Dissertation on

"Multi-Agent Reinforcement Learning for RSSI Fingerprinting-Based indoor Wi-Fi Positioning with Cross-Building Localization"

Submitted in partial fulfillment of the requirements for the award of the degree of

Bachelor of Technology
in
Computer Science & Engineering

UE22CS320A – Capstone Project Phase - 1

Submitted by:

Narayan S	**PES2UG22CS339**
Pranav Aditya B	**PES2UG22CS397**
Pranav H	**PES2UG22CS399**
Rohit Anand	**PES2UG22CS458**

Under the guidance of

Dr. Chandrashekar P Chavan
Associate Professor
PES University

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
FACULTY OF ENGINEERING
PES UNIVERSITY
(Established under Karnataka Act No. 16 of 2013)
Electronic City, Hosur Road, Bengaluru – 560 100, Karnataka, India

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(Established under Karnataka Act No. 16 of 2013)

Electronic City, Hosur Road, Bengaluru – 560 100, Karnataka, India

FACULTY OF ENGINEERING

CERTIFICATE

This is to certify that the dissertation entitled

‘Multi-Agent Reinforcement Learning for RSSI Fingerprinting-Based indoor Wi-Fi Positioning with Cross-Building Localization’

is a bonafide work carried out by

Narayan S	**PES2UG22CS339**
Pranav Aditya B	**PES2UG22CS397**
Pranav H	**PES2UG22CS399**
Rohit Anand	**PES2UG22CS458**

In partial fulfillment for the completion of Fifth-semester Capstone Project Phase - 1 (UE22CS320A) in the Program of Study -Bachelor of Technology in Computer Science and Engineering under rules and regulations of PES University, Bengaluru during the period Aug 2024 – Dec. 2024. It is certified that all corrections/suggestions indicated for internal assessment have been incorporated in the report. The dissertation has been approved as it satisfies the 5th-semester academic requirements in respect of project work.

Signature Dr.Chandrashekar P Chavan Associate Professor	Signature Dr. Sandesh B J Chairperson	Signature Dr. B K Keshavan Dean of Faculty

External Viva

Name of the Examiners	**Signature with Date**
1. ____________________________	____________________________
2. ____________________________	____________________________

DECLARATION

We hereby declare that the Capstone Project Phase - 1 entitled **“Multi-Agent Reinforcement Learning for RSSI Fingerprinting-Based indoor Wi-Fi Positioning with Cross-Building Localization ”** has been carried out by us under the guidance of **Dr. Chandrashekar P Chavan** and submitted in partial fulfillment of the course requirements for the award of the degree of **Bachelor of Technology** in **Computer Science and Engineering** of **PES University, Bengaluru** during the academic semester Aug. – Dec 2024. The matter embodied in this report has not been submitted to any other university or institution for the award of any degree.

PES2UG22CS339	**Narayan S**	
PES2UG22CS397	**Pranav Aditya B**	
PES2UG22CS399	**Pranav H**	
PES2UG22CS458	**Rohit Anand**	

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Introduction

Indoor positioning systems, or IPS, are some of the major components of smart settings. While GPS completely changed outdoor navigation, localization in a room is yet to reach perfection. Traditional technologies have some difficulty in achieving precision and scalability when obstacles like walls, ceilings, and furniture occur with signals. This project develops an innovative indoor Wi-Fi positioning system with the combination of Multi-Agent Reinforcement Learning (MARL) and Received Signal Strength Indicator (RSSI) fingerprinting to solve these problems, besides achieving reliable localization without the need for intensive retraining in different buildings and settings.

1.1 Indoor localization systems

The application of Indoor Positioning Systems is required when the typical GPS systems fail to locate the objects or people accurately in enclosed areas due to the barriers in the form of walls and ceilings that interfere with satellite signals. IPS is applied for applications such as tracking of equipment in hospitals, navigation in malls, and emergency evacuation in cases of disaster.

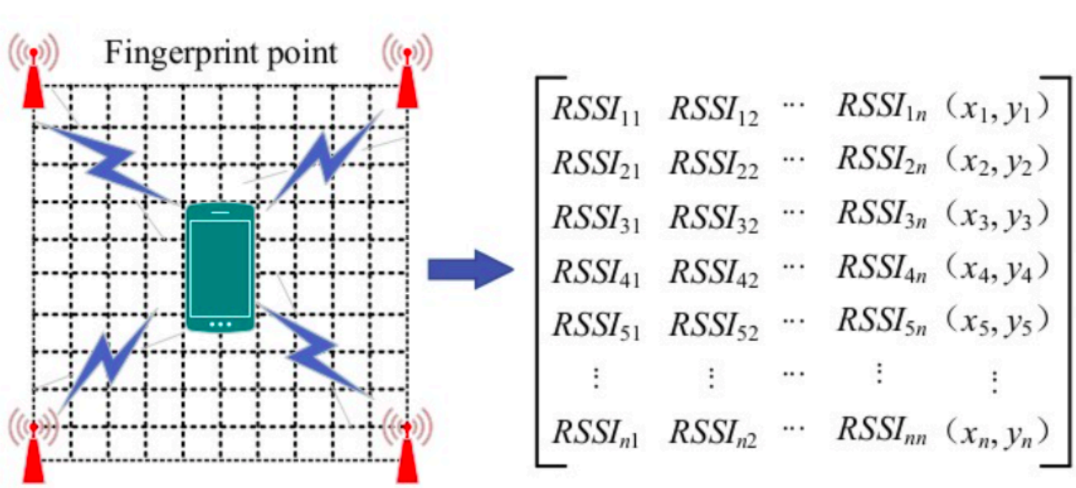

Fig 1 : **indoor positioning using RSSI**

IPS relies on several technologies such as Wi-Fi, Bluetooth beacons, and infrared. The most popular one among them is Wi-Fi due to its low cost and extensive availability. Still, interference from signals, multipath effects, and the intricacy of dynamic situations reduce the indoor locationing accuracy.

1.2 Received Signal Strength Indicator (RSSI)

RSSI is measured by the power level received from a Wi-Fi signal, which is commonly given in decibels (dBm). RSSI is used to calculate the distance between a device and an access point (AP) in Wi-Fi-based positioning systems. The closer the device is to the AP, the higher the RSSI score. Because signal strength decreases predictably with distance, RSSI is used for Wi-Fi-based indoor positioning because it allows for accurate measurement and analysis to determine location.

How RSSI Operates:

1. **Signal Measurement**: RSSI values are recorded at different environmental reference points .
2. **Fingerprinting**: A database of RSSI values and their associated locations is built during an offline phases

3.**Localization**: To identify the device's position during the online phase, real-time RSSI readings are linked with the fingerprint database .

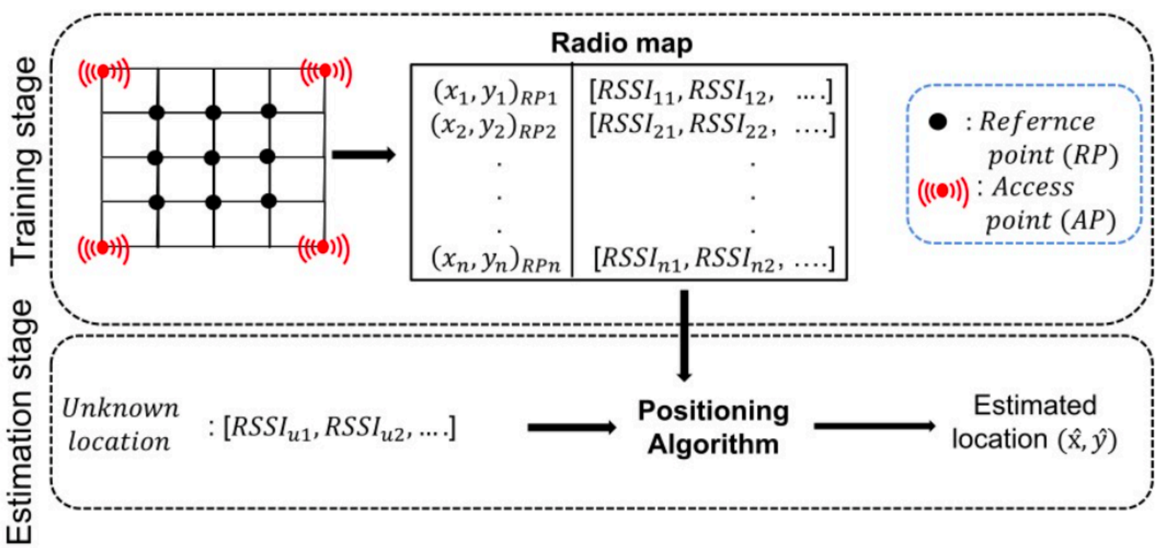

Fig: 2 **RSSI fingerprinting method**

The project's base is RSSI fingerprinting, which provides a rich dataset for the reinforcement learning agents to analyze and use.

