On-Device Localization in Smartphones

From theory to practice

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Wireless Knowledge SUMMIT

19-Dec-2024

Overview of localization

- Localization → Process of determining the precise location of a device or object in a defined space.
- Various technologies → GPS, Wi-Fi, Bluetooth, UWB, Cellular, RFID, LiDAR, and computer vision.

<u>Applications</u>

- Navigation: Guide travellers through streets or shopping malls.
- Asset Tracking: Monitor the movement of goods in warehouses.
- Search & Rescue: Locate Missing individuals in disaster zones.
- Autonomous vehicles: Enable self-driving cars, drones to understand their locations and surroundings.
- Context awareness and Personalization: Personalized routines and recommendations

Overview of localization

Outdoor

- Primarily reliant on satellite-based **Global Navigation Satellite Systems** (GNSS), such as GPS, GLONASS and Galileo.
- Uses signals from multiple satellites to **triangulate** a receiver's position on Earth's surface.
- **GNSS** has an accuracy of **5 meters** under open skies, good enough for outdoor localization applications. However the accuracy degrades during Non-Line-of-Sight (NLOS)

Indoor

- Involves **pinpointing** the position of people or objects within enclosed environments, such as offices, shopping malls, airports, or warehouses.
- Currently, most people spend approximately **80% of their daily lives indoors**. As a result, approximately **70% of smartphone usage** and **80% of data transmission** occur in indoor environments. Hence, a ubiquitous solution for indoor localization is important*.

Contextual

- Instead of precise geographic coordinates, localization systems can assign meaningful labels such as "Home", "Office", or "Gym", reflecting the user's frequently visited places.
- A blend of geofencing, pattern recognition, and contextual sensing (eg: Wi-Fi fingerprints, mobile sensors), are used to achieve this.

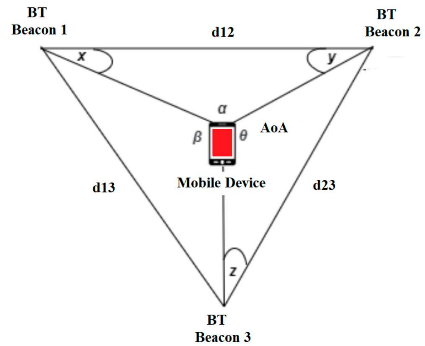
* N. Singh, S. Choe and R. Punmiya, "Machine Learning Based Indoor Localization Using Wi-Fi RSSI Fingerprints: An Overview," in *IEEE Access*, vol. 9, pp. 127150-127174, 2021, doi: 10.1109/ACCESS.2021.3111083.

Wireless localization

There are two main types of Wireless localization techniques,

<u>Geometric Approaches</u>

- Include multilateration, trilateration, and triangulation methods, for which various measurement parameters can be used.
- Time of Arrival (ToA), Time of Fight (ToF), Angle of Arrival (AoA), Time Difference of Flight (TDoF), Time Difference of Arrival (TDoA),
- Can work in real-time with minimal pre-processing once the infrastructure is set.
- Need to know the relative positions of anchors before hand. The final position will be calculated relative to the anchors.
- Signal reflections, multipath effects, and obstacles can degrade performance.



<u>Fingerprinting Approaches</u>

- Fingerprinting approaches employ Received Signal Strength Indicator (RSSI) or Channel State Information (CSI) as pattern matching parameters to determine the positions of devices.
- More robust in complex indoor environments where geometric methods struggle.

Standards Ranging Protocols

Ranging protocols are designed for estimation of distance between two devices using the radio technology.

Wi-Fi - 802.11mc 802.11az

- Both the standards use “**Fine Time Measurement**(FTM)” to calculate distances between Wi-Fi devices based on the time it takes for a signal to travel between them.
- While **802.11mc** provides **basic** location information, **802.11az** offers significantly **higher accuracy**, allowing for more precise positioning with sub-meter precision in ideal conditions.
- This is achieved by utilizing enhanced features like **wider channel bandwidth** and **MIMO signal** properties for better distance estimation.
- However, the **penetration of the AP** which support these protocols is **very low**. Also, there is no information about **angle**, hence we will need **multiple** AP.

BT 6.0 - Bluetooth Channel Sounding

- In Bluetooth Channel Sounding, an **initiator** sends signals to a reflector device repeatedly across **multiple frequencies**.
- The distance is calculated by comparing **phase differences** between transmitted and received signals over these frequencies.

