Supervised Learning Based Approach for UAV Localization in Indoor Environments

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Abstract— **In the modern era, various real-time applications in indoor environments use Unmanned Aerial Vehicles (UAVs) for their internal operations. Day by day, the usage of UAVs in indoor spaces is gradually increasing. Using UAVs in indoor environments offers numerous benefits, including enhanced surveillance, monitoring, and data collection capabilities. The growing trend of incorporating unmanned aerial vehicles (UAVs) into interior environments underscores their potential to improve operational efficiency and safety across a wide range of sectors. When indoor GPS is unavailable, UAV localization tends to rely on vision-based techniques coupled with mechanical sensing, such as a visual navigation system or simultaneous localization. This research presents a machine learning-based supervised learning approach for indoor UAV localization using LoRa technology. This approach can serve as an additional solution for situations where GPS cannot function in indoor spaces.**

*Keywords—**Unmanned aerial vehicle (UAV), mini-UAV, indoor localization, machine learning (ML), ML for signal processing***

I. INTRODUCTION

Unmanned aerial vehicles (UAVs) are the latest technological innovations that can be used for various assignments. UAV applications are confined to the outdoors and indoor environments; hospitals, greenhouses, industrial firms, nuclear power plants, hangars, shopping malls, warehouses, assembly lines, and so on are just a few examples of inside manufacturing and service sites where UAVs could be useful. In hazardous conditions, UAVs with image devices and sensors may conduct visual and sensory inspection functions [1]. UAVs can be found in a broad range of forms and sizes. Sizes range from many meters to a few centimeters. Academics are particularly attracted to mini-UAVs due to their small size, high agility, and low cost.

We often receive inquiries about the limitations of GPS availability indoors when discussing position monitoring. GPS technology has rapidly gained popularity for outdoor location applications. However, in indoor environments, GPS tracking is difficult to establish a reliable signal and maintain accuracy. There are two main reasons why GPS is ineffective indoors: weak signal strength and subpar performance. Indoor spaces, particularly buildings, can obstruct GPS signals, resulting in a significant weakening of the signal strength and a decrease in tracking accuracy. As a result, GPS tracking indoors becomes unreliable. Additionally, GPS technology itself has inherent limitations in terms of precision. While certain industrial applications require accuracy within half-meter ranges, GPS can only deliver such precision outdoors, typically within 5 to 10 meters. Due to these limitations, alternative positioning technologies have emerged for accurate indoor tracking and monitoring. These technologies include Wi-Fi positioning, Bluetooth beacons, and indoor positioning systems, which leverage local infrastructure or wireless signals within buildings to determine device location. Considering these factors when seeking indoor positioning solutions is important, as relying solely on GPS may not yield accurate results within indoor environments [2].

GPS is ineffective indoors due to the variety of conditions. Therefore, alternative indoor navigation algorithms for UAVs should be investigated. WiFi and Bluetooth have commonly used low-range signals in existing indoor and outdoor positioning systems. However, LoRa (Long Range) technology comes into play for applications requiring longer-range capabilities. LoRa offers an extended communication range, making it suitable for various scenarios. Whether indoors or outdoors, LoRa-based systems can deliver reliable and effective performance.

LoRa is a versatile technology that may be used for both indoor and outdoor applications. It provides exceptional precision while keeping a large communication range. LoRa can give accuracy within a range of up to five kilometers in metropolitan areas, allowing for dependable locating and tracking. The range extends considerably further in rural regions, reaching up to 15 kilometers. LoRa's long range makes it a perfect solution for various circumstances, providing for reliable and accurate location in various conditions. In this research, we used LoRa technology to predict the position of UAVs with machine learning techniques in the indoor environment.