1.3 Reinforcement Learning (RL)

Reinforcement Learning (RL) is a subfield of machine learning allows agents to make decisions by interacting with their surroundings. In order to allow agents to adjust to changing circumstances, the objective is to maximize cumulative incentives over time. Unlike supervised learning, RL learns using a reward-punishment system instead of labelled data.

1. Agent : The decision-making entity.

2. Environment : The environment or system the agent is interacting with.

3. State : An example of the state of the environment at the time.

4. Action : The agent's choice given the state.

5. Reward: This feedback lets the agent know how well its action works.

Why RL for Indoor Localization

RL is quite aptly suited to changing and uncertain environments. For this project, the agents learn through RSSI data to obtain optimal strategies that will make them determine exact locations. The agents can change according to the dynamic changes of the environment.

1.4 Multi-Agent Reinforcement Learning (MARL)

MARL progresses RL since it incorporates different agents who operate in tandem within the same environment. An agent can have multiple goals, policies, and action-making in MARL; however, their activities are related; they alter the overall and individual's outcome concerning learning together.

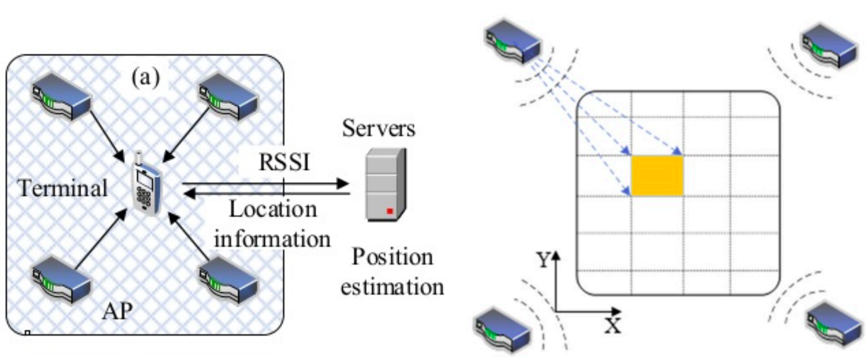

Fig: 3 **MARL for indoor localisation**

Role of MARL in the Project

1. Distributed Decision-Making: Agents calculate their location through the use of RSSI values and pass on the learning to other agents

2. Adaptive Learning : Agents learn from the environment around them and adapt to changing conditions without the central control

3. Efficient Utilization of Resources: MARL makes it possible for a large environment to function without difficulties with the distribution of tasks across the agents.

For it was through its collaborative feature, that MARL proved necessary within the project architecture because such would enhance the control power for complex indoor environments of this system.

1.5 Indoor Navigation

Indoor navigation is a subset of indoor localization. It provides routes between any two places in a building. For instance, it will navigate a visitor inside a hospital from the main entrance to a specific ward if it has an accurate route plan and real-time update.

Routing Algorithms for Indoor Navigation

1. Dijkstra's Algorithm:

- This algorithm determines the minimum distance between a source node in any graph and every other node as well.
- Most suitable to be applied to static environment conditions that don't change layout that often.

2. A* Search Algorithm :

- Dijkstra's algorithm combines with heuristics for optimal results in the search.
- Gives maximum efficiency in dynamically changing environment conditions with various paths and obstacles.

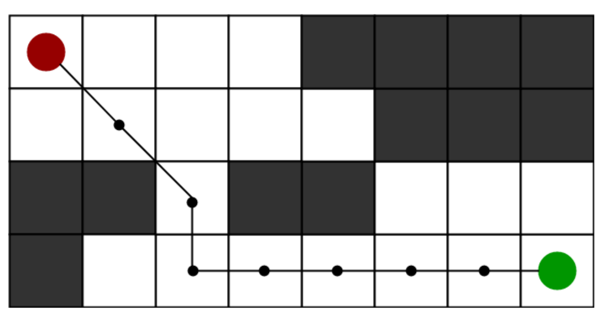

Fig: 4 **A* algorithm visualisation**

3.**Floyd-Warshall Algorithm** :

- Determines the shortest routes between every node pair in a graph .
- Helpful for calculating routes in advance in settings with set layouts .

4.**Dynamic Routing** :

- Bellman-Ford and other algorithms adjust in real time to new or temporary impediments .
- Vital in settings where layouts are regularly changed .

In this project, the integration of MARL ensures that routing algorithms are dynamically updated based on the current RSSI data, making navigation precise and responsive .

1.6 Cloud Computing and Its Relevance

Cloud computing is a model for delivering computing resources—such as servers, storage, databases, networking, software, analytics, and intelligence—over the internet ("the cloud"). It enables users to access and utilize these resources on demand, without the need to own or manage physical hardware or infrastructure. Cloud computing provides scalable , on-demand computational resources and storage , making it integral to modern large-scale systems

.

Role of Cloud Computing in the Project

1. **Data Storage and Processing**:

- Stores RSSI fingerprint databases and training data for MARL agents .
- Performs complex computations required for training and updating MARL models

2. **Real-Time Collaboration**:

- Cloud platforms allow agents in separate buildings to communicate with one another .
- Guarantees the synchronization of location data and updates in real time.

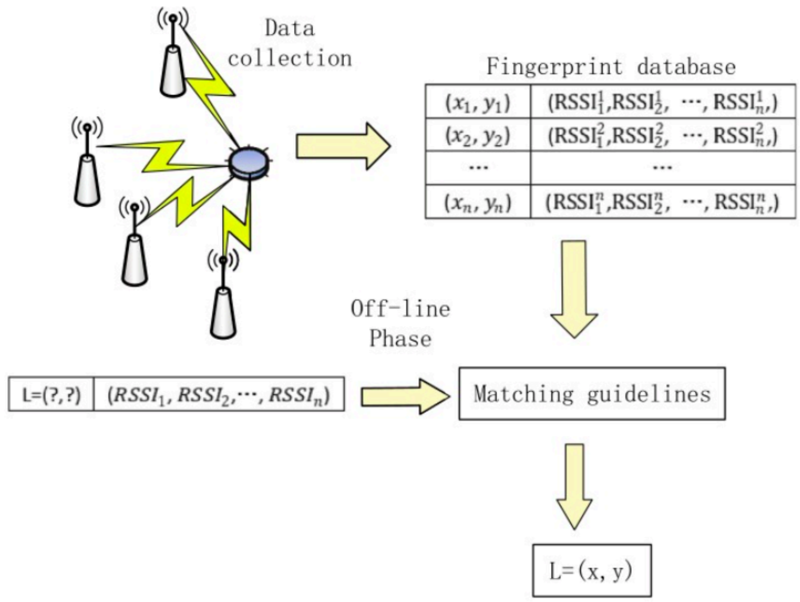

Fig: 5 **Interaction of MARL agents in cloud platform**

3.**Scalability**:

- Enables system extension across several campuses or buildings without requiring localized hardware .

4.**Cost Efficiency**:

- Makes use of cloud-based resources to lessen the requirement for pricey on-site processing infrastructure .

1.7 Simulating the System Using NS-3

NS-3 (Network Simulator 3) is an open-source, discrete-event network simulator widely used for research and educational purposes. It is designed to simulate complex computer network systems and analyze their behaviour under various conditions . NS-3 models a wide range of networking protocols, wireless and wired communication technologies, and network interactions , enabling users to test and validate network architectures , algorithms , and protocols before real-world deployment.

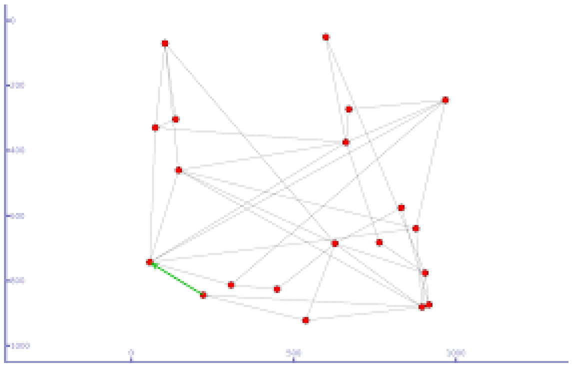

Fig: 6,7 **NS3 : a discrete event network simulator**

1. **Environment Setup**:

- Develop a virtual environment that replicates an indoor area , complete with barriers and Wi-Fi access points .
- Set up models for RSSI propagation to replicate realistic signal behaviours

2. **Agent Deployment** :

- Set up MARL agents in the simulator and give them tasks to locate and traverse the surroundings .
- To simulate agent movement, use the mobility models in NS-3 .