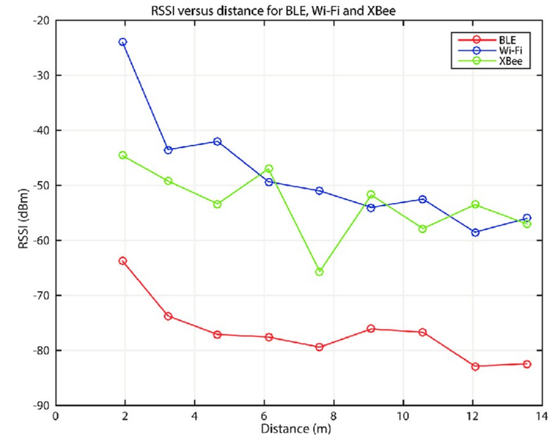
CSI fingerprinting - High level view

- CSI captures detailed **wireless channel characteristics** (amplitude, phase, delay) and reflects environmental changes, enabling **non-contact sensing** of both large and subtle movements.
- This sensitivity allows CSI to support diverse applications, including smart environment monitoring, **human activity recognition**, and precise wireless positioning.
- CSI based localization is **less sensitive** to small environmental changes due to richer signal properties.
- However, it requires specialized tools and more computational resources to extract and interpret the CSI data.
- Not all Wi-Fi devices provide easy access to CSI information and it is **difficult to obtain in STA**.
- Although not easy to implement, if the application requires precise localization, CSI fingerprinting is the best wireless solution.

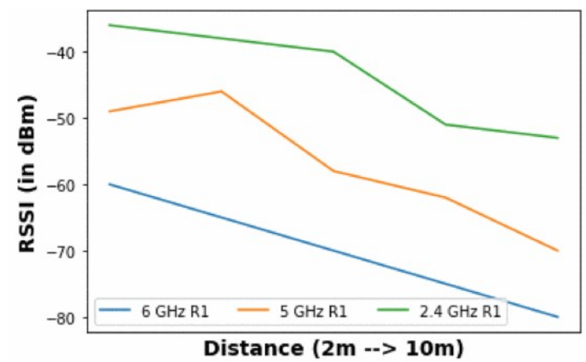
Indoor Localization -> RSSI Fingerprinting

- Using RSSI from Stationary **BT** devices:
  - BT devices broadcast device type. We used only TVs which are mostly stationary anchors.
  - After certain distance → RSSI almost constant
  - Can be good for **proximity** rather than localization.

- **Wi-Fi RSSI** highly correlated to the distance.



REF – “M. Golestanian, J. Siva, and C. Poellabauer, ‘Radio Frequency-Based Indoor Localization in Ad-Hoc Networks’, Ad Hoc Networks. InTech, May 11, 2017. doi: 10.5772/66523.”

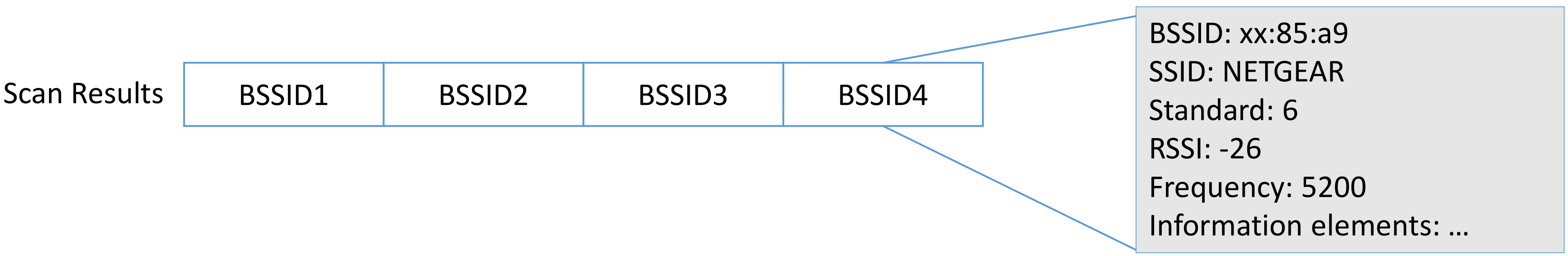


REF - S. Choi, M. R. Kanagarathinam, J. R. Kovvuri and K. M. Sivalingam, "The Band Selection Decision for 6GHz Using RSSI and Channel Utilization," 2023 IEEE Globecom Workshops (GC Wkshps), Kuala Lumpur, Malaysia, 2023, pp. 1650-1655, doi: 10.1109/GCWkshps58843.2023.10464542.