This paper aligns a project on the Supervised Learning Approach for UAV Localization in Indoor Environments. While machine learning indoor localization has been extensively researched for slow-moving objects such as humans, a notable gap exists in studies focusing on ML-based indoor localization for fast-moving objects like UAVs. This presents various challenges, including signal fluctuations and diverse multipath types, particularly in environments where UAVs are in motion. Localization in three dimensions is a major focus of this project. It consists of three fixed LoRa reference nodes, each located in three different places inside a building in a triangular position, and one moving LoRa node mounted on the UAV and moves with it. Following Fig. 01 is a diagram illustrating the basic concept of three-dimensional localization. As a result of their position, Reference Node 01, Reference Node 02, and Reference Node 03 can receive the RF signal emitted by the target node, enabling precise measurements and data analysis.

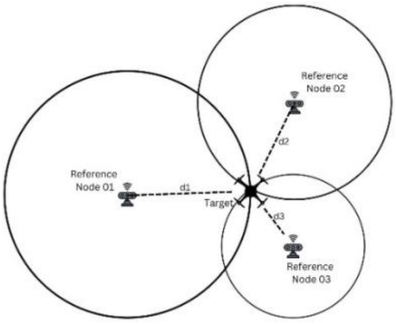

Fig. 1. Localization in indoor environments

This paper has been organized as follows. Section I gives the introduction, section II gives the Related Works, section III gives the Experimental Testbed and Dataset, section IV gives Model Training, section V gives Results and Discussion, section VI gives Future Works, and Section VII gives Conclusions.

II. Related Works

When discussing existing systems, we can learn about numerous approaches used for indoor positioning systems.

The paper [4], showcases a 3D laser radar-based UAV indoor detecting system. To estimate the UAV's velocity, they first receive the point cloud data from the UAV aerial lidar, extract its edge feature points and plane feature points, and then match the point cloud data from two successive periods. A point cloud map is being made in the meanwhile. Finally, the UAV scenario is tested using the public data set. In [5], it also presents a method with radar frequencies.

The method called Manifold Alignment with Mobile AP Detection is used in [6], and in this case, the mobile WLAN APs reduce positioning accuracy. In some research, they have presented methods with Magnetic Field Measurements for Indoor Positioning. [7] is a related research for that method, and Readings of the magnetic field are the major source of information needed to identify where the platform is. The paper [8] presents a visual-inertial odontography localization technique based on fiducial markers. That technology enables multi-rotor aerial vehicles to navigate in interior environments and handles the most challenging aspects of image-based indoor localization. The emphasis of the study in [9] is on indoor UAV localization using an Inertial Measurement Unit (IMU). They use data from onboard sensors such as accelerometers and gyroscopes to determine the UAV's position and orientation within its internal environment.

The objective of the research in [10] is to look at UAV indoor localization utilizing Bluetooth Low Energy (BLE) beacons. They deploy Bluetooth low-energy beacons around the facility and use signal strength or proximity information to predict the location of the UAV using appropriate algorithms. In the study [11] they looked at the viability of employing UWB signals to place UAVs in interior settings precisely, and they suggested a localization technique based on time-of-flight measurements. The paper [12] analyzes magnetic field patterns in the inside environment and creates algorithms to predict the UAV's position based on these patterns.

Research [13] investigates indoor UAV localization using a deep learning technique. The authors propose a Convolutional Neural Network (CNN) architecture to extract characteristics from sensor data and achieve precise localization of the UAV within indoor settings. The paper [14] describes a method for indoor UAV localization that uses Wi-Fi fingerprinting and supervised learning methods. They gather Wi-Fi signal strength data and apply machine learning techniques to pinpoint the UAV's position precisely.

In this project, we use LoRa technology with machine learning techniques to predict the location of UAVs in indoor environments as discussed before.

III. Experimental Testbed and Dataset

At the beginning of the project, we designed and fabricated LoRa-based reference and target nodes. The design and fabrication of LoRa-based reference and target nodes allowed us to adapt and optimize the hardware, particularly for our project's needs, providing accurate and efficient data collecting for indoor localization. Then, RSSI data will be collected on the second floor of the 'Suranimala Building'(the selected indoor environment area). The deployment of LoRa-based reference and target nodes enabled us to gather accurate RSSI data on the second story of the 'Suranimala Building,' offering a targeted dataset for the indoor environment of interest. Moving and reference nodes are as follows.