3. **RSSI Data Generation**:

- Model the RSSI readings between access points and devices .
- To replicate real-world circumstances , provide fluctuations in signal strength .

4. **MARL Integration**:

- Train MARL models using external libraries such as TensorFlow or PyTorch, then connect them to NS-3 for real-time testing .
- Assess the agent's performance in terms of navigation effectiveness and localization accuracy .

5. **Performance Metrics**:

- Assess network effectiveness, agent response times, and localization accuracy .

Problem Statement

Accurate indoor localization is necessary for many major buildings, including hospitals, malls, airports, and smart campuses. However, signal blockage and interference from obstacles like walls and ceilings make GPS useless indoors, even when it works well outdoors. A Wi-Fi-based positioning system (WFPS) is suggested as a solution to this problem. Using already-existing technology (Wi-Fi access points), this method creates signal strength fingerprints across multiple places. The system calculates the device's location by matching these fingerprints with real time device data. Despite its potential, traditional WFPS has drawbacks, such as limited adaptability, signal fluctuation, and an inability to adjust to cross-building or dynamic situations. These shortcomings limit the reliability of location accuracy.

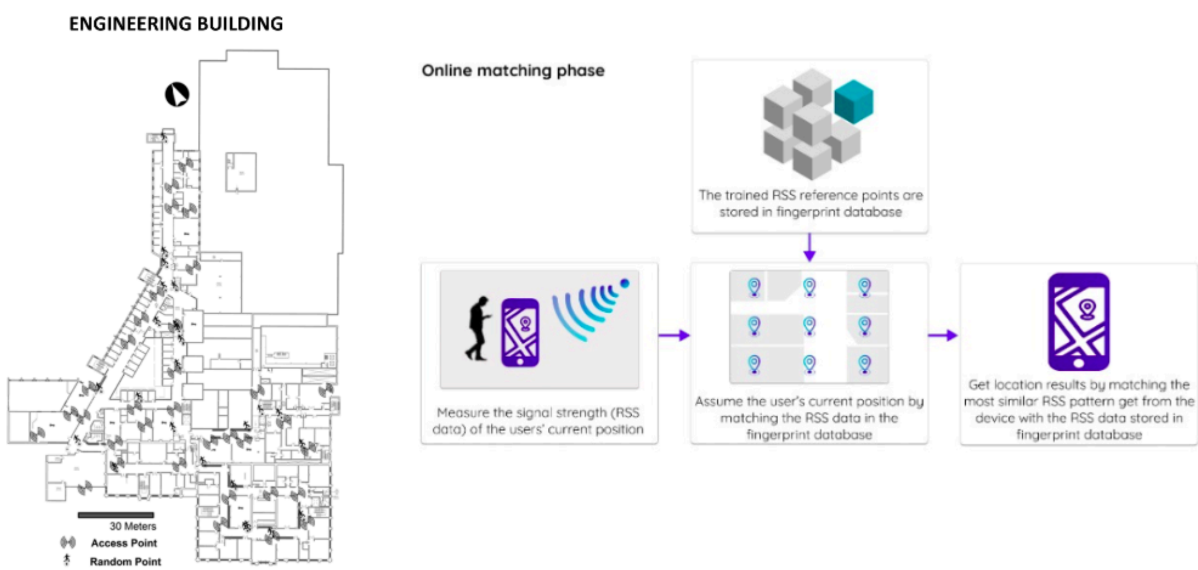

Fig: 8 **Indoor localisation using RSSI**

Abstract

The importance of indoor localization is growing in today's infrastructure as reliable,accurate and scalable solutions are needed in the majority of indoor environments like hospitals,malls, airports and University Campuses to determine the best routes in and around the environment. Current techniques such as Wifi based positioning systems struggle to work indoors because of obstacles such as walls and ceilings which gives rise to inconsistent results.Conventional WFPS that use RSSI fingerprinting are considered a promising option by using the already existing WiFi infrastructure.However these techniques face significant challenges like signal fluctuations,limited scalability and lack of flexibility in adjusting to a completely new environment.

This project develops an innovative approach to these problems already existing in the literature.The application of MARL or Multi Agent Reinforcement Learning achieves high precision by allowing numerous agents to interact in real-time. Every node gathers the RSSI values in a continuous manner and updates its position estimates. It thus reduces the dependency on centralised systems.

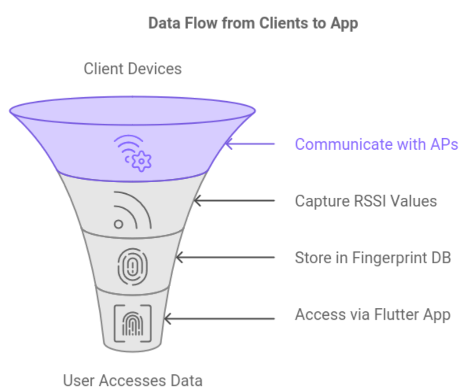

Fig 9 **Data flow**

The new system has robustness that allows it to operate at a higher level of ease in different indoor environments without needing further training.

The proposed system addresses the growing demand for indoor positioning across various applications and can also be applied to numerous innovative uses such as precise tracking of resources in hospitals and warehouses.

This project will set a new benchmark for Wifi-based indoor localization systems because it will overcome the current technology limitations and bridge pivotal gaps in scalability, accuracy, and adaptability, yet keeping in mind the affordability to open doors to future innovations in the field.

Scope

The scope of this project encompasses the design, development and the deployment of the enhanced indoor localised system that surpasses the constraints of a conventional Wifi based positioning system through MARL or in other words, Multi-Agent Reinforcement Learning. This system is bound to change the way complex, multi-storeyed indoor spaces are navigated by deploying:

- **Cross-Building Localization** : This does not like a traditional system requires training, no matter where they are first applied; transfer learning is done with this to enable it to be adapted over completely new buildings and environments, such that a building system doesn't necessarily need to be restarted with another. This makes the entire system much more pliable and efficient for any application within various settings.
- **Adaptation to Dynamic Environments** : The system is designed in such a manner that it can automatically adjust to changes in the environment. For example, if there is a change in the physical layout of a building or a room, then these changes can cause fluctuations that may lead to faulty RSSI values and hence incorrect positioning. This system can adapt to such changes on its own and remain reliable and efficient even as the environment changes over time.
- **Scalability**: System is especially tailored for large indoor spaces; it is designed to accommodate complicated and diversified environments such as hospitals,shopping malls and university campuses. It can manage complex and varied environments whether the navigation movement is to be tracked within one building or in a number of buildings; it provides a solid and dependable solution that can sustain indoor navigation in any complex environment.
- **Privacy and Security:** There is an underlying fact to this project, and the system has been developed so as to protect data with regards to privacy and security at all levels. Sensitive information is protected with the most sophisticated encryption techniques. It gives people confidence to work under such safe systems because it also secures their personal information.

Research Technology Gap

Indoor localization have advanced significantly, yet they still face significant gaps that limit their capability to perform to their maximum efficiency

- **Signal Variability** : Systems using RSSI values frequently encounter signal fluctuations caused by various factors like noise,reflections or obstacles.This change can reduce the reliability of the system especially in environments with significant signal disruptions.
- **Limited Scalability** : Current systems need a significant amount of training to work in new buildings after it's already been trained in a particular layout or building.This makes it difficult and time consuming to expand them across huge areas like hospitals and shopping malls.
- **Cross Building Localisation** : Most of the systems which are in use today face a lot of difficulty in moving from one building to another.A considerable amount of the existing indoor positioning systems are designed for very specific layouts and does not function to its full potential in different types of buildings which limits their usefulness in spaces where there are multiple buildings.
- **Latency and Real Time Performance** : Processing a large amount of real time data from multiple devices that too with minimal delay is a very challenging task and requires very high computational power
- **Adapting to Changing Environments** : The systems in use these days are unable to keep up with the dynamic environments in hospitals or warehouses, this can be anything ranging from moving of furniture to complete renovations.These changes make the systems outdated and have to be updated again which could also lead to intense manual fixes.

