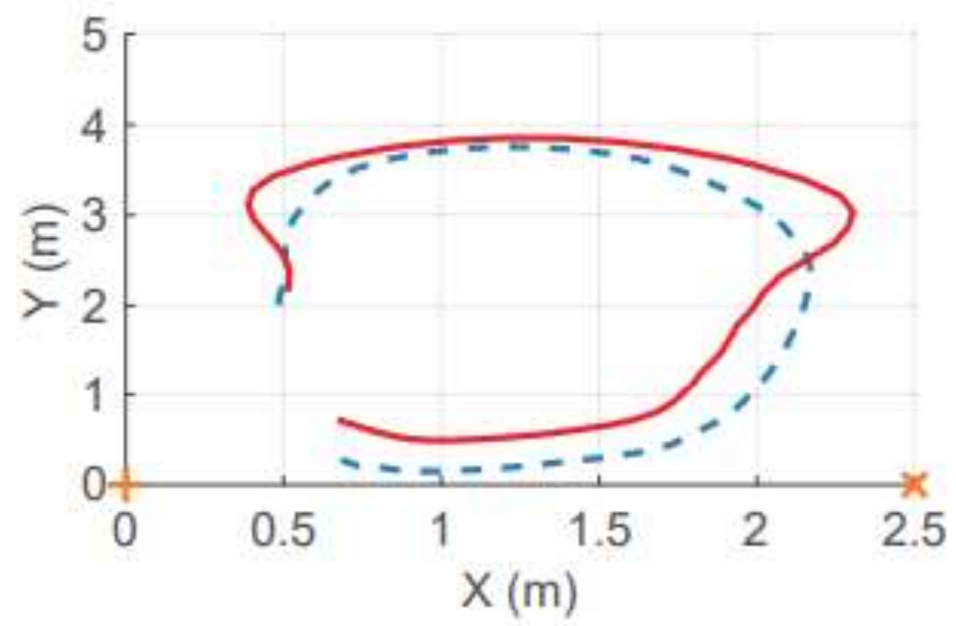



(b) Office

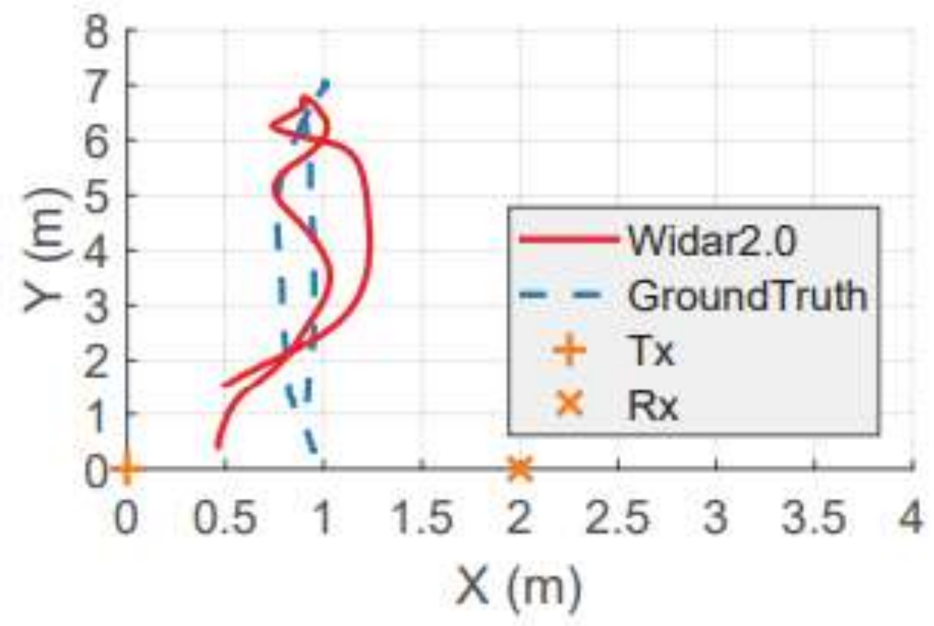

(c) Corridor




(a) Classroom




(b) Office



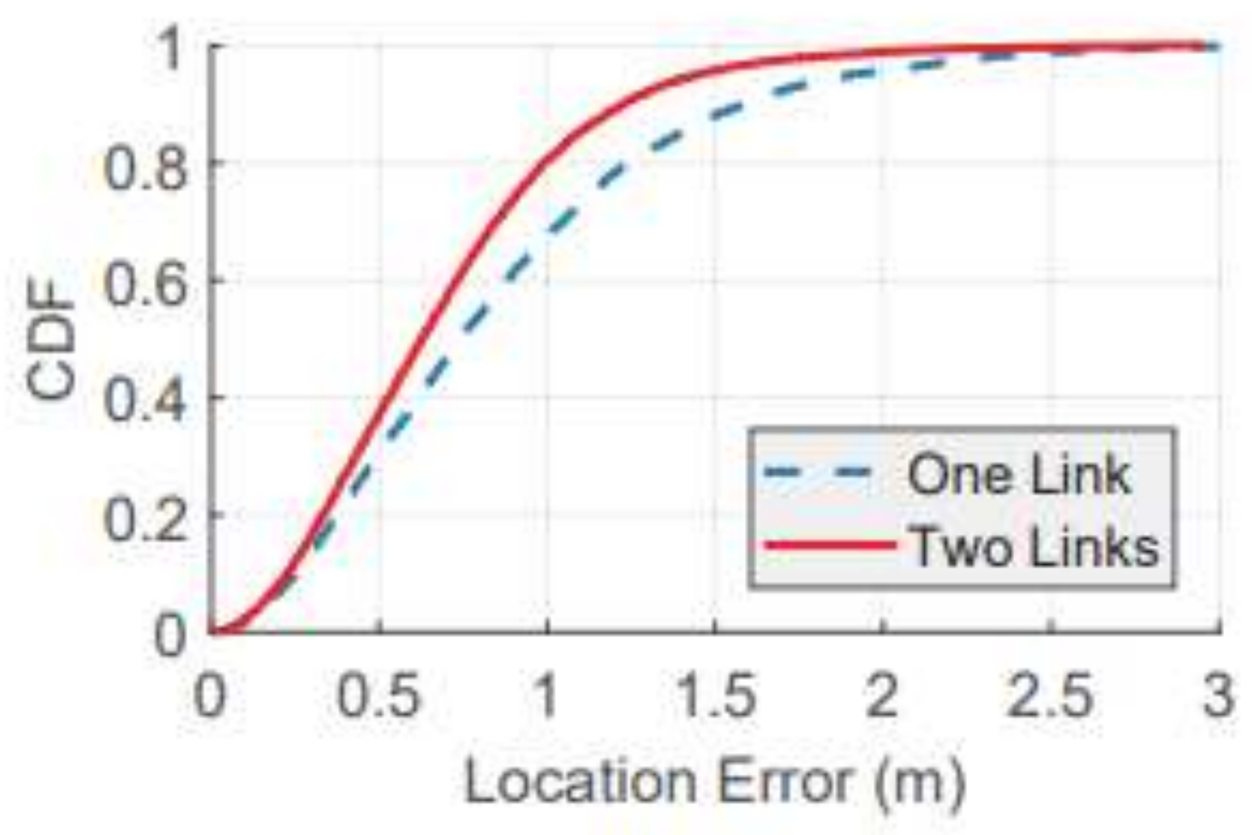

(c) Corridor

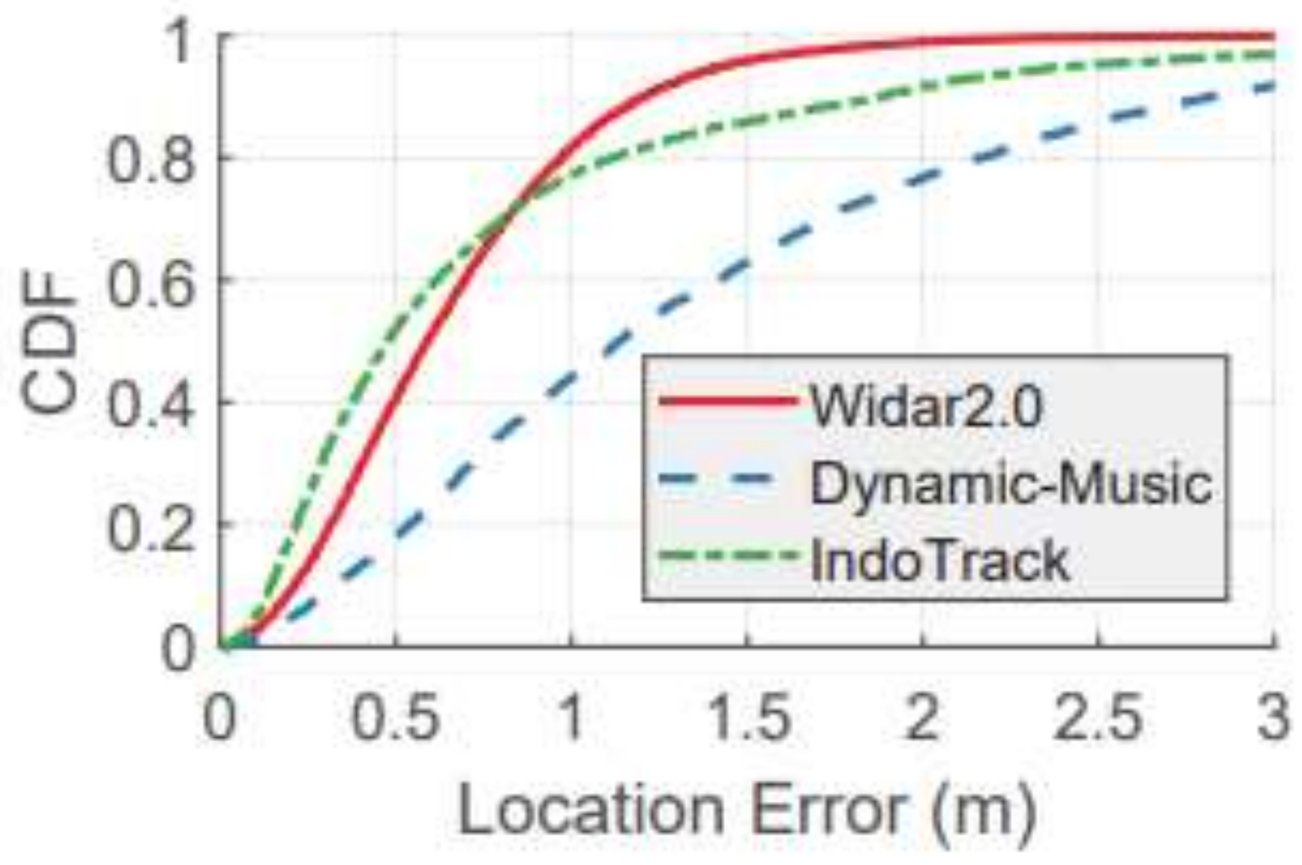
# Experiment

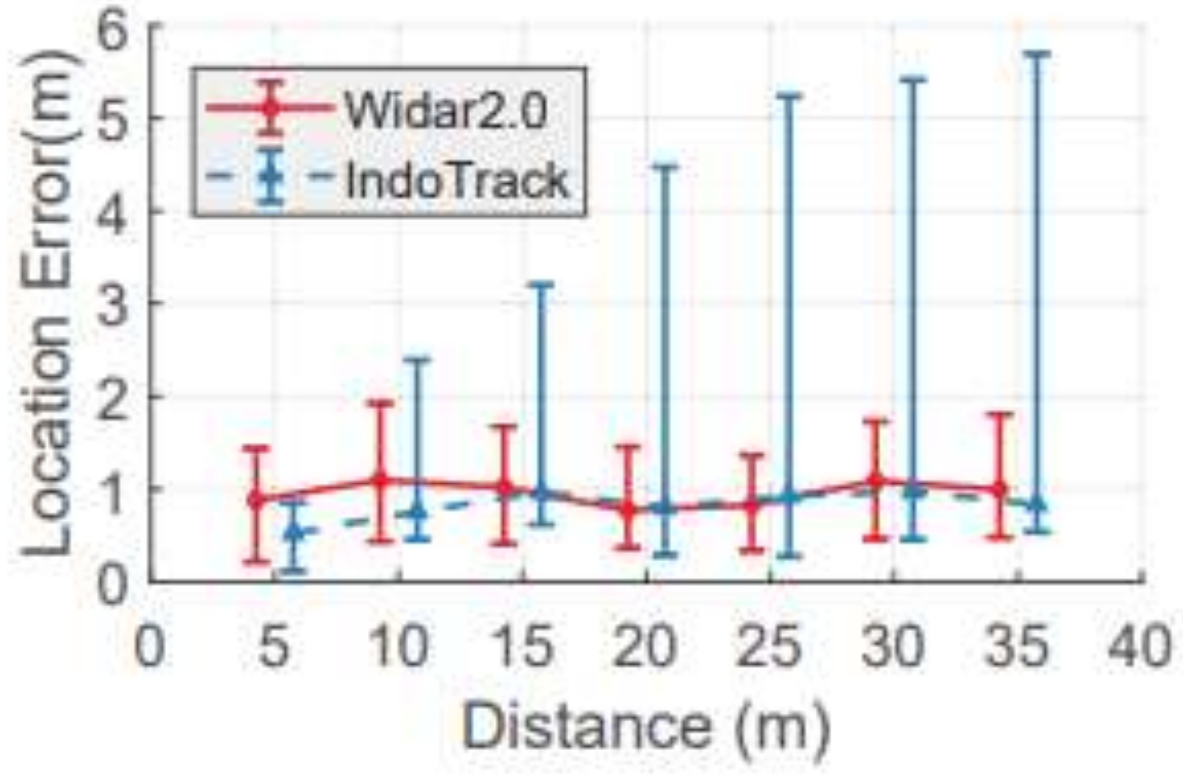
## Overall Performance

Over all performance of this work’s accuracy is 0.75m in one link and 0.63m in two link
Compared with other early proposed works Widar2.0 is better overall then Dynamic-Music. And, in long distance, Widar2.0 is better than IndoTrack.

IndoTrack is WiFi based, using parameters AoA, DFS and accuracy is 0.48m.
But, It uses more infrastructure devices then Widar2.0 (1 additional receiver and 2 more links)



# Conclusion

## Conclusion and Limitation

Achievements.
A unified model of ToF, AoA and DFS.
Average error 0.75m with single Wi-Fi link.
Using two link, it reduced to 0.63m.

Limitation of this work.
Multi-person problem : hard to separate reflect point in CSI.
Non-LoS condition problem : reflection signal is too weak to recognize in Non-LoS condition.

# THANK YOU