Fig. 2. Moving node

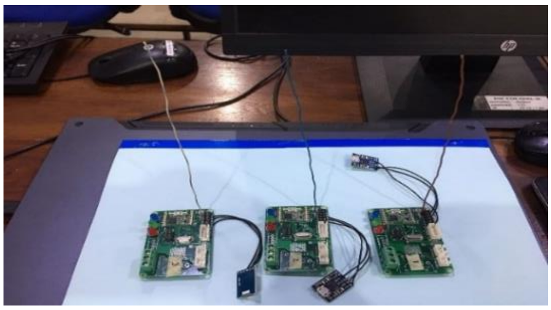

Fig. 3. Reference nodes

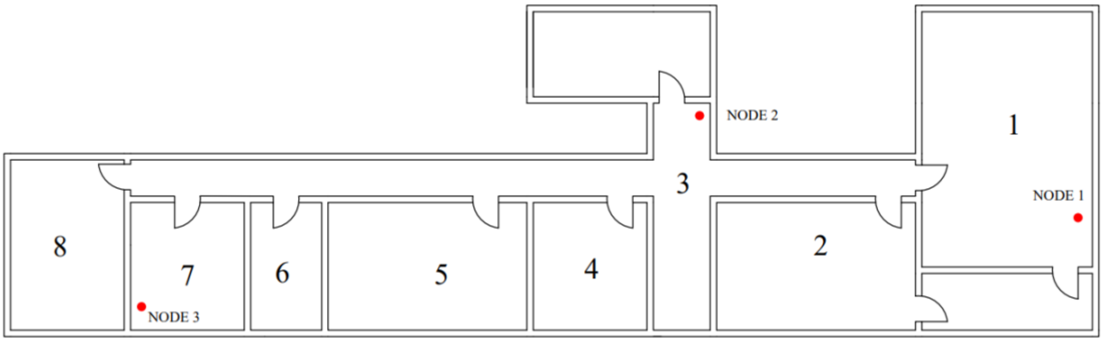

Fig. 04. Floor plan of the indoor environment

In this project, we used an indoor area within a building and chose eight distinct positions on one of the building's floors (called Suranimala building). By selecting these eight varied spots on a certain level of the Suranimala building, we hoped to capture various situations and spatial differences inside the indoor environment for comprehensive research and assessment in our project. Above Fig.04 is a sketch of the indoor environment we used.

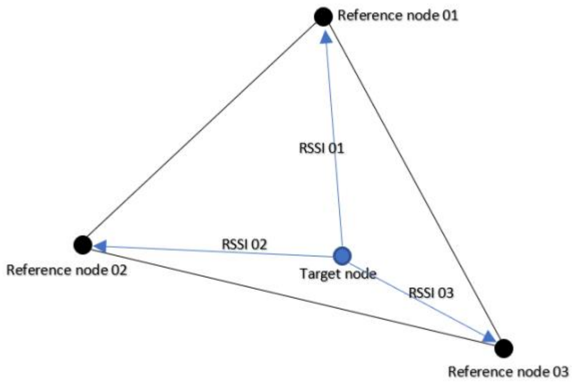

Fig. 5. Triangular method for the reference nodes

We placed the three reference nodes inside the building in a triangle arrangement. According to peer-reviewed studies, the triangle approach was the most effective method for obtaining more accurate data. In addition to implementing the best practices recommended by peer-reviewed studies[15], the three reference nodes were strategically positioned inside the structure in a triangular configuration to enable triangulation-based localization techniques, which were intended to improve the accuracy and reliability of the data collected. The figure mentions them as Node 1, Node 2, and Node 3.

The locations of the nodes are as follows.

TABLE I. LOCATIONS OF THE NODES

Node	Location
1	Lecture Theater A
2	Open Area
3	Computer Engineering Laboratory

The locations and location IDs we used are as follows.

TABLE II. LOCATIONS AND LOCATIONS ID'S

ID	Location
1	Lecture Theater A
2	Lecture Theater B
3	Open Area
4	CCNA Laboratory
5	Lecture Theater C
6	QA Laboratory
7	Computer Engineering Laboratory
8	Computer Science Department office

RSSI data were graphed for each reference node to measure variation between the eight classrooms. You can see those graphs in the following figures (Fig. 6, Fig. 7, and Fig. 8).