Shortcomings/Challenges

While the proposed system offers significant improvements on the existing positioning systems,it is also our duty to address the possible shortcomings to ensure the project's successful implementation and operation

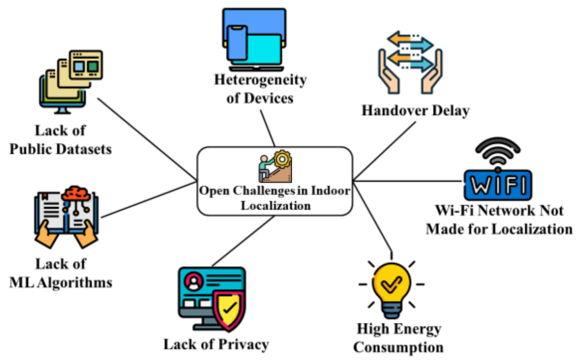

Fig: 10 **challenges of ML with fingerprinting-based indoor localization**

- **Dead Signal Zones** : Certain areas in the environment may lack adequate Wifi coverage, creating Dead Zones where accurate localisation is difficult.These zones are caused by thick walls or large metallic objects or just areas very far from the Wifi access points. While the system would try to use predictive algorithms to fill the gaps,achieving high accuracy is not guaranteed.
- **Training Time and Data Requirements** : The system depends on rigorous training to achieve high precision, especially in new or unfamiliar environments it may take a notable amount of time and computational resources which in turn will delay the deployment of the system.
- **Environmental Interference** : The changes in temperature,humidity and physical obstacles can affect Wifi signals leading to localisation errors, and overcoming these factors may need essential filtering techniques and resource heavy algorithms.
- **Signal Degradation in Dense Environments** : Environments with high Wifi congestion, such as airports or shopping malls experience prominent signal interference, even though the proposed model uses multi agent collaboration to mitigate some of these issues, maintaining high levels of accuracy remains a very challenging task.

Addressing these challenges through the proposed MARL or Multi Agent Reinforcement Learning Framework and advanced ML techniques, this project aims to establish a reliable, scalable and accurate indoor positioning system

Objectives

- **Improve indoor localization accuracy :** Design a system that is able to overcome the effects of signal variability caused by environmental noise, multipath effects, and interference.
- **Make cross-building localization smooth** : Design an adaptive approach which will allow smooth localization over several buildings without retraining**.**
- **Adapt to dynamic environments :** Provide a framework that adapts to structural and environmental changes without causing performance degradation or necessitating retraining.
- **Massivability for large areas:** Demonstrate the system capability to function in large inside spaces such as campuses, malls and hospitals.

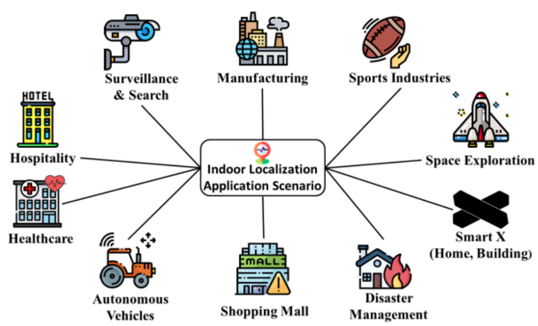

Fig 11 : **ML based indoor application Scenarios**

- **Use Multi-Agent Reinforcement Learning:** MARL would empower a variety of agents which run in real-time to accomplish location estimation
- **Low Costs :** Use existing Wi-Fi Infrastructures so that as much specialist hardware and Installation and setup cost could be recovered or should be zero.
- **Ensure privacy and data security :** Collect and manage Wi-Fi signal data in secure ways while paying close attention to privacy-related laws.
- **Make Useful Applications Available:** Provide functions related to indoor navigation, emergency response supports, and resource tracking among other.

Literature survey

[1].X. Cui et al., "**Indoor Wi-Fi Positioning Algorithm Based on Location Fingerprint**," Mobile Networks and Applications, vol. 26, no. 1. Springer Science and Business Media LLC, pp. 146–155, Jan. 06, 2021. doi: 10.1007/s11036-020-01686-1

Introduction

Indoor positioning is the one that is widely important to be applied to numerous application such as in the hospital, shopping malls, rescue missions etc.The current GNSS work worstly due to interference occurred indoors at its signal.This paper proposes a Low Cost Universal Solution for Wi-Fi based Positioning

the two innovations are:

- Signal Preprocessing Stage in conjunction with other selective use of Normal Distribution function for data distribution, Kernel Density function for representing continuous probability distributions, Kalman filtration for smoothing of signals
- Positioning Correction Stage
- Weighted K-Nearest Neighbor (KNN) algorithm
- Kalman filter and Levenberg-Marquardt method

Implementation

1.Signal Preprocessing

- RSSI samples interpretation
- Test of distribution by skewness-kurtosis normality test
- If samples are normally distributed
- Apply the function of normal distribution to get the probability density
- If the samples are not normally distributed

2. Kernel Density Function

- Kernel density function applied
- Kalman filter application to the smoothing of signal data

3. Positioning Process

- Weighted KNN applied as an initial estimate for the coordinate
- Coordinate corrected by following
- Kalman filter

- Levenberg-Marquardt optimization method

Features

- Pre-processing signals with high-order methodology
- Hybrid positioning methodology
- Large-scale indoor positioning technique that is suitable

Performance

- Measurement
    - Good improvement has been seen in the positionings by achieving 60% with an accurate comparison to Kalman filter.
    - Fewer numbers of iteration
    - Strong and stable positions.
- Comparison Analysis
    - The proposed work has been compared with other approaches, which are:
    - Conventional mean model
    - Median model
    - Gaussian model
    - Particle Filter methodology
    - Extended Kalman Filter (EKF)

Conclusion

The research develops a high-end approach towards indoor positioning that resolves important issues related to signal variation and accuracy. By integrating the best statistical techniques and filtering approaches, the algorithm significantly enhances positioning accuracy in complex indoor environments.

[2].X. Li, Z. Deng, F. Yang, X. Zheng, L. Zhang and Z. Zhou, "**WiFi Indoor Location Method Based on RSSI**," 2021 11th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (IDAACS), Cracow, Poland, 2021, pp. 1036-1040, doi: 10.1109/IDAACS53288.2021.9660916

Introduction

The paper "**WiFi Indoor Location Method Based on RSSI**" reports the latest advancement in the IPS that apply WiFi. Due to the high growth rate, precise location services are required for indoor environments. Most traditional methods face challenges in being accurate because of irregular placement of access points and complication in the environment. It thus aims to enhance the localization accuracy by incorporating an advanced access point selection method and an enhanced fingerprint matching algorithm.

Characteristics and Implementation

- The proposed methodology has been categorized into the two stages: offline and online.
- Offline Stage
    - The authors present an exhaustive strategy for AP selection based upon the loss rate of the AP along with signal stability. A measure of the loss rate depicts the reliability of a signal from each of these access points, and therefore the signal stability evaluates consistency in RSSI values along sampling points.
    - This procedure first removes APs with high values of LR and then checks stability in RSSI values from the remaining APs. This gives a fine set of APs, which are more reliable for localizing.
- Online Stage
    - During this phase, it collects real-time RSSI data and matches the database using a modified KNN algorithm, especially applying Manhattan distance for better accuracy. Shifting from Euclidean to Manhattan distance is very significant as it improves the performance in complex indoor environments.

Features

- It does comprehensive selection of AP through the merger of LR and signal stability metrics, so the noise factor due to the unreliable signal is reduced significantly, whereas only the most stable is selected for location.
- Localization Algorithm: This method improved by using WKNN: Weighted K Nearest Neighbor, that instead of absolute distances, allows for their weighted consideration, based upon the signal strength.
- High Precision: The experimental results show that the proposed method has an average localization accuracy of about 1.18 meters in 60% of cases. This is significantly better than the traditional methods.

Evaluation

- The experiments have been conducted on a controlled indoor environment in Beijing University of Posts and Telecommunications. The result is that it shows a significant improvement in localization accuracy as compared with the previous methods, MaxMean and traditional WKNN algorithms.
- The efficiency of the offline processing stage in reducing the amount of computational load in the real-time localization, making the system more responsive.
- A strong relationship between selection criteria of APs with overall positioning accuracy, making a point that robust characteristics of signals are very significant in IPS.

Conclusion

In summary, the present research significantly contributes to the field of indoor positioning in addressing common challenges associated with WiFi-based systems and offering a systematic approach to enhance accuracy and efficiency through strategic AP selection and advanced matching algorithms.

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[3].H. K. Yu, S. H. Oh and J. G. Kim, "**AI based Location Tracking in WiFi Indoor Positioning Application**," 2020 International Conference on Artificial Intelligence in Information and Communication (ICAIIC), Fukuoka, Japan, 2020, pp. 199-202, doi: 10.1109/ICAIIC48513.2020.9065227.