Indoor Localization -> WI-Fi RSSI Fingerprinting

Let us see a practical example

- In Smartphone → Wi-Fi scanning → Obtain a list BSSID in the surroundings/time.
- Mean and variance of the RSSI is stored for each BSSID
- 802.11mc and 802.11az can also be fetched → Along with distance
- Can be combined for accuracy



tag	xx:5b:42	xx:5b:41	xx:5b:38	xx:d5:06	xx:d5:07	xx:9f:41	xx:9f:40	xx:9f:42	xx:9f:42	xx:9f:41	xx:9f:43	xx:9f:40	xx:d5:07
A6	-39.5752	-48.2971	-46.0586	-44.6355	-44.5979	-47.32	-47.1273	-47.1927	-46.6379	-46.5407	-46.6624	-46.8142	-48.0755
A9	-34.6697	-44.8812	-50.3535	-40.3	-40.5	-45.943	-45.9354	-46.0608	-48.1195	-48.1164	-48.2752	-48.2616	-42.3954
A12	-36.0899	-44.9234	-49.0372	-42.0218	-41.9679	-54.83	-55.7444	-54.8266	-46.0491	-46.0503	-46.0263	-45.0949	-44.9133
A15	-35.9133	-44.6667	-51.1994	-41.4874	-41.6931	-50.5367	-50.4786	-50.4495	-48.8562	-48.9095	-48.7897	-48.939	-45.7691

An example of the stored RSSI fingerprints

RSSI Fingerprinting: Outlier removal

One of the major problems when dealing with wireless localization is the non-static sources.

- SoftAPs like Mobile Hotspot are mobile and can have vastly different RSSI at the same location.
- They are frequently turned on/off and hence are not always available in the scan results.

We created a Neural network model to classify available APs in the Wi-Fi scan list into static APs (nearby Wi-Fi routers) and non-static APs (mobile hotspots and distant routers).
Input Features of the model:
1. **SSID Pattern**: Whether the SSID resembles a known mobile hotspot pattern.
2. **RSSI Variance**: Higher variance in signal strength for non-static APs.
3. **RSSI Mean**: Lower average signal strength value for non-static APs.
4. **Availability Percentage**: Frequency of appearance in scans (lower value for non-static APs).

We got a test accuracy of **98.95**%

Based on the model's predictions, the Scan results of the **non-static APs are ignored** when building the RSSI fingerprint database.

RSSI Fingerprinting: Approaches

When we want to know the location of a device, we create the **RSSI vector from scan list** and compare it with the fingerprints in the previous data. The one that matches closely will be the determined location.

Various distance metrics can be used to match the RSSI vector with the fingerprints,

- Cosine similarity
- Manhattan norm (L1 norm)
- Euclidean norm (L2 norm), etc.,

Clusters → Assign, Update, Predict

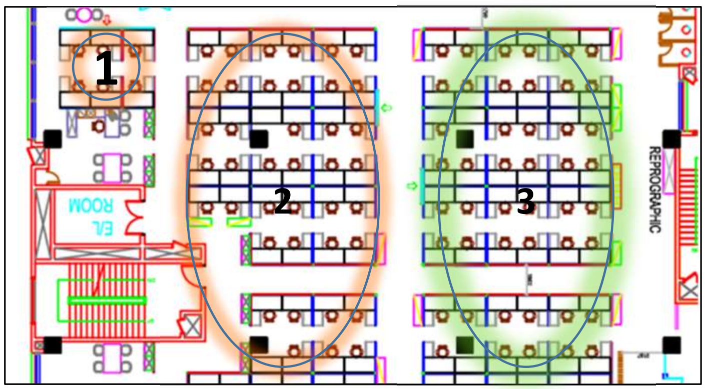
If the location virtual labels (A6, A9 etc.,) are available beforehand, then we can even train a **supervised model** to do the pattern matching for us instead of using the above distance metrics.