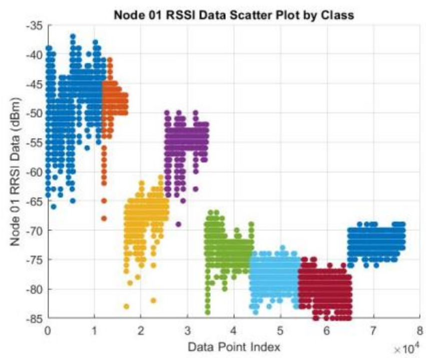

Fig. 6. RSSI data scatter plot by classes for Node 01

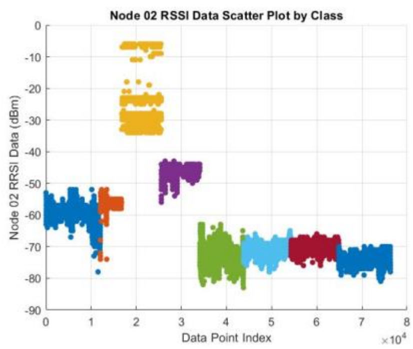

Fig. 7. RSSI data scatter plot by classes for Node 02

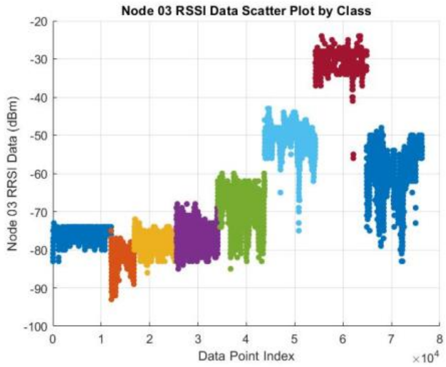

Fig. 8. RSSI data scatter plot by classes for Node 03

Fig. 9.1. Reference node 01 in lecture theater A

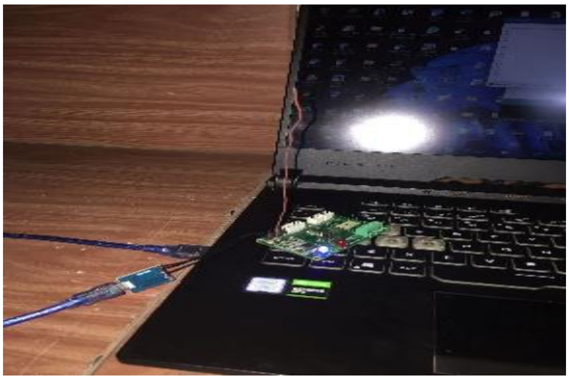

Fig. 9.2. Reference node 01 in lecture theater A

Fig. 10.1. Reference node 02 in open area

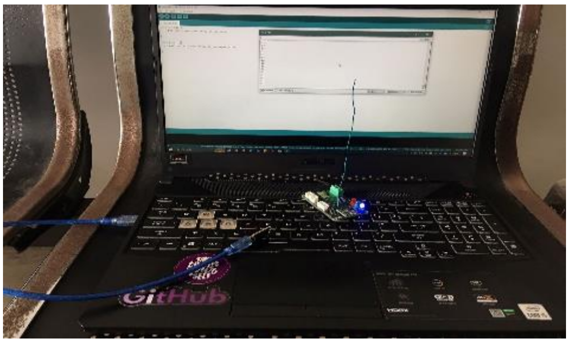

Fig. 10.2. Reference node 02 in open area

Fig. 11.1. Reference node 03 in computer engineering laboratory

Fig. 11.2. Reference node 03 in computer engineering laboratory

The images above represent the three distinct sites where the reference nodes were fixed. These carefully selected points act as secure anchors inside the system, giving a consistent frame of reference for subsequent analysis. Positioning these reference nodes is critical for appropriately measuring the system's behavior and dynamics under diverse situations.