Introduction

The paper "**AI-Based Location Tracking in WiFi Indoor Positioning Application**" by Ho Kyung Yu et al. addressed issues in indoor navigation, such as the fact that the Global Positioning System is not efficient where walls and other objects cut off the signal, by proposing a new method based on Artificial Intelligence (AI), Internet of Things (IoT), and big data that can enhance the accuracy of location through communication using WiFi. The methodology mainly focuses on a fingerprinting approach accompanied by a weighted fuzzy matching algorithm and Particle Swarm Optimization for improved user location tracking.

Characteristics and Implementation

- This system can be divided into two major phases: Offline Phase and Online Phase
- Offline Phase:
    - This stage creates the fingerprinting database by measuring the RSSI values at a number of sample points (SPs). The authors emphasize that an exhaustive database is indispensable for accurate positioning; however, it is rather time-consuming and laborious to build.
    - The fingerprinting technique allows for the collection of RSSI data from a number of Access Points (APs) deployed in the indoor environment. It is used to create a detailed map of signal strengths associated with specific locations.
- Online Phase:
    - At this stage, it fetches current RSSI values of users and estimates its location based on a weighted fuzzy matching algorithm that computes how similar its RSSI readings are to those found in the fingerprint database.
    - The PSO algorithm is used to further enhance the accuracy. This algorithm employs intelligent particles that explore possible locations based on historical data and shared information among particles. This dual approach is to minimize positional errors substantially.

Features

- Fingerprinting Technique: It establishes a robust database of RSSI values, which can be used as a reference for real-time location tracking.
- Weighted Fuzzy Matching Algorithm: Enhances accuracy because it considers several adjacent SPs to calculate the location based on the user's RSSI readings.

- Particle Swarm Optimization: It further refines the location estimates with the help of collective intelligence among particles iteratively enhancing position accuracy.

Evaluation

- The performance of this method was tested using simulations over an 8m x 8m indoor area with four APs. The authors conducted extensive testing and ran 10,000 simulations to test performance:
- The results were a reduction in average position error from about 2 meters without PSO to about 1.2 meters with PSO applied. This improvement shows the effectiveness of combining multiple algorithms for better localization.
- The study explains that even though fingerprinting offers a coarse mapping of signal strength, integration of PSO can significantly enhance the precision in environments where there are fewer sample points.

Conclusion

The outcome would be a valuable input to the development of interior position localization systems using AI algorithms. Since it can offer to solve many common difficulties found with the traditional methodologies such as signal interference as well as environmental changes; hence, the proposed system appears very promising in achieving location systems inside buildings based on Wi-Fi technology.

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[4]. J. L. Carrera Villacrés, Z. Zhao, T. Braun and Z. Li, "**A Particle Filter-Based Reinforcement Learning Approach for Reliable Wireless Indoor Positioning**," in IEEE Journal on Selected Areas in Communications, vol. 37, no. 11, pp. 2457-2473, Nov. 2019, doi: 10.1109/JSAC.2019.2933886

Introduction

This paper introduces a hybrid Particle Filter and Reinforcement Learning (PFRL) method for wireless indoor positioning. It addresses issues such as localization errors caused by signal fluctuations, multipath effects, and the "kidnapped robot problem." The framework integrates particle filtering with reinforcement learning to enhance robustness and accuracy, targeting sub-room level localization precision.

Characteristics and Implementation

- Particle Filter: It uses the indoor zone predictions, IMUs, wireless ranging, and floor plans to perform location tracking.
- Ensemble Learning: HMMs are applied to enhance the indoor zone predictions by fusing different machine learning algorithms.
- Reinforcement Learning: It gives a resampling mechanism in order to ensure that particles concentrate on areas with high probability of ground-truth locations, which helps to mitigate catastrophic localization failures.
- Two-Tier Architecture: Lightweight operations on mobile devices, complex computation offloaded to edge servers for real-time processing.

Features

- Reinforcement-based particle resampling for robustness to localization failures.
- Scalability: distributed computation between client and edge layers.
- Dynamic adaptation for environmental changes and transitions across zones.

Evaluation

- System was tested in complex environments using five different motion paths. The experimental results were as follows:
  - Accuracy: Reduced the average localization error up to 0.97 meters.
  - Reliability: Failure recovery latency 1.5 seconds
  - Convergence: Outperforms traditional solutions with faster and better stability of results

Conclusion

PFRL is capable of surpassing the weak points associated with the older indoor location systems. It provides high-accuracy indoor localization, being reliable, and adaptable; it would be a wonderful solution to real-time mass indoor localizations.

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[5].F. Dou, J. Lu, T. Zhu and J. Bi, "**On-Device Indoor Positioning: A Federated Reinforcement Learning Approach With Heterogeneous Devices**," in IEEE Internet of Things Journal, vol. 11, no. 3, pp. 3909-3926, 1 Feb.1, 2024, doi: 10.1109/JIOT.2023.3299262

Introduction

The paper provides an FRL framework for indoor positioning; this paper focuses on ensuring the privacy of the data while learning a global localization model through federated and few-shot learning, otherwise known as FSL.

Characteristics and Implementation

- Federated Learning : Local RL models can be learned on the device without even any need to share user data, saving privacy.
- Personalized FL: It holds both global and local models updated, which decreases their gap, considering the client's different data distributions.
- Few-Shot Learning (FSL): It focuses on data augmentation and also uses pre-trained models for adaptability to new users and a few data samples available.
- Decentralized Workflow: Clients train the models of RL locally and update in batches with the central server.

Features

- Federated learning principles are used in privacy-preserving training.
- It can effectively manage heterogeneity in devices and data by personalized updates
- Fast convergence for novel users with FSL and, therefore, saves time on localization initialization

Evaluation

- The proposed algorithm is experimentally tested on the dataset UJIIndoor Loc
- Precision: It has yielded high localization precision compared to standard FL methods
- Stability: It has taken device heterogeneity without any oscillation during training
- Efficiency: It has managed quick adaptation for new users having sparse data

Conclusion

The suggested FRL framework bridges the gap between privacy and performance in indoor localization by providing a scalable, accurate, and privacy-aware approach that can be adapted to diverse devices and environments.

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[6]. Wang, J.; Park, J. "**An Enhanced Indoor Positioning Algorithm Based on Fingerprint Using Fine-Grained CSI and RSSI Measurements of IEEE 802.11n WLAN**". Sensors 2021, 21, 2769. https://doi.org/10.3390/s21082769

Introduction

This paper addresses the issues of indoor positioning that cause instability due to multipath effects and environmental noise. The authors propose a hybrid fingerprinting that uses RSSI along with CSI.

Characteristics and Implementation

- Data Collection: This paper uses OFDM-MIMO devices for fine-grained CSI and RSSI signal collection.

- Data Processing: It applies Gaussian and Kalman filters to the denoising of RSSI and CSI amplitude values. Linear transformation is applied to the CSI phase values for robustness.
- Algorithm: WKNN algorithm is used for the matching fingerprints in the online phase for the reduction of computational complexity and errors.

Features

- Cross-layer fingerprinting with the combination of MAC and PHY layer data.
- Utilization of RSSI for coarse-grained localization and CSI for fine-grained localization.
- It reduces computation complexity by reducing the dimensional features of CSI.

Performance Evaluation

Experiments. The results presented here confirm that the proposed hybrid system is more precise than previous approaches, which include methods like CSI-MIMO and FIFS, for a better noise-resistance with stability in an AP, especially in an environment with high-load.

Conclusion

The indoor localization system that is being proposed here by using RSSI-CSI algorithm turns out to be highly accurate and dependable.

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[7].R. Jurdi et al., "**WhereArtThou: A WiFi-RTT-Based Indoor Positioning System,**" in IEEE Access, vol. 12, pp. 41084-41101, 2024, doi: 10.1109/ACCESS.2024.3377237

Introduction

The paper discusses the implementation of a WiFi RTT-based positioning system, relying on the Fine Timing Measurement method. The proposed algorithm boosts precision while employing existing Wi-Fi infrastructure; therefore, the presented algorithm has commercial feasibility.

Characteristics and Implementation

- Algorithm: Two components:

    - A distance-dependent measurement model in order to reduce the statistics of the noise of observation.
    - A step-and-heading-based filter integrating the data from the inertial sensors.
- Data Gathering: Both the RTT and the data obtained by IMU are used in the updates for trajectory estimates.
- Infrastructure: Works on off-the-shelf FTM-capable smartphones and Wi-Fi access points.