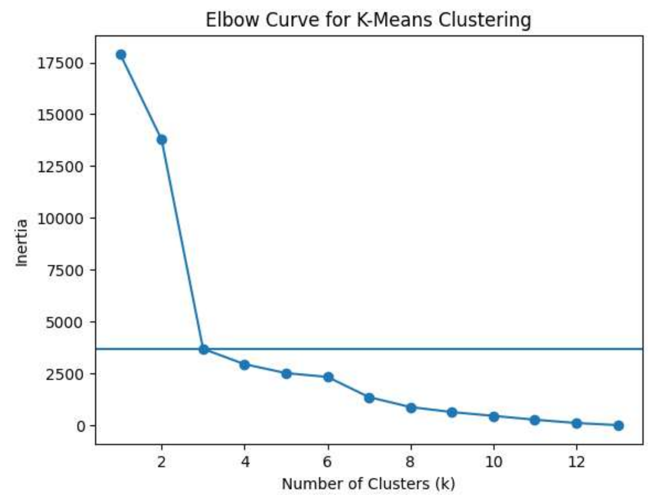
The above approach works seamlessly when the fingerprint database already exists and the fingerprints are already labelled.

However, this is not always the case. Especially when the localization is user-specific and personalized.
In this case,

=> The fingerprint database needs to be built/updated as the user keeps visiting new locations.
=> There are no named labels available (not required in most cases)

RSSI Fingerprinting: Challenges in Clustering





Near Far Problem: How do we cluster?

Closer but different locations being grouped together

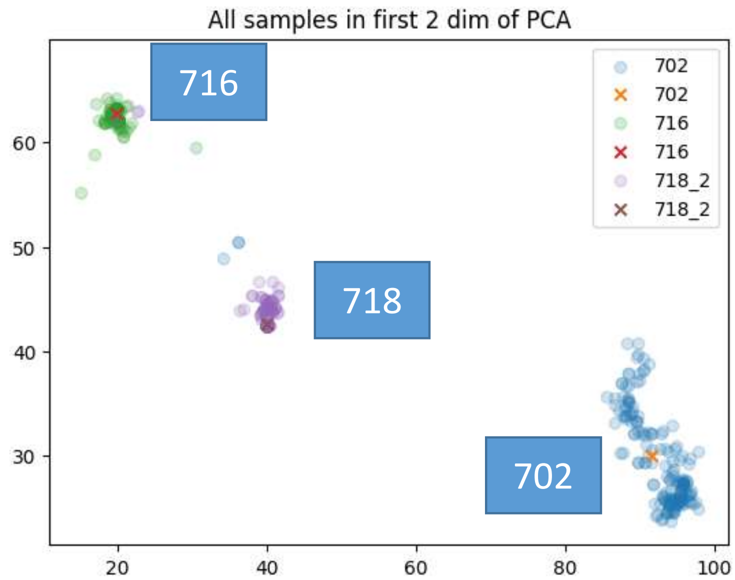
Even after dimensionality reduction techniques like PCA, the problem exists. The closer locations are still grouped.

RSSI Fingerprinting: PGM Challenges

Probabilistic Generative Models (PGMs)

PGM is a **AI method** that first estimates the **probability** distribution (Gaussian - most commonly used) of each cluster. Next, for a given RSSI vector, the likelihood of it belonging to each cluster is estimated. The point is then assigned to the cluster with highest likelihood.

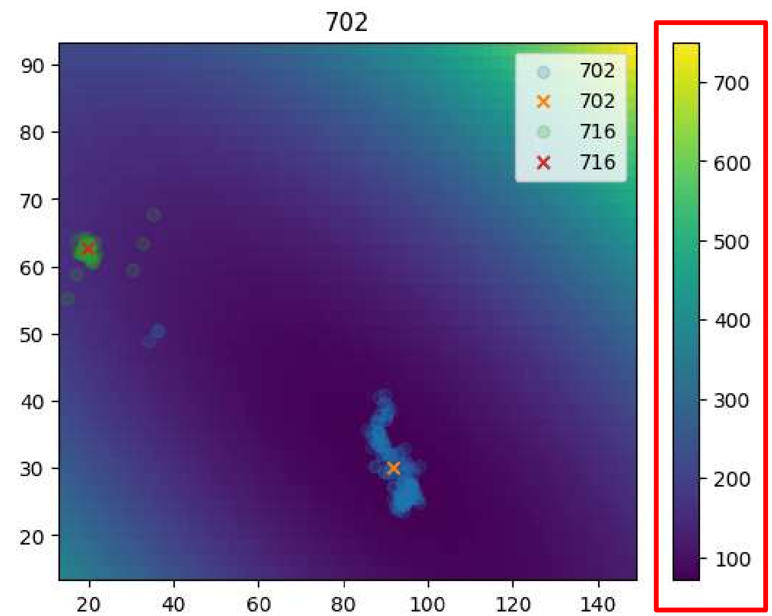
- Should the green(716) have **higher likelihood** of belonging to blue or purple cluster?