IV. MODEL TRAINING

We used Supervised Learning machine learning algorithms to develop a model to work in this project. We tested with different ML algorithms and got metrics like accuracy, precision, recall, and f1 score as the results for the collected dataset. SVM Classifier, Naive Bayes, kNN Classifier, Random Forest Classifier, Decision Tree Classifier, and Gradient Boosting(ensemble learning) are the Supervised Learning machine learning algorithms we used to take the above results. The performance of the machine learning algorithms was evaluated using the metrics obtained to determine their efficacy in the specific project. These metrics provide helpful information about the algorithms' ability to identify and predict the expected results accurately. The performance of each evaluated algorithm varied, emphasizing the significance of picking the best algorithm for the individual project needs. Examining several algorithms enables a thorough study, which aids in the decision-making process for model selection and future enhancements.

TABLE III. RESULTS FOR THE MATRICES

Algorithm	**Accuracy**	**Precision**	**Recall**	**f1**
SVM Classifier	97% (0.975197618225773)	0.975197618	0.975983075	0.975137382
Naive Bayes	97% (0.976236239734405)	0.977850854	0.97782008	0.977720322
kNN Classifier	98% (0.98169666258955)	0.983258433	0.982793815	0.983024892
Random Forest Classifier	98% (0.982526646863533)	0.983864206	0.983502461	0.983678867
Decision Tree Classifier	98% (0.9824392800978)	0.983647066	0.983589162	0.983614874
Gradient Boosting(ensemble learning)	98% (0.983880831731609)	0.985112829	0.984620901	0.984844812

V. RESULTS AND DISCUSSION

The results of the Supervised Learning algorithms serve as the foundation for creating the model in this project, allowing informed judgments about algorithm selection and future changes to maximize its performance. Tab. 3 reveals that all approaches provide a high accuracy percentage for all of the ML algorithms we tested but with tiny differences. As a result, we can select the Gradient Boosting algorithm as the most effective approach for the particular hardware needs based on the performance of the various Supervised Learning algorithms on hardware devices. However, after applying filtering techniques to the acquired dataset, we should repeat this step. We hope to modify and improve the performance of the selected Supervised Learning algorithms by combining filtering techniques into the acquired dataset, establishing a robust and accurate model for UAV localization in indoor situations.

VI. FUTURE WORKS

In this project, we have used LoRa reference and target nodes to develop a system for position tracking of UAVs in an indoor environment. We have collected an RSSI dataset in this project and used supervised learning algorithms to predict the location. The ML algorithms we have used are only SVM, Naïve Bayes, kNN, Random Forest, Decision tree, and Gradient boosting. Other supervised learning techniques could be used for this project as well. In addition, we only experimented on a single building floor. This LoRa approach might be used in a building with several floors with the same structure. Also, if the UAV is outside the building, this may be tried for indoor and outdoor surrounding environments simultaneously and predict its location. Exploration and experimentation with additional supervised learning techniques, expanding the experiment to multiple floors within a building, and extending the LoRa approach to indoor and outdoor environments can all lead to more robust and versatile UAV position-tracking systems in various settings.

VII. CONCLUSIONS

We presented an experimental low-power RSSI data-gathering testbed based on LoRa wireless technology that will aid in the design of indoor positioning systems in this paper. GPS is a locational solution that does not function well indoors. Wi-Fi's constrained sensing range makes it unsuitable for large-scale indoor applications. LoRa is suggested over currently used techniques because of its high sensing capacity. Microcontrollers were used to design reference and target nodes to reduce energy and costs. The three reference nodes are located in different places inside the building in a triangular position and the moving node was fixed to the UAV and located in eight different places on the same floor of the building to collect. The dataset was developed with the RSSI data collected with this test bed. The dataset obtained from the low-power LoRa-based RSSI data-gathering testbed provides valuable insights and potential for developing accurate and cost-effective indoor positioning systems, taking advantage of the benefits of LoRa technology, energy-efficient microcontrollers, and strategically placed reference and target nodes for comprehensive data collection.

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