Features

- Accurate positioning with a 90th percentile error less than 1.6 meters.
- Sensor fusion for accuracy improvement.
- Reports results using a variety of metrics, such as Euclidean distance and maritime-inspired errors.

Evaluation

Experiments are conducted on 18 hours of walking data collected from different devices and locations. The experiments have shown the consistency of the system. Human-body blockage effects are analyzed, and techniques to counter them are presented.

Conclusion

This is a cost-effective, scalable system for accurate indoor localization, integrating RTT-based positioning with sensor fusion for real-world applications.

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[8].S. A. Magsi, N. Saad, M. H. B. M. Khir, G. Witjaksono, M. A. Siddiqui and L. Sameer, "**Wi-Fi Based Indoor Navigation System For Campus Directions**," 2020 8th International Conference on Intelligent and Advanced Systems (ICIAS), Kuching, Malaysia, 2021, pp. 1-5, doi:10.1109/ICIAS49414.2021.9642629

Introduction

This paper discusses the development of an indoor navigation system using Wi-Fi infrastructure for a university campus. The system uses proximity and RSSI-based techniques to help users navigate complex indoor layouts.

Characteristics and Implementation

- Simulator: Network Simulator 2 (NS2) is used in designing and testing the system.
- Methodology: Combines RSSI-based distance measurement with trilateration for determining user location. Access point mapping is integrated with campus layout for real-time navigation.
- Hybrid Method: Proximity to ascertain proximity and RSSI to determine location.

Features

- Low cost exploitation of deployed Wi-Fi infrastructure.
- Map creation and dynamic hand-over between the access points
- High accuracy through trilateration

Evaluation

Theoretical simulations clearly indicate that it can accurately navigate a person throughout the campus. It provides solutions for weak signal problems at critical spots by providing additional access points

Conclusion

It is very suitable for campuses and other spaces because it will be scalable, and such complex indoor regions can be covered with more flexibility.

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[9].C. -H. Ko and S. -H. Wu, "**A Framework for Proactive Indoor Positioning in Densely Deployed WiFi Networks**," in IEEE Transactions on Mobile Computing, vol. 21, no. 1, pp. 1-15, 1 Jan. 2022, doi: 10.1109/TMC.2020.3001127

Introduction

Indoor positioning is fundamental in location-based services, primarily within environments where GPS cannot effectively penetrate. This framework uses sparsely deployed Wi-Fi for proactive indoor positioning. In this approach, Wi-Fi access points are used for high resolution location. This eliminates the effect of signal interference and multipath effects.

Characteristics and Implementation

- Proactive Data Gathering: Models consider environment factors and signal behavior.
- Systematic Positioning: Uses environmental modeling along with RSSI data to perform real time localization.
- It uses machine learning algorithms for predicting the actual location of the user relying on dense deployments of Wi-Fi access points that enhance granularity along with precision. The framework makes use of contextual data such as spatial layouts in order to attain better performance in complex environments.

Features

- Granular Positioning: Obtains a sub-meter error in optimal conditions.
- Dynamic Flexibility: In real time, adjusts to environmental change, like the creation of new access points.
- Scaling: Accommodates wide spread deployments in multi-floor building
- Energy Efficiency: It is optimized to have the minimal computational and power requirement thus friendly for IoT devices

Analysis

- The system was benchmarked against a dense deployed Wi-Fi environment. Key measurements taken were:
  - Precision: Errors for position had fallen under 0.5 meters.
  - Robustness: Maintained high levels of precision even when exposed to the interference from signal sources.
  - Time Efficiency: Latency reduction in real-time localization scenarios

Conclusion

The framework demonstrates the ability of Wi-Fi-based systems in providing high-accuracy indoor positioning. It addresses shortcomings by proactively incorporating environmental data and using advanced algorithms for conventional approaches. It would include integrating machine learning into its model for predictive enhancement.

[10].Batoul Sulaiman, Saed Tarapiah, Emad Natsheh, Shadi Atalla, Wathiq Mansoor, Yassine Himeur, "**Radio map generation approaches for an RSSI-based indoor positioning system**",Systems and Soft Computing,Volume 5,2023,200054,ISSN 2772-9419,https://doi.org/10.1016/j.sasc.2023.200054

Introduction

The paper handles the generation of the radio map for indoor positioning using the RSSI. Radio maps are needed for fingerprinting methods, wherein precollected signal strength data have to be taken for a user localization process. It discusses the techniques that facilitate the speed and efficiency of making radio map generation with minimal compromises on precision.

Characteristics and Implementation

- Three major techniques for the radio map generation have been analyzed :
  - Experimental Data Collection : Collecting RSSI data in a highly experimental manner through the mobile application
  - Biharmonic Spline Interpolation(BSI) : It makes use of sparsity in the dense radio map construction
  - Simulation : Using Wireless InSite for simulating the RSSI propagation model with regard to environmental details like building material etc.
- Implementation : Hybrids: This implementation provides the right balance between the effort put into designing the systems and the potential accuracy that the system might suffer from, optimizes the entire process during training

Features

- Hybrid Approach: All real, interpolated, and simulated data are utilized to make full radio maps.
- Data Collection is Improved: Manual data collection is reduced by 50%. It takes so much time.
- Improved Precision: Reaches localization errors of as little as 0.45 meters due to the sophisticated interpolation algorithms
- Versatility: It can be used with any environment, from tiny rooms to large campuses

Evaluation

- Both simulated and experimental datasets were used in testing the approaches. The results were as follows:
- Reduces Effort: Produces half the length of the maps as it used to without compromising the accuracy.
- Accuracy: Improved highly compared to the traditional methods of fingerprinting, especially the BSI interpolation.
- Plasticity: Suitable for any indoor environment; this also applies to multi-level spaces of complex buildings.

Conclusion

The proposed methods show that the generation of accurate and efficient radio maps for RSSI-based indoor positioning is feasible. This work reduces the time and effort required for training and improves system reliability by incorporating simulation and interpolation. Real-time map updates in dynamic environments could be further explored.

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[11].Wei, Z., Chen, J., Tang, H., & Zhang, H. (2023). "**RSSI-based location fingerprint method for RFID indoor positioning: a review**". *Nondestructive Testing and Evaluation*, *39*(1),3–31. https://doi.org/10.1080/10589759.2023.2253493

Introduction

IPS is a critical component of such applications as emergency response, healthcare, logistics, and complex-environment navigation. Although GPS is quite effective in open-space environments, indoor environments have different challenges, such as signal attenuation and multipath propagation. Among the various IPS technologies, RSSI-based systems are widely deployed because of their simplicity and compatibility with existing infrastructures like RFID and Wi-Fi. These are fingerprinting techniques that create a database of signal strengths and match it against real-time data for location determination

Characteristics and Implementation

They rely on the principle that strength is inversely proportional to the distance. Generally they consist of

- Data Collection (Training Phase): The signal is sampled at known locations to generate a radio map.

- Localization (Testing Phase): In this phase, the radio map is matched against the real-time signals for estimation of the position.
- Features such as adaptability to the environment, low cost of deployment, and high compatibility with the IoT devices make RSSI-based systems favorable. Multipath effects, noise, and environmental interference pose various challenges. Innovative preprocessing methods involving Gaussian filtering and Kalman filtering have to be evolved to increase accuracy

Features

Characteristics of RSSI-based systems are as follows:

- Accuracy: Dependent on the radio map reference points' density, Advanced filtering and clustering make the localization highly precise
- Scalability: Readily scalable to extensive interior domains through the already laid infrastructure of RFID or Wi-Fi.
- Cost-Effective: Setup without additional hardware on substantial ground.
- Flexibility: It may work integrally with more sophisticated algorithms like neural networks, and which also gives adaptation learning.

Evaluation Parameters

Evaluable parameters for an RSSI-based IPS are :

- Localization Accuracy: Measured in error distances; recent advancement achieves an accuracy of about 1 meter in laboratory conditions.
- Robustness: Experimented in other environments, materials or interference levels
- Efficiency: Simulation tools like Wireless InSite cut the time needed to gather data and interpolation methods prolong the datasets that enhance the results

Conclusion

RSSI-based indoor positioning systems continue to evolve in terms of signal processing and algorithm optimization that allows them to be very adaptive to even more complex environments due to fingerprinting interpolation and clustering. In the future, however, machine learning and edge computing may become directions to be able to cope with some of the remaining challenges to maintain real-time adaptability and dynamic interference.