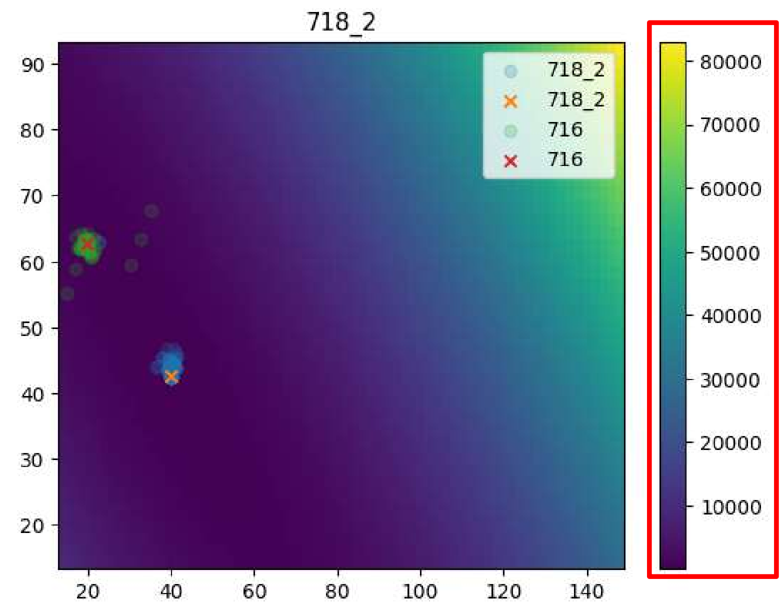


However, likelihood results show that green has higher chance of belonging to blue because of variance and data spread

RSSI Fingerprinting: PGM Challenges

The purple points are more clustered with less variance.
But blue points have more variance in the direction of the purple and green clusters. Hence its distribution is more spread out.