[12].B. Yuen et al., "**Wi-Fi and Bluetooth Contact Tracing Without User Intervention**," in IEEE Access, vol. 10, pp. 91027-91044, 2022, doi: 10.1109/ACCESS.2022.3201645

Introduction

Contact tracing is the most important tool for the control of infectious diseases as it helps authorities to identify and isolate potential cases. The conventional process is based mostly on manual data, which is slow and riddled with possible errors due to human mistakes or forgetfulness. Automation, in this case, with Wi-Fi and Bluetooth technologies, offers new solutions. This review reviews the nature, implementation, features, assessment, and overall impact of a new contact tracing system not requiring user intervention.

Features and Deployment

- The suggested system breaks the dependency chain on human usage through the custom-designed ESP32C3 routers that observe signals from the devices (cell phones, tablets). The features deployed include three types of technology:
    - **Data Gathering**: Indoor localization through Wi-Fi and Bluetooth signals at an accuracy of 1.0m.
    - **Neural Nets**: Forecasting user movement using the BiLSTM model, with the dataset gathered by a robot.
    - **Privacy**: Storage of encrypted data and anonymous MAC address tracking.
- The ESP32C3 routers collect data without any interaction with devices to the contrary of the systems currently in place: user apps or manual logins.

Features

1. **Device independence**: Tracks passively without needing an app install or connection to an internet network
2. **Precision**: Matching the accuracy of far pricier camera or genome sequencing techniques at a fraction of the price
3. **Combination:** Merging multiple router sources to perform more robust trajectory mapping.
4. **Privacy Focus:** MAC addresses and model-specific identifiers are used for data collection, so there is no violation of data privacy legislation.

Evaluation

Results were quite encouraging with the testing done in university floors and open spaces:

- **Accuracy**: System localization was less than 1.0m at point of time with the usage of both Wi-Fi and BLE data.
- **Robustness**: The system performance improved by inclusion of Wi-Fi FTM (Fine Time Measurement), as ambiguity could be considered less with regard to feature mapping.
- **Scalability**: Results showed successful operation in a range of indoor environments, with minimal infrastructure needs.

Conclusion

This scalable, accurate, and user-independent solution can handle major limitations of traditional and semi-automated contact tracing systems. The combination of machine learning, autonomous site surveying, and enhanced privacy safeguards makes it a very valuable tool for public health agencies More work would be more in the area of calibration of algorithms for outdoor use and further reduction of localization errors in complex indoor settings.

Overview of Datasets

This section outlines the data used in this project toward the implementation and testing of this proposed MARL system to indoor localization. Data used encompasses positioning data via WiFi for the purposes of this project that were based on RSSI measurements, which are imperative to indoor localization.

Description

Indoor localization systems are one of the most integral parts of modern infrastructure in environments where traditional GPS-based solutions are not reliable or inapplicable. This project dataset is developed specifically to implement WiFi-based positioning for overcoming the shortcomings of current indoor localization systems using MARL. It includes data from diversified real-world environments like multi-floor university campuses, a complex hospital layout, busting shopping malls, and large warehouses that provide challenges like signal attenuation caused due to walls, interference coming from other devices, and dynamic variation due to human movement.

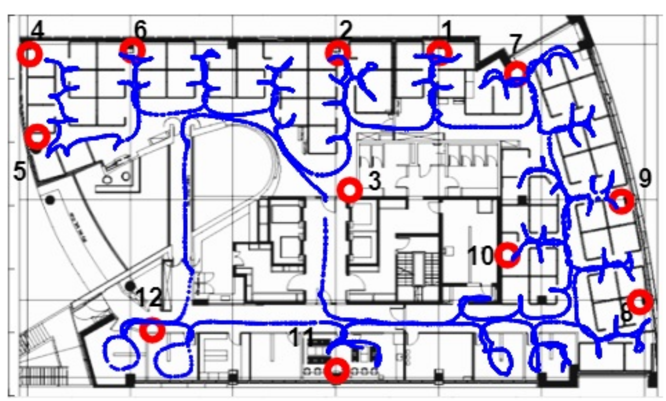

Fig: 12 **Representation of RSSI fingerprinting a building**

In this study, the particular focus is on RSSI, which is one of the most commonly used techniques for distance measurement between devices and WiFi access points. Nevertheless, instead of basing the method on central systems for data gathering, this scheme improves on that by decentralizing the collection using multiple agents. These agents, equipped with WiFi sensors, are autonomous and continually collect environmental data. Every agent scans available WiFi APs, measures the signal strength, and makes a record of metadata in terms of timestamps and positions. This ensures that scalability is met, while flexibility when it comes to new environments is enhanced with minimal costly retraining.

The emphasis of the dataset is in the values of RSSI (Received Signal Strength Indicator) and Signal Quality Index (SQI) employed to calculate distances between the devices and WiFi access points (APs). High RSSI values mean close proximity to routers and correspond to high received (RX) powers. Low RSSI values indicate that mobile devices are farther away, so RX power is smaller. For example, SQI as a function of RSSI and noise power gives much more detail on the status of the signal quality; naturally, high values of SQI relate to high RSSI and low noise power. Although increases in noise levels may be accompanied by undesirable RSSI values, SQI can only decrease. Some also report noise power on certain channels and packets within the wireless interfaces to further enrich the dataset with these contextual insights. These features constitute essential fingerprints for localization, providing a solid basis for the MARL-based system to determine the positions accurately.

In addition, this dataset captures a wide variety of signal scenarios such as fluctuations due to interference from neighboring devices, attenuation caused by structural obstacles such as walls and ceilings, and variations in signal strength due to people moving or objects. As such, these variations provided this dataset with a realistic and challenging foundation for training and evaluation of MARL.

Another significant aspect of this data set is that it saves money and is cost-effective in the sense that it doesn't require any additional hardware such as LIDAR, beacons, or ultra-wideband (UWB) devices. This eliminates expensive infrastructural overheads, thus making it both accessible and deployable in resource-constrained environments like public hospitals and educational institutions.

In detail, privacy measures were taken when collecting data. Sensitive information like identifiable WiFi SSIDs or MAC addresses was anonymized. Moreover, all the collected data was encrypted both in transit and rest, making sure that the system is safe for deployment in certain fields where data privacy is critical, such as airports and hospitals.

Moreover, the dataset is expandable; it offers space for adding more sources if required. For instance, environmental sensors such as temperature and humidity or maps of floors can be introduced for improving the localization model flexibility and accuracy. Closing Remarks The emphasis was made on scalability, adaptability, and security in an attempt to ensure that such a dataset offers robust indoor localization systems which overcome the problems related to modern infrastructure.

Data Attributes and Features

The dataset for this indoor localization project is carefully designed to capture essential WiFi signal characteristics and environmental data critical for accurate and scalable positioning. Some of the major attributes and features included in the dataset are given below:

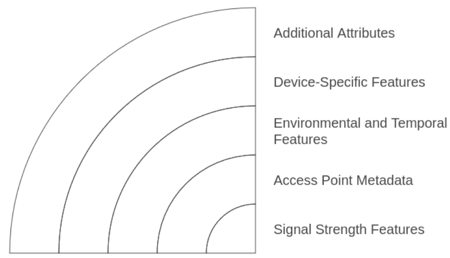

Fig: 13 **Schematic Representation of Dataset**

1. **Signal Strength Attributes**

These are the attributes that form the bulk of the data and determine localization precision:

RSSI (Received Signal Strength Indicator):

Is the strength of signal received by a WiFi AP.

In terms of dBm, higher values indicate stronger signals; closer to 0 means it's stronger.

An indicator of distance; more so between a mobile device and a router.

Signal Quality Index: It is obtained as an expression of RSSI and noise power.

Provides normalized measure of quality of signal, accounting for interference in the environment.

High SQI values reflect good signal conditions, but noise or weak signals low values.

Noise Power:

It detects noise interference present in an environment or on particular channels/packets.

Its high value reduces SQI. An increase in noised power worsens system localization.

Fig: 14 **Signal Strength Attributes**

2. **Access Point Metadata**

Every WiFi signal has associated metadata regarding the access point that's providing the signal:

Access Point MAC Address:

This is a unique identifier for the access point.

Anonymous in data collection to protect against being recognized.

Used to differentiate signals coming from various routers

SSID. (Service Set Identifier):

It's a name for the WiFi network.

It helps further contextualize when there are networks within the environment.

Channel Frequency:

Specifies the frequency band (e.g., 2.4 GHz or 5 GHz) in use by the AP.

It helps to distinguish overlapping networks and to analyze frequency-dependent attenuation.

3. **Environmental and Temporal Characteristics**

These characteristics explain why the indoor environments are time-dependent.