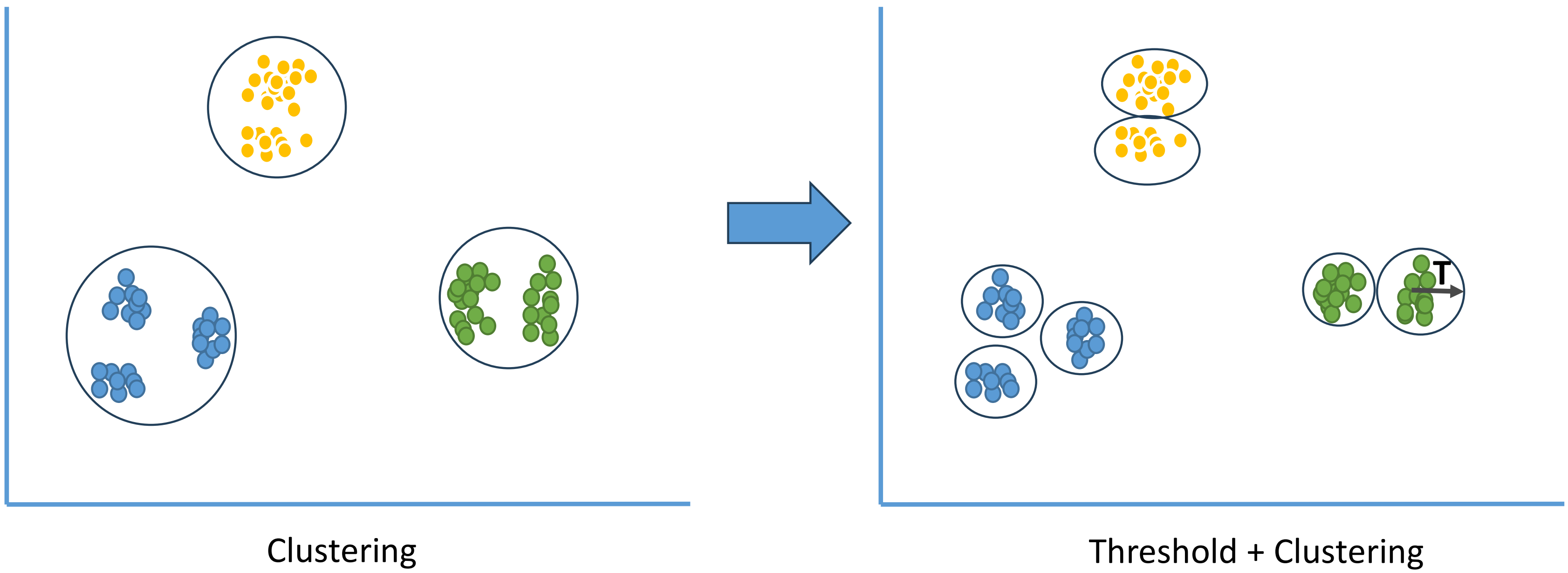


If the RSSI at a location is fluctuating, it will look closer to locations compared to locations where RSSI is stable.
In few cases, this caused farther locations to look nearer compared to close locations.

RSSI Fingerprinting: Threshold + Clustering

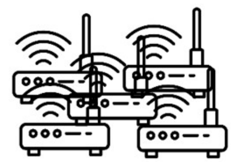
Standard implementations of unsupervised learning algorithms → several challenges faced

Threshold on distance ➔ Decide whether a location is new.



RSSI Fingerprinting: Threshold + Clustering

Challenge: The L2 norm increases as the number of dimensions(bssids) increase.

	A ↔ B [-65] [-66]	 A ↔ B [-65, -65, -65, -65, 65] [-66, -66, -66, -66, 66]
L2 norm	1	$\sqrt{5}$
RMS	1	1

When using L2 norm in high dimensions, the distance between two fingerprints gets amplified even when they are very similar. RMS distance takes the effect of dimensions into account and gives similar results in sparse as well as dense Wi-Fi areas.

From extensive testing, we have come up with the following condition for determining a new location,

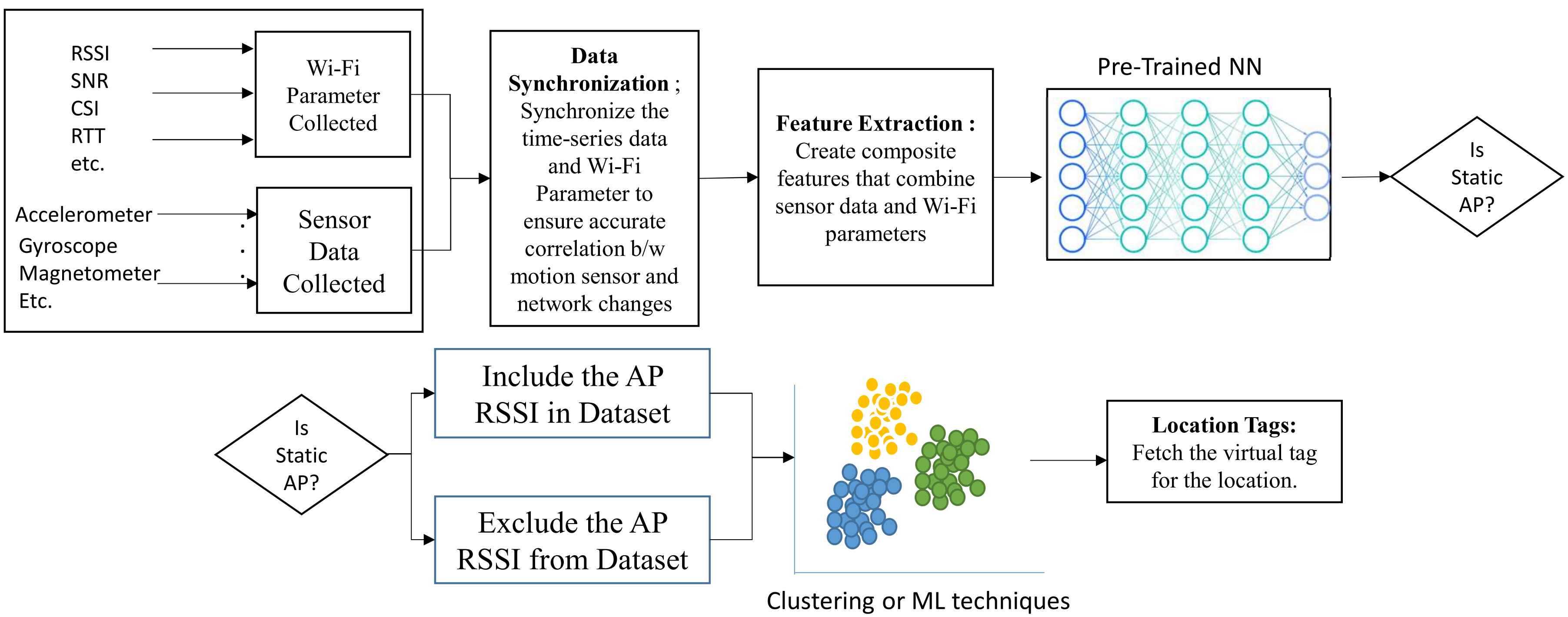
RMS distance(RSSI vector, fingerprint) < 4

This gives a localization range of of 2-3 m radius, i.e. locations that are farther than 3m will be considered different.

Interplay with Sensors

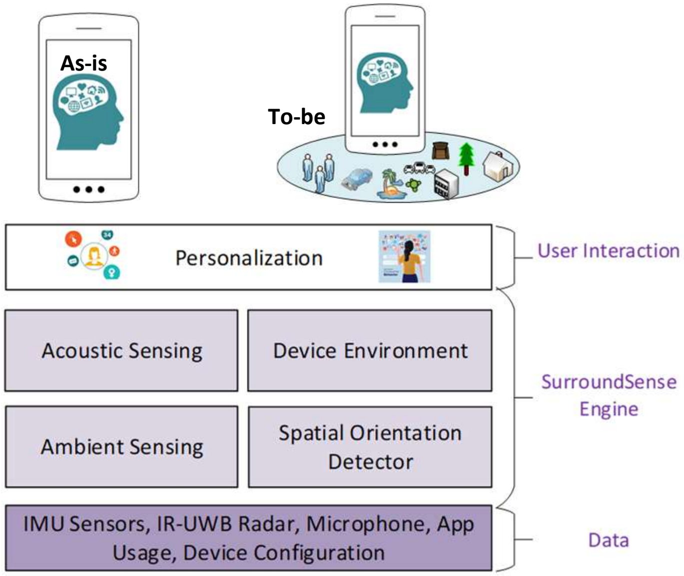
When the tagging has to be automatic we need to have triggers for collecting data as the data cannot be collected always and in undesirable scenarios.

Station → Mobility → Station Sensor → Active Context → **Collect, Tag**



UWB – Surround Sense

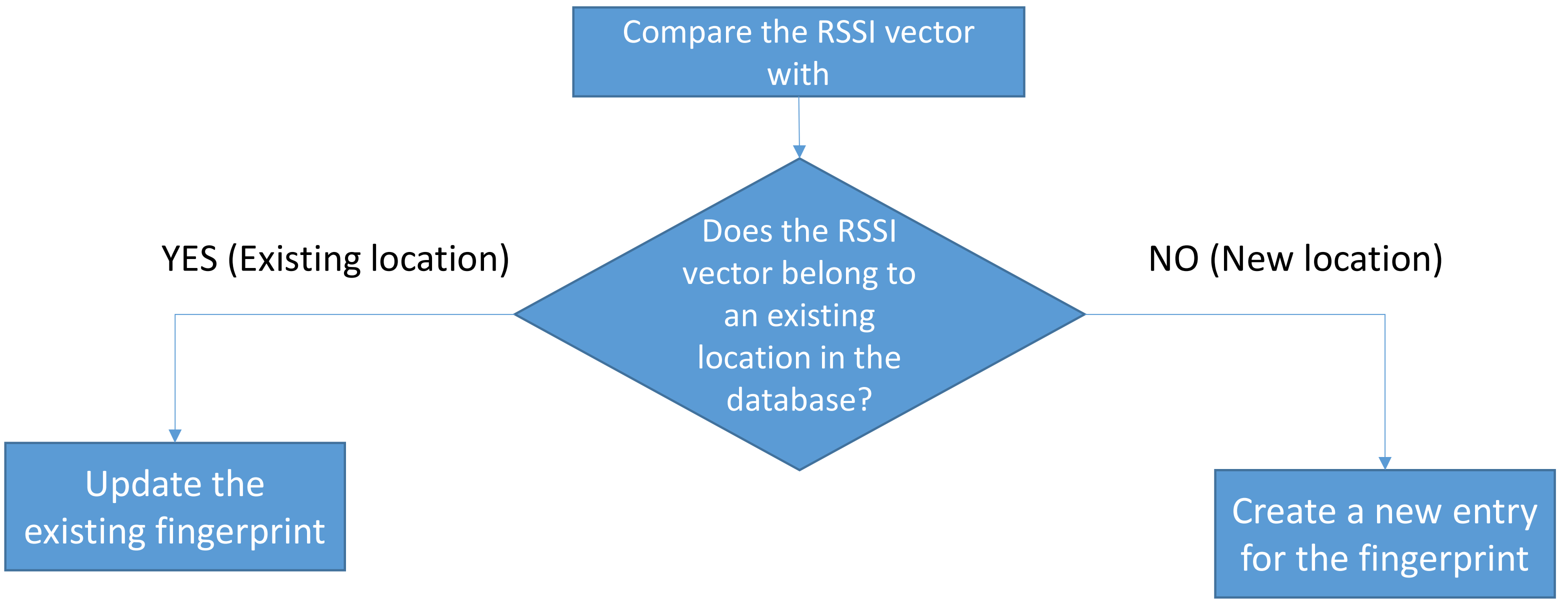
- UWB for Ranging and Sensing
- Context and personalization
- Power
- Will be discussed in IEEE CCNC 2025 – Las Vegas