Timestamp:

This characteristic records the exact timing at which a signal was captured. It allows for the analysis of time-dependent phenomena, including signal changes due to human locomotion or interference from devices.

Ground Truth (Spatial Coordinates):

The actual device location while a signal was captured. It forms the basis for supervised learning and performance metrics.

Floors and Rooms:

Indicates the specific location, such as floor number, room name/ID, of a multi-floor building.

Adds spatial context, important to environments with vertical overlap.

4. **Device-Specific Features**

These features describe the mobile device or the agent that collects the data:

Device ID:

Unique identifier for the device gathering the data.

Enables tracking and analyzing variations in signal reception due to device-specific variations.

Orientation and Movement:

Describe the direction and motion of the device at the time of data collection (stationary, moving, rotating, etc.)

Important to understand Doppler effects and signal changes specific to orientation.

Conclusion of Capstone Project Phase-1

The completion of Phase 1 of our capstone project marks a significant milestone in developing an advanced indoor positioning system using Multi-Agent Reinforcement Learning (MARL) and RSSI fingerprinting. Throughout this initial phase, our team has successfully established the project's foundation through comprehensive research and feasibility studies.

We have performed a thorough analysis of the methodology for collecting RSSI data, and selected an appropriate MARL algorithm that will become the heart of our implementation. Technical feasibility has been validated with a positive economical justification for minimum additional hardware.

We had a look at the state of the art in modern positioning systems. We found significant shortcomings when compared to traditional techniques-first signal variation within a dense environment and cross-building multi-agents' scalability. Such knowledge has driven our architectures very strongly and has shaped the solutions we will present. We discuss a set of major aspects that one might reasonably conceptualise relevant to degradation of signal in denser environments, complexities arising from working in multi-agents and privacy issues relating to data collection.

Fig: 15 **Phase 1 Deliverables**

Protocols are framed for secure data sharing between agents, developing preliminary strategies for dealing with environmental interference. Specifications of the environment wherein our simulation works have been defined. Comprehensive testing and validations will be done at later stages. The critical metrics for our assessment purpose have been identified along with the validation procedures for cross-build functionalities.

While challenges remain-especially concerning attainment of the desired accuracy levels and the management of signal interference-our assessment and our mitigation strategies keep us on good footing for the next phase. Completion of Phase 1, therefore has proven the project's feasibility while demonstrating that the project is much more scalable and adaptive to dynamic environments in the furthering of indoor positioning technologies. We are now ready to begin with the core implementation of our MARL framework and design the first prototype for the RSSI fingerprinting system during Phase 2.

Plan of work for Capstone Project Phase-2

In the second phase of our capstone project, we will develop the development stage of our proposed Multi-Agent Reinforcement Learning (MARL) system for indoor-WiFi positioning. We will start with the development of our core (MARL) framework based on what we learned in Phase1 foundational research and feasibility studies by using Python and specialized machine learning libraries such as PyTorch and TensorFlow.

This framework will be designed such that multiple agents can communicate and learn from each other with minimal interference. Each agent would run and collect RSSI independently. The first few weeks will mainly comprise setting up basic infrastructure: acquiring the development environment, implementing the base RSSI fingerprinting system, and forming fundamental agent architecture.

We will then proceed to develop the reinforcement learning algorithms, focusing on implementing Q-learning and deep reinforcement learning approaches that enable our agents to learn and adapt to varying indoor environments. Particular attention will be paid to designing efficient state representations and reward functions that accurately capture the complexities of indoor positioning.

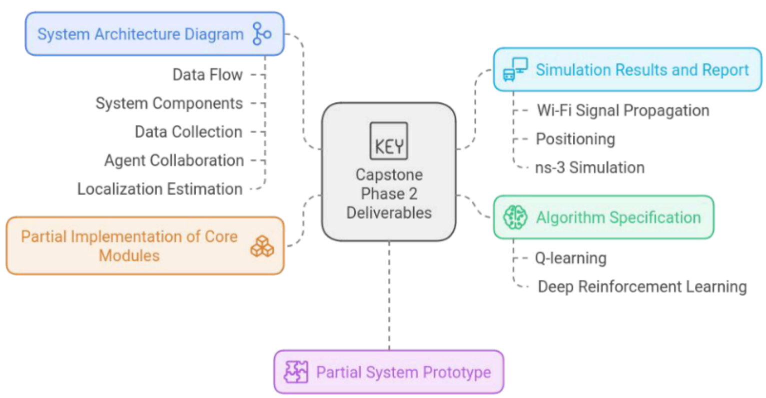

Fig: 16 **Phase 2 Deliverables**

A good part of our work would be creating a simulation environment based on NS3 or a similar framework that we would then use to test and validate our algorithms under various conditions and scenarios. The simulation framework would indeed serve us as very useful tools while we debug and optimize the system before deploying it in the real world. We will implement comprehensive data collection mechanisms that gather RSSI fingerprints while keeping strict privacy standards and security protocols in mind.

Our localization capabilities in cross-building developments will be mainly addressed using sophisticated transfer learning techniques as well as adaptive algorithms that generalize across indoor environments. To this end, we will also implement several signal processing techniques and filtering mechanisms to ensure reliability in the system by filtering out signal degradation and environmental interference.

A preliminary user interface will also be developed for testing and demonstration purposes, so we can eventually see the positioning results and agent interactions in real time. Throughout Phase 2, we will perform ongoing testing and validation sessions. We will record in detail how the system performance goes and where improvements can be made. We will implement extensive logging and monitoring of the agents' learning progress and overall system accuracy. Special focus will be placed on the protocols for communication between agents: optimizing such protocols to ensure efficient collaboration on the one hand and to avoid network overhead on the other.

The last weeks of Phase 2 will be devoted to integrating all components into a cohesive system, thorough performance evaluations of the system, and making detailed documentation about our implementation. We also begin writing our research paper with documentation of methodologies, challenges encountered, and solutions developed.

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APPENDIX A: Definitions, Acronyms, and Abbreviations

Definitions

1. **Indoor Positioning System**: A system that is aimed at the determination of any object's or person's location in a building based on the radio waves, magnetic fields, acoustic signals, and so on.
2. **Received Signal Strength Indication (RSSI)**: The value of received power in a particular device for measuring distance between transmitter and receiver.
3. **Radio Map:** Spatial representation of signal strength values at different reference points inside an indoor space, for fingerprinting.
4. **Fingerprinting:** Technique for positioning that depends on matching the actual-time RSSI measurements against pre-collected reference data stored in the radio map.
5. **Multi-Agent Reinforcement Learning (MARL):** Subset of reinforcement learning that focuses on interaction among several agents with their environment and the learning of policies to maximize collective or individual rewards.
6. **Localization**: Finding where the device or person is inside a building.
7. **Cross-Building Localization**: A method for extending indoor localization systems so that they may be deployed across multiple buildings, accommodating the challenges imposed by different buildings' layouts and environmental effects.

Acronyms and Abbreviations

1. **IPS:** Indoor Positioning System
2. **RSSI:** Received Signal Strength Indication
3. **Wi-Fi:** Wireless Fidelity
4. **MARL:** Multi-Agent Reinforcement Learning
5. **RFID:** Radio Frequency Identification
6. **ML:** Machine Learning
7. **CNN:** Convolutional Neural Network
8. **RNN:** Recurrent Neural Network
9. **AI:** Artificial Intelligence
10. **IoT:** Internet of Things
11. **MLP:** Multilayer Perceptron

12. **NS-3:** Network Simulator 3
13. **BSI:** Biharmonic Spline Interpolation
14. **MSE:** Mean Squared Error
15. **SQI**: Signal Quality Index
16. **SSID**: Service Set Identifier
17. **Wifi**: Wireless Fidelity
18. **AP**: Access point
19. **FTM**:Fine Time Measurement
20. **UWB**: ultra-wideband
21. FIFS: fine grained indoor fingerprint system

Terms that appear in References

1. **Predictive Modeling:** It involves predicting future signal propagation features based on historical data as well as environmental changes.
2. **Simulation Tools**: This will use software such as NS3 to simulate networks.
3. **Dynamic Signal Mapping:** Updating maps, which are radio, at real-time to adjust with a change in the environment in terms of movement or interference.
4. **Multipath Propagation:** The phenomenon in which radio signals reach the receiver by multiple paths because of reflection, diffraction, and scattering.
5. **Scalability:** Capability of a system that maintains levels of performance in the increasing number of devices or sizes of the environment.
6. **Kriging**: Semi-automatic geo-statistical interpolation approach for generation of radio map.
7. **Bayesian Learning:** Probabilistic approach modeling uncertainty on signal strength based positioning system.