THANK YOU

Indoor Localization -> RSSI Fingerprinting

We need to be able to separate a new location from existing location. We need an algorithm to implement the following flow,



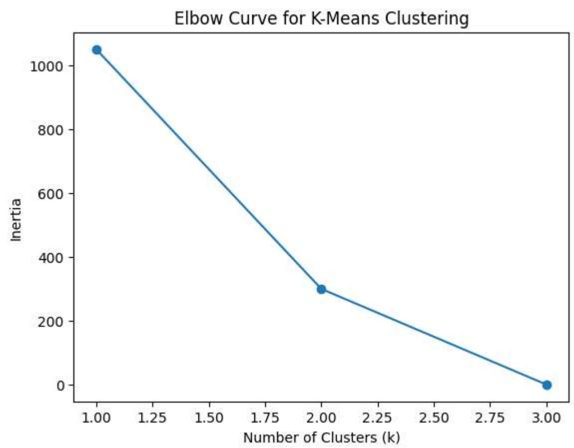
Since we are dealing with unlabelled data, A reasonable approach would be to use unsupervised learning. That is, we can use clustering to group the RSSI data. Vectors in a single cluster belong to one location and number of clusters determine the number of unique locations.

Indoor Localization -> RSSI Fingerprinting

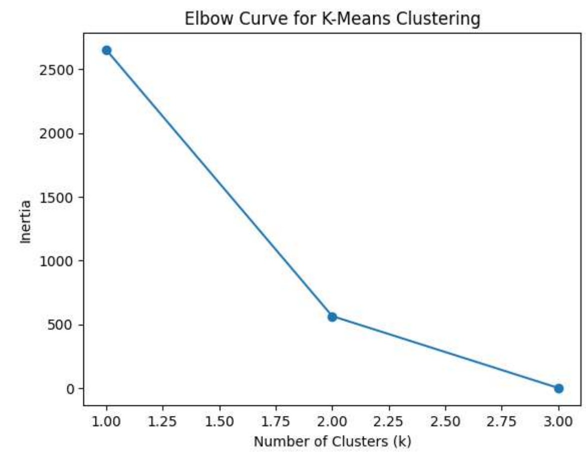
We ran K-means clustering by setting different number of clusters starting from a single cluster. The optimal number of clusters is the elbow point of the graphs. This will be the number of different locations in the data.

Experiment 1

Three same locations



Three different locations (separated by 4m distance)



The major reason for easy separation of data even at the same location is due to the high dimensionality. Any two points will be easily separable making look data at same location as different locations.

Problem-1: Same locations being separated and shown as different locations

AI and RSSI Fingerprinting

ML based methods that can be applied based on the application.
Supervised
-> No tags

Unsupervised
-> All data easily separable in high dimensions.
-> Dimensionality reduction not suitable as it hampers with the information about distance.

Transformers and sequence models
-> Superior performance
-> Takes previous predictions into account as well